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Intra-Organizational Mobility:

Movers, Incumbents, and Communication Networks

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Intra-Organizational Mobility: Movers, Incumbents, and Communication Networks

A growing body of research suggests that intra-organizational mobility represents an important source of value creation and retention. Internal hires who are embedded in organizational social networks have greater resources and experience than external workers who are less socially connected. Notwithstanding the great practical and theoretical interest in the benefits of intra-organizational mobility at the organizational level, little is known about how individuals' intra-organizational careers unfold and the influence of social networks toward that end.

This dissertation combines findings from three separate projects to investigate the mechanisms underlying the phenomenon of intra-organizational mobility—the structural factors that explain why people move within an organization, how movers and incumbents do or do not benefit from mobility, and the individual differences in network behavior for mobility.

More specifically, in the first chapter, I examine how pre-existing communication contacts affect the mover's performance upon joining the new group. I expect that movers are more likely to join business units to which they have pre-existing ties. Nonetheless, the ties that facilitate movers' joining business units are oftentimes not those that help them to perform well subsequently. In the next chapter, I explore gender differences in network behavior as they impact on intra-organizational mobility. I argue that when a mover retains ties to the working unit that is being left, it improves the mover's post-move performance. And women are more likely to maintain such persistent social ties, whereas men are more likely to establish new ties. In the final chapter, I assess the effects on the receiving group when a mover joins, and I argue that low-ranking incumbents embedded in stable performance hierarchies suffer from the introduction of high-performing newcomers and the induced unfavorable social comparison.

I test my predictions using time-series data on the internal inter-branch transfers of retail sales employees at a US-based financial institution between November 2014 and April 2016. The dataset is composed of individual demographic information, monthly performance metrics (in dollars), and meta email communication among all employees. The data permits several methodological advancements: (1) the use of objective and consistent performance measures; (2) analysis of the temporal changes in the networks of the movers and their contacts; (3) analysis of communication network and its impact on performance, and (4) robustness checks that apply instrumental variable techniques. The approach taken in this dissertation adds a new perspective on the relationship between intra-organizational mobility and competitive advantage.

Keywords: Intra-organizational mobility; Social Networks; Performance

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EXPLORING INTRA-ORGANIZATIONAL MOBILITY

The practical and theoretical case for understanding mobility within organizations and its effects on persistent competitive advantage is compelling (Bidwell, Briscoe, Fernandez-Mateo, & Sterling, 2013; Bidwell & Keller, 2014). Frustrated by the difficulties of finding good external candidates, more and more organizations are opting to exploit their existing knowledge base, and hence, are increasingly investing in their internal hiring capabilities (Crispin & Mehler, 2013; Keller, 2017). Such investment pays off in practice. For example, Bidwell (2011), in a study of investment bankers, shows that job candidates hired from within an organization routinely outperform externally hired ones. Intra-organizational mobility, defined as job moves that take place within rather than between organizations, is the primary process that allocates human resources within organizations (Keller, 2017). Intra-organizational mobility has been demonstrated to facilitate knowledge sharing (Argote & Ingram, 2000), motivate employees (Bidwell & Keller, 2014), increase job satisfaction (Jackson, 2013), decrease turnover (Allen, Bryant, & Vardaman, 2010), and develop organizational competitive advantage (Campion, Cheraskin, & Stevens, 1994). Taken together, these studies suggest that intra-organizational mobility represents an important resource for value creation and retention in organizations.

Notwithstanding the great practical and theoretical interest in the benefits of intra-organizational mobility for organizations (i.e., Bidwell, 2011; Rosenkopf & Almeida, 2003), little research has been conducted on how to facilitate the process for internal movers beyond simply removing bureaucratic barriers to intra-organizational moves. As organizations have shifted away from hierarchical and centralized decision-making structures, employees have been tasked with exerting control of their own careers (Cappelli & Keller, 2014). The process of channeling mobility thus becomes crucial to understanding the variation that exists in movers' post-move performance. For example, Keller (2015) demonstrates that the ways in which managers search for and select among potential internal candidates account for the variance in hiring outcomes. If the process by which jobs are entered affects post-move performance, then the benefits of intra-organizational mobility that employers are able to realize are likely to depend on movers' experience during the job change. This dissertation examines the factors linking employees' prior experiences to their post-move performance, which has the potential to inform employees of the consequences of their career decisions.

In addition to its direct effects on movers, intra-organizational mobility has an indirect impact on post-move outcomes. The arrival of a new member (the mover) to the receiving unit is a social phenomenon that can indirectly shape incumbent members' social dynamics and performance. If the indirect effect is positive, the benefit of intra-organizational mobility is larger than the mere outcome. By contrast, if the indirect effect is negative, meaning incumbents' performance decreases because of the introduction of the new member, the organization reaps less net benefit, and may even be harmed. This dissertation investigates the conditions that enable or disable intra-organizational movements' positive indirect effects; in so doing, it provides insights facilitating organizations' strategic incorporation of newcomers, management of hiring activities, and promotion of talent retention.

To examine how an employee's intra-organizational career unfolds and to assess the direct and indirect effects of intra-organizational mobility, I focus on the influence of social networks. Studies on external labor markets have emphasized the importance of intra-organizational social networks for performance. For example, research has shown that, all else being equal, the use of formal versus informal hiring processes shapes not only who is hired, but also their pay, performance, and turnover in the external labor market (Fernandez, Castilla, &

Moore, 2000). Groysberg et al. (2008) find that star investment bankers oftentimes cannot replicate their previous levels of performance as a result of the loss of social capital associated with moving to a new organization. Sterling (2014) finds that having social ties prior to joining an organization helps employees to form extensive social networks post entry, especially when the quality of the new hire is not obvious. More generally, network ties are crucial when experiencing changes in the workplace, because they can work to mitigate the ambiguity and uncertainty often experienced by movers (Morrison, 2002; Srivastava, 2015). I therefore expect that intra-organizational social networks have similar consequences for those who experience mobility within an organization. I suggest that social networks function as the primary mechanisms not only placing organizational members in jobs, but also influencing their career outcomes such as performance.

DISSERTATION OVERVIEW

In this dissertation, I develop theories on intra-organizational mobility in order to understand the social-network-related mechanisms underlying the phenomenon—the structural factors that explain why people move within an organization, how movers and incumbents do or do not benefit from that mobility, and the individual differences in network behavior for mobility.

Chapter 1: Intra-organizational Mobility and Performance Disruption

Chapter 1 is a joint project with Adina Sterling and Brandy Aven. In this chapter, we ask two related but distinct research questions. First, how does an internal move affect the mover's performance? Second, how do pre-existing communication ties, or ties to those in a different business unit, affect an employee's likelihood of moving and their post-move performance? These two questions are motivated by the puzzling effect of intra-organizational mobility on movers. On the one hand, intra-organizational mobility can facilitate knowledge sharing (Argote & Ingram, 2000), boost motivation (Bidwell & Keller, 2014), increase job satisfaction (Jackson, 2013), and lower turnover (Allen, Bryant, & Vardaman, 2010). On the other hand, changing positions can be disruptive, and movers might not be able to replicate their prior performance in the absence of social networks they left behind (Groysberg, 2010; Groysberg, Nanda, & Lee, 2008).

First, building on the literature on external mobility (mobility between organizations), we develop arguments on why we expect performance to suffer when employees move across business units within the firm. Disruption arises from changes both in the content of tasks and in the organizational context in which the work is carried out (Groysberg et al., 2008; Huckmand & Pisano, 2006; Kristof, 1996). Moreover, prior experience acquired in one working context could hurt the mover's subsequent performance by inhibiting adjustment to the new context (Dokko, Wilk, & Rothbard, 2009).

Given the uncertainty inherent in mobility, we argue that a network perspective holds considerable promise for explaining both the choice of job positions and variation in movers' post-move performance. The labor market literature suggests that social networks influence individuals' job search (Granovetter, 1985; Fernandez & Galperin, 2014; Marsden & Gorman, 2001; Sterling, 2014). In a similar vein, we expect that the likelihood of a mover joining a new unit increases with the total number of pre-move communication ties that the mover has to that unit. Nonetheless, the ties that facilitate movers' joining the receiving unit might not necessarily be the ties that can help them perform in that new unit. We argue that pre-move communication ties might exacerbate, rather than attenuate, the performance disruption that movers experience, because movers might make career decisions based on the social influence from network ties, ending up with a suboptimal fit between the movers and the receiving business units.

This chapter examines social-structural mechanisms of intra-organizational mobility and highlights the paradoxical role played by communication networks. The results show that pre-existing communication ties positively increase the likelihood of movers joining a business unit. Challenging the existing theory that relationships benefit movers' adaptation, we find that moves, especially those driven by social ties, could be disadvantageous. The more movers rely on communication ties for information searching and moving decisions, ironically, the weaker their post-move performance. For employees looking to manage their careers, this research identifies the structural limitations that can prevent them from sustaining their competitive advantages. For managers who care about supporting internal transfer activity, this research brings to light challenges individuals face as they move across boundaries within an organization.

Chapter 2: Gender, Mobility and the Persistence of Communication Ties

Chapter 2 is a joint project with Brandy Aven and Adam M. Kleinbaum. In this chapter, we investigate the effect of gender on the persistence of movers' communication networks. We propose that persistent social ties can help movers, especially female movers, to overcome some of the challenges associated with mobility.

Persistent communication ties, because they oftentimes coincide with easy communication and high trust, tend to increase employees' job performance. Persistent relationships promote easy and effective communication (Dahlander & McFarland, 2013; Marsden & Campbell, 1984), encourage the transfer of information (Uzzi, 1997), and facilitate reciprocal forms of exchange (Katz, 1982). Amid the conversations on how the strength, reciprocity, and presence of a common third-party significantly increase the possibility of tie persistence (Dahlander & McFarland, 2013) and decrease the likelihood of tie decay (Kleinbaum, 2017), we still lack understanding of how individuals' tendencies to maintain extant social ties differ as a consequence of career changes. As individuals move from position to position throughout their careers, these changes inevitably result in alternations to the structures of their social networks.

Building on prior work investigating gender differences in social networks, we first argue that women are more likely to maintain persistent communication contacts whereas men are more likely to establish new communication contacts when they move within an organization. Social network and gender inequality findings suggest that women and men tend to maintain different networks, and moreover, that the differential allocation of network rewards partially account for gender differences in career outcomes (Forret & Dougherty, 2004; Ibarra, 1997). Voluminous research indicates that women in organizations are more likely to be embedded in a gender-homophonous and close-knit network; men, by contrast, are more likely to connect with higher-status sponsors, strategic network partners, and powerful coalitions (Burt, 2005; Ibarra, 1992). Moreover, women more frequently use their networks for social support whereas men use theirs for self-promotion (Forret & Dougherty, 2004; Ibarra, 1992). Correspondingly, women's networks tend to be negatively associated with positional power and positively associated with emotional support. Such networks are easier to sustain throughout career changes (Podolny & Baron, 1997). Therefore, I expect that women, relative to men, are more likely to sustain their social ties, both in general and after experiencing career changes.

In exploring the resulting performance implications, we expect that women's higher likelihood of maintaining persistent communication ties will mean they tend to suffer less job disruption arising from internal mobility than men. Analyses reveal that maintaining persistent communication ties does benefit performance on average. When experiencing job mobility, both women and men significantly increase their interaction with new contacts; the difference is that women still maintain a significantly higher proportion of persistent communication ties than men. Men's performance tends to suffer more than women's due in part to their lower likelihood of maintaining persistent ties.

This chapter provides empirical evidence that gender helps to explain differences in networking behaviors and associated performance changes when individuals move between jobs. By doing so, this chapter contributes to the research that links social networks and workplace inequality. Inequality refers to the allocation of rewards based on factors other than or in addition to an employee's work qualifications (Lin, 2000). Women oftentimes enter organizations with low-level job roles and suffer from limited opportunities to improve performance. This work highlights a potential mechanism through which women might be able to overcome the challenges in the workplace and outperform their male counterparts.

Chapter 3: Exploring the Effects of Newcomers on Incumbents: The Role of Social Comparisons

In Chapter 3, I examine how the introduction of a high-performance employee affects the performance of incumbent group members. The commonly held expectation is that the introduction of a high-performing newcomer can benefit incumbents. This view holds that hiring a high-performing employee provides incumbent members with "stretch opportunities" that allow them to interact with and learn from that newcomer. In academic research taking this view, incumbents have indeed been shown to reap several benefits, including acquiring externally developed knowledge (Song, Alemieda, & Wu, 2003), collaborating with newcomers (Singh & Agrawal, 2011), and drawing upon their knowledge or expertise for innovation (Slavova, Fosfuri

& De Castro, 2016; Tzabbar, 2009). The introduction of a high-performing newcomer is therefore understood as a means of transferring knowledge to incumbents.

The aforementioned positive view builds on the assumption that incumbent group members are equally motivated to acquire new knowledge and improve their performance; this assumption neglects individual variations in their response to the introduction of the newcomer. In contrast to this positive view, it is also possible that the introduction of a high-performing newcomer will have no benefit or even negative effects. The introduction of a high-performing newcomer could, despite the positive influence through the lens of learning, result in social comparison, causing incumbents to reevaluate their perspectives, abilities, and performance (Festinger, 1954; Kilduff, 1990). Such comparison, when the results appear to be unfavorable, is oftentimes associated with negative emotions (Edelman & Larkin, 2015), reduced self-esteem (Kuhnen & Tymula, 2012), and low effort provision (Flynn & Amanatullah, 2012; Greenberg, Ashton-James, & Ashkanasy, 2007). In turn, the introduction of a high-performing newcomer can be a source of unfavorable social comparison and consequent demoralization of low-performing incumbents, which could undermine their ability to learn or improve.

Integrating insights from social comparison theory, I argue that under a certain condition – when the group performance-ranking hierarchy is very stable – the influence of a high-performing newcomer on an incumbent depends on the incumbent's relative position in the group performance hierarchy. Stable performance rankings facilitate consensus on where members rank, which consequently reinforces individuals' reliance on the performance hierarchy to assess individual competencies and status (Bunderson & Reagans, 2011). In groups with a stable performance ranking, low-ranking incumbents are more likely to experience unfavorable social comparisons and, thus, to interpret the arrival of a high-performing newcomer as a "threat" to their already low intra-group standing instead of an "opportunity to improve." (Scheepers, 2009). Low-ranking incumbents might thus feel demoralized, exhibit low willingness to improve, and become trapped in a vicious cycle in which their performance only worsens.

Analyses indicate that when group hierarchy is stable and an incumbent's intra-group ranking is low, the performance of the incumbent declines upon the arrival of a high-performing newcomer. When group hierarchy is dynamic and an incumbent's intra-group ranking is low, the performance of the incumbent improves upon the arrival of a high-performing newcomer. I also find that the effect of the two-way interaction is mediated by the extent to which incumbents exhibit a winnowing-network response (i.e., communicating with a smaller and network of colleagues).

The results suggest that hiring a top performer is double-edged: it can either propel or impede an incumbent's performance depending on group ranking stability and the incumbent's prior intra-group ranking. In essence, the mere presence of a high-performing newcomer cannot guarantee learning or motivation to learn; rather, a positive outcome depends on an incumbent's response to the introduction of the newcomer. To take full advantage of experienced newcomers, incumbent groups should attempt to activate internal knowledge sharing and learning processes. Moreover, prior knowledge of internal newcomers enables incumbents to compare themselves with them. The research provides a case in which having day-to-day performance information potentially hurts the performance of the employer's incumbent members through unfavorable social comparison.

Intra-Organizational Mobility in a US-Based Financial Institution

To test my predictions, I collected data from a US-based private financial institution's retail sales department. There are several features that are unique in this empirical setting, in which the social-network-related mechanisms are not only relevant but also empirically measurable through communication behaviors.

First, this context promotes collaboration and competition simultaneously. A retail sales department is an important and highly autonomous organizational context that operates in a relatively intensive environment. Each employee belongs to a local branch (business unit), where they co-locate and work with others. Different business units provide similar financial services to their local customers. Their assets are their people, their reputations, and their client relationships, all of which are largely possessed by the business units. On the one hand, individual workers rely heavily on their local branches for support and client base; on the other hand, employees work independently in selling products to their customers. The major proportion of their pay reflects their total monthly sales. Employees in this department, exhibiting certain degrees of autonomy in choosing how to perform their daily tasks, face resource limitations in terms of both available customers and internal support, which require them to keep looking for efficient ways to boost productivity.

Second, this context generates an atmosphere conducive to frequent communication and learning, which consequently could lead to possible performance externalities including knowledge spillovers and shared tactics. Email communication is often used to help employees gain both task-related knowledge (for example, products they are going to sell) and context-specific knowledge (for example, the environment of the new business unit). By transmitting private information and facilitating socialization amongst employees, an intra-organizational communication network serves as the lubricant of exchange necessary to expedite mobility within the organization.

Third, the present financial institution provides a unique opportunity to understand intra-organizational mobility. The firm adopts a “market hiring” strategy in that business units post positions to job candidates from both within and outside the organization. Moving from one business unit to another is thus a voluntary choice initiated by the mover rather than top-down or centralized human resource allocation decided by the organization; this permits an examination of the role that social relations play in the process.

Data Set

I collected individual demographic information including gender, race, age, job role, job grade, organizational experience, role experience, supervisor, and branch location. I also collected monthly-updated performance measures of employees in the retail sales department between November 2014 and April 2016. Individual performance was captured in the form of the dollar value of retail products an employee sold during each month. In addition, I collected all of the employees' meta email-communication variables including sender, receiver, timestamp, and the size of each message for the same observational period. Indeed, email communication is only a partial representation of an employee's communication networks, yet nonetheless, it is a powerful source of observations and is largely consistent with communication patterns through other means (Quintane & Kleinbaum, 2011). As a conservative representation of communication network, I limit the analysis to one-to-one emails, excluding all one-to-many emails, and the focus is on communication patterns that emerge as employees' structural conditions change over time.

My dissertation substantively moves our understanding of intra-organizational mobility and social network dynamics. I explore the carry-over effects of internal hiring practices with respect to individual performance, and specifically highlight that intra-organizational mobility not only affects the movers but also the incumbents. It also helps to explain the variation in internal hires' career success through the lens of communication network dynamics. By and large, the studies of social networks in labor markets (i.e. Granovetter, 1974) and career attainment in internal markets (i.e., Bidwell, 2011; Keller, 2017) are two literatures that have barely conversed with one another. This work suggests that intra-organizational mobility and its underlying micro processes represent a fruitful avenue for future theory development.

RUNNING HEAD: THE EFFECT OF MOVERS' PRE-MOVE COMMUNICATION

Chapter 1: Intra-organizational Mobility, Social Networks, and Performance Disruption

Evelyn Zhang, Adina Sterling, and Brandy Aven

Dec. 15, 2017

Abstract

Despite the prevalence of intra-organizational mobility in organizations, the consequences associated with such activities remain undertheorized. In this paper, we investigate email communication amongst employees to examine how pre-move communication contacts (PMCs), contacts with the business unit receiving the movers, affect movers' post-move performance. Using data on lateral moves within a large financial institution, we contend that movers suffer a performance disruption when they move, and moreover, movers with more pre-move contacts will exhibit a greater performance decrement than those with fewer or no pre-move contacts. The mechanism of social influence that could account for this pattern of results is examined. Our study provides insight into the structural factors that explain when and why movers do not benefit from intra-organizational mobility.

Keywords: Intra-organizational Mobility; Communication Networks; Pre-move contacts; Performance

INTRODUCTION

Intra-organizational mobility, or movement between jobs within the same organization, provides employees with a unique opportunity to advance their careers (Bidwell, 2011; Bidwell & Keller, 2014; Bidwell & Mollick, 2015; Keller, 2017). The literature to date has extensively privileged the positive career outcomes associated with intra-organizational mobility by focusing on contrasting internal movers with external hires and highlighting the impact of internal-hiring programs on organizational outcomes (i.e., Bidwell & Mollick, 2015). It is implicitly assumed that internal movers benefit from their organizational experience and perform consistently well. Nonetheless, changing positions can be challenging for movers (Groysberg, 2010; Groysberg, Lee, &Nanda, 2008; Dokko, Wilk, & Rothbard, 2009). Movers may not perform as well as anticipated, and in fact, internal hires vary significantly in performance and turnover (Cappelli & Keller, 2014; Burks, Cowgill, Hoffman, & Housman, 2013; Keller, 2017). The question that arises, then, is what factors can explain the consequences associated with lateral intra-organizational mobility?

It is repeatedly demonstrated that social networks strongly influence individuals' job choices. Because of the challenges arising from mobility and the high expectations associated with it, individuals tend to make their choices depend strongly on social networks when they make career changes. Individuals tend to trust those with whom they have developed relationships (Uzzi, 1997); correspondingly, they are more likely accept offers from organizations their social network contacts work in or refer them to (Granovetter, 1995; Marsden & Gorman, 2001). Also, employers prefer hiring individuals who have been recommended by incumbent employees (Fernandez & Galperin, 2014; Sterling, 2014). In light of these findings, the effect of social networks has not been explored systematically for individuals who move within the same organization. Moreover, the extant network literature almost exclusively focuses on mobility across organizational boundaries (i.e., Castilla, 2005), whereby individuals can leverage existing social networks to gather more detailed *information* or knowledge about job positions.

The present paper, in exploring the effects of social networks on intra-organizational mobility, departs from most of the previous studies by explaining another mechanism that social networks can channel: *social influence*. Employees are embedded in intra-organizational social networks where they likely develop pre-move communication ties with colleagues at other business units. These pre-move communication contacts (PMCs), although oftentimes not the colleagues who can provide the most relevant job information (Casciaro & Lobo, 2008), can greatly influence individuals' perspectives, opinions, and career decisions (Krackhardt & Porter, 1985; Krackhardt, 1999; Loewenstein et al., 2001; Rider, 2012). Of course, if we examine only mobility events such as where movers move to, we would not be able to discern whether the underlying mechanism linking social networks and intra-organizational mobility is information, social influence, or a combination of both. Thus, to isolate the operative social-network-related mechanisms, we proceed to theorize with respect to the impact of PMCs on a mover's post-move performance.

The "information" and "social influence" arguments generate opposing predictions on the link between PMCs and movers' post-move performance. Specifically, while the information argument indicates performance gains for the mover, the social influence argument predicts performance losses. This difference reflects the fact that internal movers are less likely to use existing intra-organizational relationships for instrumental or economic gains, for fear that to do so might damage the social capital they have built over time. In this spirit, Casciaro and Logo

(2008) suggest that movers might privilege social factors such as trust or likeability over the pursuit of productivity. Shwed and Kalev (2013) suggest that social relationships might generate bias in favor of their acquaintances when movers evaluate potential positions; relatedly, Krackhardt (1999) argues that social ties can increase social pressures and conformity, which in turn might unduly constrain the mover's career choices. Keller (2017) finds that network-based hiring limits job-search activities within organizations, resulting in mismatches between individuals and positions.

We test our predictions in a retail sales department of a large US-based financial institution (hereafter, Big Bank). We collected data on the monthly performance of all of Big Bank's retail sales employees between November 2014 and April 2016. We also collected metadata on their email exchanges, including the sender, receiver, timestamp, and file size of each message. Big Bank is notable as a research subject for several reasons. First, mobility within Big Bank is not only very common, but also is considered to be an important avenue for transfer and accumulation of experience among its employees. Second, the availability of an objective and comparable performance measure, namely monthly sales figures, permits us to evaluate the effects of intra-organizational mobility on individual outcomes. Lastly, the metadata on email exchanges, as coupled with objective monthly performance measures, gives us the ability to analyze intra-organizational communication networks and their impact on performance. Big Bank's business units post positions to job candidates both within and outside the organization, and positions are staffed in both ways. While we have looked at the descriptive differences between movers that their non-mover peers, in the main analyses, we exclusively focus on lateral mobility, which represents movement within the same vertical level to a different business unit. Such activities are generally expected to expand horizons, achieve greater fits, and hence, improve performance (Bidwell, 2011). We examine 672 employees who voluntarily moved from one business unit to another, with their job level, role, and title remaining unchanged.

THEORETICAL BACKGROUND: THE EFFECTS OF SOCIAL NETWORKS

As organizations have shifted away from hierarchical and centralized decision-making structures, employees have been tasked with exerting control over their own careers (Cappelli & Keller, 2014). Because of both the challenges and expectations associated with changing jobs, the identification of potential career moves constitutes the type of action in which one might depend strongly on social networks to inform one's choices. There are two distinct channeling mechanisms by which social networks could affect intra-organizational mobility: information and social influence.

Social Networks Channel Information. The labor market literature widely documents how social network ties alleviate information asymmetries for both job candidates and hiring organizations. A well-established perspective in the labor market literature holds that social networks channel *information* between job candidates and organizations (Granovetter, 1973; Marsden and Gorman, 2001; Sterling, 2014). For example, Fernandez and Weinberg (1997), using data from a retail bank, find that pre-existing social networks provide job candidates with knowledge of job requirements and the most appropriate timing to submit applications.

Social Networks Channel Social Influence. In addition to information, social networks channel *social influence*, which determines how employees seek for, interpret, and utilize information that they have acquired (Friedkin, 1998). Employees are embedded in intra-organizational social networks where they can develop PMCs with colleagues at other business units. Social influence occurs when an individual's opinions, perspectives, or behaviors are affected by these connected network contacts, regardless of the information or knowledge shared through such ties.

A straightforward corollary from the literature is that social networks facilitate mobility. PMCs within social networks significantly increase an employee's odds of undertaking an internal move by bringing to their attention opportunities that become available at other business units (Feld, 1981). Above and beyond making employees aware of specific job openings, both mechanisms, information channeling and social influence channeling, predict that movers will likely join the business units where they have more PMCs. The information access provides movers with the job knowledge that is essential to their moving decision. It could also help to assuage worry and instill confidence that the move will proceed smoothly. Meanwhile, with regard to social influence, the favoritism arising from prior interactions likely enhances the perceived trustworthiness and cultural fit of a business unit, which in turn, increase the probability that the mover will accept a lateral job offer.[1]

Although it is not surprising that PMCs facilitate moves to receiving business units, it is less certain how they might affect mover performance. Extant studies in the labor market literature, by and large, suggest that pre-existing social network ties could attenuate, and even fully remediate, a mover's performance detriment. To the degree that PMCs provide information that yields a "better match" of the employee to business unit, we might suspect employees with well-paired skills and abilities to move (Jovonavich, 1979). Additionally, to the degree that PMCs socialize the mover on the norms, practices, and tasks of the receiving business unit, we might expect that the more PMCs an individual has, the better the outcomes (Fernandez, Castilla, & Moore, 2001; Sterling, 2015).

[1] We replicate these findings with our data empirically, yet we choose not to theoretically hypothesize it because the findings are well established in the labor market literature and both network arguments (information and social influence) predict the effects in the same direction. The empirical tests are summarized in the descriptive findings section, and are explained with details in the Appendix.

Nonetheless, the labor market literature also provides mixed evidence on the link between pre-existing ties and performance. Specifically, it has been found that the longer-term impact on performance is contingent on the duration of PMCs, and might not persist (Castilla, 2005; Shwed & Kalev, 2013). Merluzzi and Sterling (2017) suggest that the anticipated positive performance effect of network-based hiring practices only appears for historically-disadvantaged groups, and Burks et al. (2013) find that the positive performance effect associated with pre-existing ties ensues only when a "better pool" of candidates is formed. Taken together, these studies point to the need to understand the mechanisms through which social networks affect the performance of internal hires.

SOCIAL NETWORKS AND POST-MOVE PERFORMANCE

One of the most consistent findings has been that mobility across organizational boundaries is disruptive for movers (i.e., Groysberg et al., 2008). Performance disruption arises from both the change in the nature of the tasks that someone performs and the change in the organizational context in which the work is carried out (Groysberg et al., 2008; Huckman & Pisano, 2006; Kristof, 1996). Both sources of performance disruption are encountered by intra-organizational movers who change jobs between business units.

Intra-organizational movers need to cope with changes in the nature of their tasks. Not surprisingly, such changes can be challenging and disruptive, as movers have to spend time and effort acquiring the knowledge and skills requisite for performing well in their new jobs. Moreover, the synergies available from working effectively require social integration and rarely can be achieved without colleagues who are willing to cooperate. In this way, changes in the social context wherein tasks are performed also can be disruptive for movers; even when the nature of tasks remains constant from the intra-organizational mover's former position to the new one, job performance still worsens. Furthermore, the prior working experience of movers can form routines, working habits, and other behaviors that might or might not be helpful within a new context. Experienced workers bring with them their "repertoire of cognitions and behaviors acquired from prior jobs," along with their knowledge and skill (Beyer & Hannah, 2002). This can substantially affect individuals' perceptions on how work should be done, which in turn can dull their ability or responsiveness to adapt to the receiving working context. Such incapacity can negatively impact performance (Dokko et al., 2009). Altogether, intra-organizational change can prove challenging for the movers. As a baseline expectation, we hypothesize that:

Hypothesis 1: Movers experience a performance disruption when they move.

We proceed to theorize how PMCs affect the performance disruption that movers experience. Herein we contend that while both the information channeling and social influence channeling arguments predict that employees prefer joining business units where they have more PMCs, they generate opposing predictions of post-move performance. Specifically, while the information argument predicts performance gains for movers, the social influence argument predicts performance losses.

If the information channeling mechanism is the dominant one, greater PMCs could aid the mover/hiring unit matching process. In line with this reasoning, studies on external hiring have found that social-network-based hiring practices lead to higher-quality hires and higher starting salaries than hiring through other means (i.e., Seidel, Polzer, & Stewart, 2000; Castilla, 2005; Brown, Setren, & Topa, 2016). The key mechanism contributing to such quality difference is access to information. Job candidates can reduce information asymmetry between themselves and the organizations they are joining through their PMCs (Morrison, 2002). For example, job candidates can benefit extensively from their social network ties by obtaining tacit information on job requirements; consequently, these job candidates can prepare their CVs so as to present a better fit to the positions and apply at the most appropriate time (Castilla, 2005).

With PMCs' help, movers can, prior to a move, start to accumulate context-specific knowledge about business units that they will potentially join. Such knowledge oftentimes is implicit and not transparent to outsiders. Importantly, PMCs can provide more transparent assessments of business units than mere job postings or even hiring managers would share directly (Uzzi & Lancaster, 2004). Thereby, PMCs can help movers to select positions that fit them better and thus improve their post-move performance.

On the other hand, if the social influence channeling mechanism is the dominant one, a greater number of PMCs could hinder the matching process between movers and business units. The reasons are multifaceted. First, PMCs might lead to mismatching by restricting job-search activities. Social network relations oftentimes connect similar individuals and those in the same places; in the workplace this might mean employees working in the same segments of the market or sharing similar backgrounds. Or, biased beliefs in favor of the individuals sharing a greater number of ties could lead to superficial scrutiny (Shwed & Kalev, 2013). Feeling more familiar with certain business units, movers might invest less time and effort in assessing underlying compatibility. Insufficient variety of choices in a job selection can pose problems, both in terms of skills development in the short run and career development in the long run (Keller, 2017).

Relatedly, even if movers have pre-existing connections to all of the most appropriate business units, movers might privilege social factors, such as trust or likeability, over the pursuit of productivity (Cascirao & Logo, 2008). Direct interaction engenders a sense of preference (Molm, Takahashi, & Peterson, 2000). When interpreting gathered information, movers might view a potential receiving unit with multiple PMCs in an overly favorable light; and so too, the receiving business unit might over-evaluate known movers relative to other job candidates. The favoritism can be more salient when movers connect with many PMCs at a receiving business unit (Krackhardt, 1999; Uzzi, 1997).

Moreover, social ties can increase social pressures and generate constraints, which in turn can unduly bias a mover's career choices (Krackhardt, 1999). Movers could experience pressure in the form of a sense of increased obligation to PMCs and in the form of peer monitoring. Peer pressure partly arises from social commitments or obligations. Employees care about what their PMCs think, and they may feel obligated to their PMCs who facilitate mobility processes. The mutual care between movers and PMCs would encourage movers to be more willing to enhance their relationships and make career decisions accordingly (Dabos & Rousseau, 2004; Fernandez et al, 2000). Peer pressure also arises from social monitoring, which provides the organization and a worker's peers with better information about the worker's behavior and performance results and reduces the worker's opportunities to engage in hidden action. Consequently, prospective movers are less likely to engage in self-centered decision making, such as breaking promises for better offers, when changing jobs within an organization (Barron & Gjerde, 1997; Loughry & Tosi, 2008). Taken together, social influence exacerbates the costs that intra-organizational mobility imposes on movers, for example by potentially limiting the search to a narrower segment of the opportunity space, by exercising biases in favor of positions without a clear assessment of quality, and by acting on a sense of increased obligations to PMCs.

We propose that social influence channeling is likely to be the dominant mechanism for intra-organizational mobility for three reasons. First, access to information is of less challenging for internal movers, which diminishes the role of information channeling in making the decision to move. The challenge for internal movers is how to use the information they have access to and how to find the most relevant information (Keller, 2017; Obukhova & Lan, 2012).

Second, internal movers are less likely to use existing intra-organizational relationships for instrumental or economic gains, for fear that to do so might damage the social capital they have built over time. In other words, intra-organizational movers have a high need for maintaining social capital. Even when the enacting social relationship is a repayment of a past obligation, there is an opportunity cost, that of the "credit slip" used up by the mover (Coleman, 1988).

Third, intra-organizational movers do not have high pressure to prove themselves to their colleagues, especially when they move to units where they have a number of PMCs. Familiarity with PMCs and prior organizational experience would lead the movers to be more relaxed regarding proving themselves worthy in the new situation and demonstrating their capability on performing job tasks. Taking together the low need for information, the high need to maintain social capital, and the low need to prove oneself, PMCs are likely to channel social influence for prospective movers, which in turn, could lead to performance losses.

Hypothesis 2: As pre-move communication contacts in the receiving units increase, movers experience a higher level of performance disruption.

Social Networks, Geographic Proximity, and Intra-Organizational Mobility

Geographic proximity facilitates information access, because it is likely to be a proxy for a host of possible mechanisms that could channel information, of which social network tie is one. Information on jobs and work-related knowledge can spread by numerous means, including social network ties, shared socialization during training, casual gatherings, and other hosts of social dynamics that could result from various associations taking place among geographically proximate individuals (DiMaggio & Powell, 1983; Rosenkopf & Almeida, 2003).

Geographic distance increases the movers' need for information. Indeed, job-related-information-channeling PMCs, while perhaps more prevalent among employees working in proximate business units, are made across distant business units as well. While access to information obtained through a PMC is likely to be available through other means when mobility occurs between proximate business units, it might not be readily available through other means when the tie is contained between geographically distant regions. Thus, information access is largely localized and the value of social networks as information channels is less pronounced for those who move between geographically proximate business units than for those who move between distant ones. This is consistent with what we know from the sociological argument that connections to socially distinct contexts, rather than proximate ones, channel the most helpful or valuable information (Burt, 1992; Corredoira & Rosenkopf, 2009; Granovetter, 1985).

By contrast, the effects of social influence are more pronounced for those who move between geographically proximate business units than for those who move between distant ones. This means that the closer in the distance PMCs are, the larger the impact they have on one's daily working life, and the more likely that social influence is dominant. Distant job changes, however, are more similar to inter-organizational job changes, where individual movers are less constrained by intra-organizational network structures. Prospective movers, in the case of a distant move, have more freedom to both broaden their job search and research the job extensively, are less vulnerable to evaluation biases, suffer less peer pressure, and tend to be more serious both in searching for jobs and deciding to make a move.

Hypothesis 3: The negative association between PMCs and a mover's subsequent performance is stronger when the mover moves between geographically proximate business units than between distant ones.

EMPIRICAL SETTING

To investigate how social networks (particularly PMCs) influence an employee's choice of business units to join and the subsequent post-move performance, we collected data from Big Bank. Many organizations, frustrated with the difficulties of finding good external candidates, are opting to draw from their existing talent base, and hence, are increasingly investing in their internal hiring capabilities (Bidwell, Briscoe, Fernandez-Mateo, & Sterling, 2013; Crispin & Mehler, 2013; Keller, 2017). Big Bank is one such firm that has shown great interest in utilizing its talent base. The business units at Big Bank are autonomous, with interactions concentrated within them. For example, to fill jobs, a business unit would post positions to both internal and external job candidates. Thus, moving from one business unit to another is a largely voluntary choice initiated by the mover rather than a top-down or centralized human resource allocation decided by the organization.

As a US-based large retail bank, Big Bank aims to provide a wide range of financial services to its customers. Big Bank is organized into four large departments: retail, asset management, corporate and institutional banking, and mortgages. We focus our analysis on the retail sales department because of the availability of individual monthly performance data. Retail salespeople strive to provide products and services, such as residential mortgage loans, saving plans, investments, and property purchases, to customers and generate value for the bank. Retail sales employees work independently to sell financial services to their local customers, and are financially rewarded accordingly. Each employee belongs to a local business unit where they work with others. The department computer automatically calculates the total dollar amount of sales each employee makes by the end of each month.

Email communication is often used to help employees gain both task-related knowledge (i.e., products they are going to sell) and context-specific knowledge (i.e., the environment of the new business unit). By transmitting tacit information and permitting socialization amongst employees, the communication network in the form of emails serves as the lubricant of exchange necessary to facilitate mobility within the organization. Altogether, this context provides us with a unique opportunity to study the phenomenon of intra-organizational mobility and its relational mechanisms.

Data

We collected individual demographic information including gender, race, age, job role, job grade, organizational experience, role experience, supervisor, and branch location. With this information, we created a data file with entry and exit histories for each employee in a business unit (branch). An entry was registered when the employee appeared for the first time on a business-unit list; an exit was recorded when the employee no longer appeared on the list. An intra-organizational move was recorded when an employee exited one business unit and entered another. During the observation period between January 2015[2] and April 2016, 672 lateral movers changed business units within Big Bank. We collected monthly-updated performance data on the retail sales department employees. The dollar value of retail products or services sold by the end of each month represents individual performance.

Additionally, we collected the complete record of the internal email exchanges during the observation period from Big Bank's servers. Indeed, email communication is only a partial representation of an employee's communication network, and yet nonetheless, it is a powerful source of observations that is largely consistent with other communication patterns (Quintane & Kleinbaum, 2011). To protect the privacy of individuals, Big Bank stripped all messages of email content, leaving only the metadata (sender, receiver, size, and timestamp). The dataset includes 135 million dyadic communications. In the core models, as a conservative

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[2] Mobility in the first two months of the observation period was excluded due to the need to construct pre-move communication contacts.

representation of Big Bank's intra-organizational communication network, we limit the network analysis to one-to-one emails,[3] excluding all one-to-many emails, interactions with external contacts, or interactions with temporary workers. The final dataset contains 70 million communications sent and received over the course of eighteen months.

DESCRIPTIVE FINDINGS ON INTRA-ORGANIZATIONAL MOBILITY

This section explores two distinct but related questions that arise naturally in describing intra-organizational mobility: who moves, and where do they move? The first question is well documented in the literature. It is widely considered advantageous for an individual to maintain an extensive network—an idea expressed most succinctly in Lin (1999)'s "extensity-of-ties" proposition—so that individuals may access information on career opportunities. Recent work by Rider et al. (2017) further tests the proposition that individuals with more ties are more likely to access job opportunities and make career changes than individuals with fewer ties. Particularly, they find that NFL coaches with extensive ties to other teams' coaches (i.e., degree centrality) are more likely to change employers than their less-connected peers.

In light of these studies, it is not surprising that individuals with more extensive ties (i.e., degree centrality) to other business units are more likely to make intra-organizational moves. We test this expectation with the full sample of observations. The full sample consists of observations on 12,916 employees over 100,042 individual-months. A multi-level regression (where individuals are nested in business units) is conducted. The dependent variable is the likelihood of intra-organizational mobility and turnover, and the independent variable is an individual's social network characteristics.

The results, shown in Table A2 in the Appendix, replicate the findings in the labor

[3] Fully 96.7% of all internal email exchanges have no more than four recipients; 83.5% of those are one-to-one emails.

market literature. Analyses suggest that social network characteristics predominantly affect the likelihood of intra-organizational mobility. Specifically, an individual's prior performance does not predict that individual's likelihood of moving between business units, but does affect the individual's likelihood of getting promoted and leaving the organization. Analyses suggest that individuals with extensive ties to colleagues outside their focal business units are more likely to make intra-organizational moves in the subsequent months, more likely to get promoted in the subsequent month, but less likely to leave the organization compared with their colleagues who are less connected.

Relatedly, regarding the second question, where movers move to within the organization, we expect movers are more likely to move to the business units where they have greater numbers of PMCs. We estimate the effect of PMCs on the likelihood of a mover joining a receiving business unit by adopting a case-match design where we pair each actual receiving business unit with observationally equivalent business units that a mover could have moved to but did not. By doing so, we take the perspective of the movers and assume individuals will consider observationally similar business units as their potential selection sets. For each mover, from our original population of 2,830 business units across 36 unique markets, we constructed a case-matched sample. In particular, out of all 1,901,760 unit-month possibilities (672 movers * up to 2,830 business units in the month of moving), we matched 607 cases to 12,032 matched controls. As we constructed the case-match sample by matching the observed business units that movers actually joined to the possible business units that movers could have joined, the model adopted a within-mover comparison. Because business units essentially drive the hiring of employees, with movers making decisions on whether they would accept a job offer, we analyzed the intra-organizational mobility events with a logistic regression.

The results, shown in Table A4 in the Appendix, suggest that movers are more likely to move to business units where they have more PMCs than where they have fewer or no PMCs. The effect of PMCs on the likelihood of joining the business unit is nonlinear. The nonlinearity effect partly comes from a ceiling effect: that probability cannot increase at the same rate when approaching one. Above and beyond the ceiling effect, the nonlinearity of PMC also speaks to the two mechanisms that social networks can channel. If the dominant mechanism driving intra-organizational moves is information, we should be able to observe a stronger curvilinear effect as the marginal increase of one more PMCs decreases in "value" in terms of channeling information. Alternatively, if the dominant mechanism driving intra-organizational moves is social influence, we should be able to observe a weaker curvilinear effect, because the marginal increase of one more PMC increases for social influence. Further analyses support the latter case, that the curvilinear effect is indeed stronger when the distance associated with mobility is greater, indicating that social influence is likely to be the dominant mechanism in the context of intra-organizational mobility.

Taken together, these descriptive findings help us to reaffirm that social networks greatly affect intra-organizational mobility. In the subsequent section, we proceed with the main analyses on PMCs, intra-organizational mobility, and its performance consequences across the movers.

MAIN ANALYSES

Sample

To test our three hypotheses, we examined the effect of PMCs on the movers' post-move performance. To do so, we modeled the performance of the 672 movers over 10,042 individual-months. All of the movers in the sample made one intra-organizational move over the course of our observation period. We eliminated the movers who moved at the very beginning (Nov. and Dec. 2014) and at the very end of our observation period (Mar. and Apr. 2016) to ensure that we had observations on the pre- and post-move performance for each mover.

Modelling Strategy

The purpose of this paper is to examine lateral intra-organizational mobility and the effects of social networks on that end, by systematically exploring the linkages between movers' PMCs and their performances. To do so, we examine the lagged effects of intra-organizational business-unit changes and PMCs on individual performance in the subsequent period. As sales performance is calculated on a monthly basis, so too do we condense the observations to monthly observations, being careful to leverage the more granular data, and perform mixed-level regressions predicting next-period performance.

Given the unbalanced-panel data structure, we first ran the analysis with a generalized linear regression on movers' monthly performance at the mover-month level, including both individual- and month-fixed effects to test hypothesis 2. The model is represented by Equation 1,

$$P_{i,g,t} = \beta_0 + \beta_1 X1_{i,g,t-1} + \beta_2 X2_{g,t-1} + \beta_3 M1_{i,t-1} + \beta_4 M2_{i,t} + \varepsilon_{i,g,t}$$

Equation 1

where $i = 1,\ldots.n$ individual movers, g = 1,…m business units, and t = 1,…k months. Individual i works in business unit g in month t. The dependent variable P represents the individual's performance in month $t+1$; $X1$ consists of the individual-level controls in month $t\text{-}1$; $X2$ consists of the business-unit-level controls in month $t\text{-}1$; M1 is a binary variable indicating whether the individual changes job location, and M2 is a continuous variable representing the total number of months that have passed since moving. Specifically, if individual i moves from one business unit to another in month t, M2 starts counting from month $t+1$. $\in_{i,g,t}$ is the residual error term.

The fixed-effect model essentially represents a single intercept as a mean value and a set of individual deviations from that mean. Individual fixed-effects can be understood as "fixed" or persistent differences across individuals in the sample. Having examined a performance variation arising from intra-organizational mobility within individuals, we next turn to a discussion of our analytical strategy to test Hypothesis 3, or the relationships between PMCs and the post-move performance variation across movers.

As PMC is not a time-variant variable (in that we only have a one-time observation for each observable intra-organizational move, we run a linear random-coefficients model (RCM) – also known as a mixed-effects model with varying or random coefficients—to estimate its effects (i.e., Knott, 2008). Such models include one or more coefficients that are not fixed (in our case, across individuals) but are instead comprised of two components: a mean effect on the outcome, and a randomly distributed component that varies for each sampling unit (herein, the individuals). In this way, the model allows for individual-specific heterogeneity in slopes. The heterogeneity in random coefficients reflects individuals' ability to adjust to location changes (intra-organizational mobility) and perform well subsequently. The random-effect model accounts for the possibility that observationally equivalent individuals differ on unmeasured characteristics (Hausman & Taylor, 1981).

The random-effect determination we have presented examines the changes in individual performance as a response to the mobility "treatment," allowing individual coefficients to vary. This estimation focuses on movers' variations in responding to mobility. Thus, in the context of our study, one can think of the random coefficient as estimating each mover's ability to adjust to a location change compared with an average individual, capturing the disruption of performance that results. We proceed to test how the random coefficients – in this case, the random slopes for the mobility independent variables *location change* and *time since move* – are explained by total PMCs. As we have argued, *location change* should be disruptive for the movers. In the third hypothesis, we hypothesize that the total number PMCs will be associated with the degree of performance disruption an individual would exhibit in response to the moving. That is, PMC should account for the heterogeneous coefficient associated with the *location change*, which essentially represents the extent to which individuals differ in the performance shock they exhibit in response to moving.

To examine the effect of PMCs on movers' post-move performance, following standard practice (Gelman & Hill, 2006), we include interactions between the mobility variables (*location change* and *time since the move*) and PMCs, such that we can obtain estimates of how PMCs affect the performance disruption an individual experienced. Holding the mobility variable constant, we will be able to determine whether the number of PMCs predicts larger performance disruption resulting from mobility. The mixed-effect model with random coefficients is represented by Equation 2.

$$P_{i,g,t} = \beta_0 + \beta_1 X1_{i,g,t-1} + \beta_2 X2_{g,t-1} + \beta_3 M1_{i,t-1} + \beta_4 M2_{i,t} + \gamma 1_i PMC \times M1_{i,t-1} + \gamma 2_i PMC \times M2_{i,t} + v_{1i/g} + \varepsilon_{i,g,t}$$

Equation 2

Compared with the fixed-effect model, the random-coefficient model includes the "slopes" $\gamma 1_i$ and $\gamma 2_i$, representing the variation in an individual's response to mobility variables. v_{1i} is the individual-level random intercepts where an individual is nested in a business unit, and $\in_{i,g,t}$ is the residual error term.

To test Hypothesis 3, we adopt a "split sample" approach and run the mixed-effect models on each subsample respectively. We use this "split sample" approach here because the main independent variable, PMC and intra-organizational mobility (in the form of location changes), is already a two-way interaction, and thus examining the moderating effect of geographic distance will require us to include a three-way interaction. The inclusion of the three-way interaction between PMC, location change indicator, and geographic distance not only involves complexity in interpreting the coefficient of the interaction terms, but also can lead to estimation errors due to the correlation between PMC and geographic distance. Specifically, the two sub-samples we are: mobility events with *above median* distance and those with *below median* distance. We also test the effects for same-city and same-state mobility events.

Measures

Individual Performance. The performance of retail sales employees is captured by their monthly sales in dollar amounts. In detail, we measure individual performance using the total dollar value of products that a retail sales associate sells per month in any given month. The dollar value provides a good measurement of how productive the sales employee is, as it is not subject to the common issues of subjective performance ratings (i.e., supervisor evaluations). In the main models, we report the estimation with the z score of the performance. The results remain robust on a log scale.

Geographic distance. Geographic distance measures the absolute distance in meters between a mover's prior working unit and the receiving (or controlled) business unit. For each business unit, we use the R package "geosphere" to obtain the precise point distance between the two zip codes, particularly between the centroid of the zip code areas. The distance between two business units located in the same zip code is therefore zero.

Location Change. This variable is binary and calculated for each employee, and indicates whether or not the individual changes branches (locations) in month *t.* If the employee moved from one business unit to another within Big Bank in month *t*, the variable is marked as 1.

Time Since Move. This is a continuous variable for each mover in the sample, and indicates the number of months passed since the individual changed branches (locations) in month *t.*

PMCs. The main independent variable is the total number of PMCs. As the persistence of pre-existing relations affects movers' subsequent performance (Castilla, 2005), in the main models that we report, we calculate PMCs by counting the total number of unique email receivers that a mover has communicated with two months *prior to* the move and *continues* communicating with for at least two months after the move.[4] For 95.2% of the movers, a two-month window prior to the move captures all of the unique pre-move email recipients that they communicate with. The other 4.7% of the movers have few communication contacts with whom they communicated at least once three months (and longer) prior to the move but never communicated again. We exclude these communication contacts when we count the total number of PMCs. In other words, in the main analyses, we focus on pre-move email recipients that the movers maintain continuous interactions with. We additionally tested the robustness of the effects by determining the PMCs using other alternative means, specifically, we also test the effects using ties with a high mutual volume of the email exchange, symmetrical ties, and simmelian ties.

Control Variables. To increase the confidence in the proposed effects of PMCs on individual performance, we also consider and control for the alternative mechanisms that can affect individual performance, explained as follow.

[4] Table A5 reports robustness checks on the two-month time window.

Individual Demographic Characteristics. Particularly, we control for individual *gender, race, age, organizational experience*, and *role experience*. Additionally, we include individual random intercepts where each individual is embedded in a local business unit so as to account for unobservable individual heterogeneity.

Individual Network Characteristics. Individual network centralities have been widely documented to affect individual performance (Burt, 1992). To control for the variation in an individual's social network, we calculate individual ego-network characteristics. The individual ego-network represents the email recipients with whom the focal individual communicates and how they communicate with each other. This is an efficient way to capture individual network variation when the whole network is large. Particularly, in the models, we include ego-network *size, density* (the total number of observed communications divided by the total number of all possible communication channels), *degree centralization* (the extent to which communication is distributed equally), and the *clustering coefficient* (the extent to which communication exhibits high transitivity).

*Business-unit Characteristics***.** Individual performance can also be affected by colleagues and the working context wherein tasks are performed (Groysberg et al., 2008). Thus, in addition to including the random intercepts associated with business units, we control for *unit size, average past performance, the total number of organizational levels (hierarchy), the total number of supervisors, average organizational tenure*, and *average role tenure*.

Market-fixed Effects. We include the *market* dummy variables to control for the unobserved differences across the 36 different markets in the United States.

Month-fixed Effects. We include the *month* dummy variables to control for the unobserved differences associated with months of the year.

MAIN RESULTS

Hypotheses 1 and 2: Intra-organizational Mobility, PMCs, and Movers' Performance

Descriptive statistics on the panel sample are reported in Table 1.1. Table 1.2 presents the estimated effects on individual performance in the period following a move. The baseline model is a fixed-effect model (including both individual- and month-fixed effects) as shown by model 1 in Table 1.2. From the baseline model, we confirm that intra-organizational mobility is challenging in that changing business units negatively affects the mover's performance in the subsequent month. Model 2 adds *time since the move* to the individual-fixed-effect model and shows that as *time since the move* increases, individual performance increases. Model 3 includes both *location change* and *time since the move*, and indicates that the effects persist. Models 1, 2, and 3 together suggest that movers suffer a short-term performance decrement after moving to a new location and that their performance slowly recovers after the initial disruption, supporting Hypothesis 1.

[INSERT TABLES 1.1 AND 1.2 ABOUT HERE]

Model 4 includes the individual random intercepts that allow performance level to vary by individual. The random-intercept models provide consistent estimations as models 1, 2, and 3 in Table 1.2. In model 5 in Table 1.2, we include the interaction between PMCs and the mobility variables (*location change*). Model 5 suggests that individuals suffer more disruption from *location change* when they have more PMCs (indicated by the negative interaction effect between PMCs and *location change*). Moreover, in model 6, we include the interaction between PMCs and *time since the move*; this model suggests that individuals' performance recovers more slowly when they have more PMCs (indicated by the negative interaction effect between PMC and *time since the move*). Model 7 includes both interactions, and the results hold. Together, models 5, 6, and 7 in Table 1.2 confirm that the performance disruption is greater for movers who have more PMCs than for those who have fewer or no PMCs, thus supporting Hypothesis 2.

Hypothesis 3: The Role of Geographic Proximity

[INSERT TABLE 1.3 ABOUT HERE]

To test the effect of geographic distance/proximity in Hypothesis 3, we differentiate proximate and distant mobility events and re-estimated the specification in Models 5, 6, and 7 in Table 1.2 for each type of intra-organizational moves. The results are reported in Table 1.3. Particularly, models 1, 2, and 3 in Table 1.3 estimate the effects of proximate job changes where the move distance is smaller (more proximate) than the median while models 4, 5, and 6 report the effects of distant job changes. The proposed negative interaction between PMCs and job changes on performance only holds for proximate moves, but not distant moves, supporting Hypothesis 3. Moreover, we included tests for the same-city moves and same-state moves, to capture the ease of inadvertent interaction underlying the distance effects. The proposed negative interactions between PMCs and changing business units are significant for both same-city and same-state moves. The contrast indicates that social influence as the likely dominant mechanism for intra-organizational mobility.

ALTERNATIVE EXPLANATIONS

The main results support the three hypotheses formulated above. Together, they suggest that movers suffer a short-term performance disruption as a result of the intra-organizational *location change*. This performance disruption is greater for movers with more PMCs than for those with fewer or no PMCs. Moreover, the performance recovery rate is also slower for movers with more PMCs, suggesting that movers with a greater number of PMCs end up with positions providing a worse fit. Taken together, the results support that social influence as the main driver between PMCs and movers' intra-organizational job changes.

[INSERT TABLE 1.4 ABOUT HERE]

In order to further test the relationship between social networks and movers' post-move performance, in Table 1.4, we present supplementary analyses including controls for alternative mechanisms. We first assess the robustness of the results to a broader range of individual-level controls and business-unit-level controls. in Table 1.4, model 1 reports the analysis controlling for individual ego-network characteristics; model 2 reports the analysis controlling for business-unit-level characteristics such as size and average performance in the prior quarter; model 3 presents the analysis controlling for all predictors; models 4 and 5 present the analyses for proximate and distant job changes, respectively. All of the hypothesized effects remained robust.

ROBUSTNESS CHECKS

Thus far our findings show a performance disruption on average as the result of an intra-organizational move, and provide evidence to support all three hypotheses toward a deeper understanding of how this performance disruption varies across movers. We further proceed with three sets of analyses to test the robustness of our results. While we have longitudinal data that helps mitigate against a number of empirical concerns, one that remains is that the PMCs are not randomly assigned (Mouw, 2006). An ideal empirical approach for testing the effect of PMCs involves random assignment of PMCs and a subsequent analysis of lateral mobility and performance. Unable to implement this approach, in the first two sets of robustness analyses we seek to leverage exogenous variation in the number of PMCs to estimate the effect of ties on outcomes of interest. Additionally, to confirm that our results are robust as to the number of PMCs, we also test to determine that the results hold using different ways to quantify PMCs. Table 1.5 compares the results from the main models with all predictors (Model 3 in Table 1.4) with the coefficients from these robustness-checking models.

[INSERT TABLE 1.5 ABOUT HERE]

Examining movers moving from "closed" branches. A robustness check of the proposed relationship between PMCs and performance loss was performed for the movers who were working at business units that were eventually closed. This set of movers were forced to move due to external factors they could not control, mitigating the concerns of endogeneity with regard to the mover's motives for moving. That is, one might be concerned that movers are a select group of individuals moving for reasons that would lead them to have poor performance post-move (i.e. they do not "play nice in the sandbox" with other employees). The analysis with this subset of movers helped to identify the relationship between PMCs and the exacerbated performance decline associated with moving. Model 1 in Table 1.5 reports the results. The effect remained robust despite the decreased sample size.

Instrumental Variable. We used *the total number of employees coming from the receiving units to movers' home units prior to a mover's move* as an instrumental variable to help identify the relationship between movers' PMCs and post-move performance. On average and all else being equal, our identifying assumption is that colleagues coming from the receiving units to a mover's original unit would facilitate communication between the two business units, but would not affect movers' post-move performance, given that the employee is no longer there.

Like recent studies seeking to establish network effects by leveraging exogenous variation in individuals' network ties (i.e., Sterling, 2015; Hasan & Bagde, 2015), we used an instrumental variable estimation approach that exogenously varies individuals' ties to colleagues in other business units. Importantly, this variation is independent of individuals' job-changing intentions or post-move performance. This shock essentially inflates variation in individual-branch communication tie counts, allowing us to test the argument that communication ties affect movers' post-move performance and not vice versa.

A valid instrumental variable must satisfy several additional statistical conditions (Wooldridge, 2002). In our case, we expect the variation in *the total number of PMCs* to increase with the total number of employees coming from the receiving unit. Our instrumental variable influences the movers' post-move performance through its effect on the communication ties established between the mover and the receiving unit, conditioning unit-specific variation on the probability that is common to all movers.

The results using the traditional 2SLS approach are reported in Model 2 in Table 1.5. The count of employees coming from the receiving units to movers' home units must be correlated with the independent variable (i.e., PMCs). The instrument variable and PMC variable are significantly correlated ($r = 0.25$, $p < 0.05$). The first-stage estimation revealed no concerns about instrumental weakness ($\beta = 0.43$, $p = 0.031$). The results are largely consistent with the findings reported above; aside from the magnitude of the coefficients, the main differences are that the IC models reveal no significant relationship between PMCs and their performance recovery rate. The overall interpretation of the results remains unchanged.

Other ways to measure PMCs. We additionally tested the robustness of the effects by determining the PMCs using ties with a high mutual volume of email exchange (measured by calculating the total number of email exchanges between each pair, counting only the pairs with higher than median volume as pre-move contacts), symmetrical ties (measured by comparing the total number of email sent from the mover to the contact and received by the mover from the contact, counting only pairs with lower than median difference as pre-move contacts), and simmelian ties (ties with a third-party connected with both ends, calculated as suggested by

Krackhardt, 1999). Models 3, 4, and 5 in Table 1.5 report the estimations. The analyses with control variables show consistent results with the findings reported in the main models where we measure PMCs by the total number of ties that are retained after the move. All interpretations remain.

DISCUSSION AND CONCLUSION

This paper examines social structural mechanisms of intra-organizational mobility and finds that communication networks play a paradoxical role. Challenging the existing theory that relationships benefit a mover's adaptation, we find that moves, especially those driven by social ties, are disadvantageous in terms of performance. The more that movers rely on communication ties to search for information and make moving decisions, ironically, the weaker their post-move performance.

The results presented in this paper highlight that intra-organizational mobility comes at a cost to movers. Building on literature that investigates pre-entry social ties and post-entry job outcomes, we propose that pre-move communication could help movers overcome the liabilities coming from both information asymmetry and socialization. Nevertheless, not all communication ties are equally effective, and moreover, our theory casts doubt on a more-is-better expectation for the benefit gained from pre-move communication. The actual benefit that movers enjoy highly depends on the network characteristics of their PMCs.

Our main contribution to the theory is to provide understandings of intra-organizational mobility, the performance of movers, and the social structural mechanisms leveraging these effects. The link between social networks and mobility has not been completely absent. Researchers have long recognized that networks play a key role in external mobility; research has found that pre-entry trust ties significantly increase individuals' probability of getting a job

(Castilla, 2005; Fernandez et al., 2000; Seidel et al., 2000) and increase new hires' networks after they join the organization (Morrison, 2002; Sterling, 2014; 2015). For example, trial-employment programs that allow employees to work at the organization before more permanent hiring decisions are made not only facilitate the twin selection between employees and organizations, but also improves post-hiring performance (Cappelli & Keller, 2013; Sterling, 2015). Despite this knowledge, a network perspective on intra-organizational mobility, job changes within an organization, remains underdeveloped. This underdevelopment partly reflects a data issue: it is very difficult to observe relational data over time in a context where employees move within an organization, which is the approach pursued in this paper. Practically, our theory challenges the conventional wisdom that intra-organizational mobility helps with organizational growth and development. Intra-organizational mobility can be counter-productive because movers are structurally restricted.

We have highlighted that the benefits movers gain from pre-move communication might not be as great as anticipated, and social influence might lead to less quick adjustment after the move. The findings of this paper also point to some interesting directions for possible field interventions. It is an interesting future direction is to examine whether or not organizations can facilitate movers' integration into the new working business units by launching mentor programs. Mentors are believed to be helpful in this regard because they help new business unit members' formation of network ties (Sterling, 2015). In fact, organizations invest in mentoring programs to help improve employee commitment, particularly among its diverse members (Chatman, 1991; Kalev, Dobbin, & Kelly, 2006). Whether or not mentors can act as a "substitute" for PMCs in helping the movers to fit into the new working environment remains to be explored. In addition, when launching mentor programs, it is crucial to explore the "best" set of mentors. A future direction along this line is to explore the “ideal” combination of PMCs that can maximize the benefit for movers. One direction to explore is the variations in the relational composition of the PMCs and how various compositions can help movers reconcile the widely-documented structural trade-off between cohesion and brokerage (i.e., Aven & Hillmann, 2017). In particular, a set of PMCs with structural complementarity, composed of both individuals who occupy brokering positions and individuals who embed in cohesive clusters, might benefit the movers most.

RUNNING HEAD: GENDER, MOBILITY, AND COMMUNICATION NETWORK

Chapter 2: Gender, Intra-organizational Mobility, and Persistent Communication Ties

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Abstract

While it is widely noted that job mobility can lead to a short-term performance disruption, we know little about gender differences in the performance disruption that movers suffer. Using monthly observations on individual performance from a retail bank, we examine the performance variation associated with intra-organizational mobility. We argue that female movers are less disrupted than their male counterparts. We propose that the underlying mechanism for this pattern involves the persistent communication ties women tend to retain at higher rates than their male counterparts. This behavior enables them to maintain connections with colleagues at the positions they leave, helps them to overcome the uncertainty associated with job changes, and has been shown to elicit brokerage opportunities. Analyses support our predictions. We discuss the implications of these findings for the study of dynamic social networks, for the literature on gender differences at the workplace, and for our understanding of intra-organizational mobility.

Keywords: Gender; Communication Networks; Intra-organizational Mobility

INTRODUCTION

While mobility can be an effective way for employees to build their careers (Bidwell & Mollick, 2015), it can also lead to a performance disruption for the movers (Groysberg, 2010). For example, scientists who moved to less productive departments show substantial decreases in productivity (Allison & Long, 1990); surgeons' performance does not benefit from experience in other hospitals (Huckman & Pisano, 2006); and star security analysts face great difficulties in replicating their prior success after they move (Groysberg, Lee, & Nanda, 2008). Moreover, experience acquired in one working context could hurt the mover's subsequent performance by inhibiting adjustment to a new context (Dokko, Wilk, & Rothbard, 2009). Thus, even when occupation remains unchanged, job performance of the movers can get worsened.

A network perspective holds considerable promise as a solution to the performance disruption associated with mobility (Bidwell, Briscoe, Fernandez-Mateo, & Sterling, 2013; Dokko & Jiang, 2017; Keller, 2017; Sterling, 2015). The literature has explored social relations between the movers and the colleagues at the positions they join (i.e., referrals or individuals who move together). For example, referrals could positively affect individual performance by facilitating the twin selection between an employee who seeks to move and an employer that is hiring (i.e., Castilla, 2005; Fernandez, Castilla, & Moore, 2000; Petersen, Saporta, & Seidel, 2000; Yakubovich & Lup, 2006). And moving together with prior teammates helps the star security analysts to alleviate the performance disruption that they would otherwise suffer (Groysberg & Lee, 2009). The literature has also explored the social relationships with clients. If movers can keep their client relationships or the revenue associated with those relationships, then their performance can be maintained post-move (Broschak, 2004; Carnahan & Somaya, 2013; Somaya, Williamson, & Lorinkova, 2008).

This paper departs from previous studies by examining another type of social relation that could help us to understand movers' performance variation: the persistent social ties to colleagues at the positions they leave. Persistent social ties are social contacts that are sustained or do not decay over a relatively long period of time. As movers transfer from the positions they leave to the positions they join, their persistent social ties to prior colleagues generate communication channels between both jobs. In this paper, we explore how movers' persistent social ties affect variation in their post-move performance.

We propose that persistent social ties can help movers, especially female movers, to overcome some of the challenges associated with mobility. Our starting assumption is that not all movers are equally likely to retain persistent social ties with colleagues at the positions they leave. Building on the literature studying gender differences in social networks (Brass, 1985; Forret & Dougherty, 2001; Ely, Ibarra, & Kolb, 2011; Obukhova & Kleinbaum, 2017), we argue that female movers are more likely to retain persistent communication ties to their prior job positions than male movers. These persistent communication ties have a demonstrated association with reduced communication barriers (Dahlander & McFarland, 2013; Marsden & Campbell, 2012), knowledge and information exchange (Hansen, 1999; Uzzi, 1997), and increased returns to brokerage (Bidwell & Fernandez-Mateo, 2010). When movers change jobs, these processes translate into female movers relying on persistent social ties for knowledge exchange, social support, and bridging opportunities. We therefore expect these persistent social ties to help women to improve their post-move performance.

This chapter specifically investigates the effect of gender and persistent social ties in the context of intra-organizational mobility. This focus on intra-organizational mobility permits us to compare pre- and post-move performance and estimate the consequences of the job movements.

Moreover, a nascent literature has documented the benefits associated with intra-organizational mobility on talent retention and creation compared with inter-organizational mobility (Bidwell, 2011; Bidwell, Briscoe, Fernandez-Mateo, & Sterling, 2013; Crispin and Mehler, 2013; Keller and Bidwell, 2014); however, we know little about the social processes underlying intra-organizational mobility (Breaugh, 2013; Keller, 2017). Thus, examining the social-network related factors associated with the performance variation across the intra-organizational movers has far-reaching theoretical and practical implications.

We investigate the effects of gender, social networks, and intra-organizational mobility on individual performance in the retail sales department in a US-based financial institution (hereafter Big Bank). Retail sales employees at Big Bank work independently to sell the same products to different customers across 36 markets. Their performance is measured by the dollar amount they have sold by the end of each month and determines a large proportion of their pay. From Big Bank, we collected data on the monthly performance and job changing histories of all the 12,916 retail sales employees between Nov. 2014 and Apr. 2016. Moreover, we collected data on meta email exchanges among all employees, including sender, receiver, timestamp and the file size of each message. The objective performance measure permits us to compare individual outcomes over time. Additionally, the rich email dataset allows us to differentiate individuals' "persistent" versus "new" communication contacts, couple communication networks with performance, and examine how communication networks evolve as employees' careers unfold.

MOBILITY AND PERFORMANCE DISRUPTION

Given the relatively free job movement of individuals in contemporary labor markets, and the emphasis on experienced individuals as a key element of strategic human resource management, it is increasingly important to understand the consequences associated with job mobility. One of the most consistent findings has been that mobility can be disruptive for movers (i.e., Groysberg et al., 2008). The performance disruption arises from both the change in the content of the tasks that someone performs and change in the organizational context in which the work is carried out (Groysberg et al., 2008; Huckman & Pisano, 2006; Kristof, 1996). Experienced workers bring with them their "repertoire of cognitions and behaviors acquired from prior jobs," along with their knowledge and skill (Beyer & Hannah, 2002). This can substantially affect individuals' perceptions on how work should be done, which in turn can dull their ability or responsiveness to adapt to the receiving working context. Such incapacity can negatively impact performance (Dokko et al., 2009).

One specific type of career mobility is intra-organizational mobility. Intra-organizational mobility represents the movement between jobs within the same organization (Keller, 2017). Earlier conceptions of intra-organizational mobility view jobs as being arranged in the form of career ladders, assuming that skills from one position would prepare individuals for their next job as a "line of progression" (Bidwell, 2011; Doeringer & Piore, 1971). As organizations shift away from hierarchical and centralized decision making structures, employees have been tasked with exerting control of their own careers (Cappelli & Keller, 2014). Individuals no long follow the predictable career patterns and climb up internal career ladders, rather, their careers are becoming more diverse, involving changes in multiple forms. Intra-organizational mobility provides employees a unique lens to advance their careers compared to job changes across organizational boundaries (Bidwell, 2011; Bidwell & Mollick, 2015).

Intra-organizational mobility presents a great context to examine the performance disruption associated with job changes. First, changing positions is not necessarily easy for the intra-organizational movers. Challenges associated the performance disruption all remain for intra-organizational movers who move between business units. Indeed, internal hires vary significantly in performance and turnover (Burks, Cowgill, Hoffman, & Housman, 2013; Keller, 2017). Second, the focus on intra-organizational mobility permits us to compare pre- and post-move performance and estimate the consequences of the job movements. Moreover, despite great practical and theoretical interests on the benefits of such movements at the organizational level (i.e., Bidwell, 2011; Rosenkopf & Almeida, 2003), we know little on intra-organizational mobility and its underlying social processes (Breaugh, 2013; Keller, 2017). Thus, examining the factors associated with the performance variation across the intra-organizational movers has far-reaching theoretical and practical implications.

GENDER, PERSISTENT COMMUNICATION TIES, AND MOBILITY

In this paper, we set out to explore how movers' persistent social ties of the movers affect the performance variation. Losing touch is common—the inevitable by-product of a mobile workforce, with employees moving between jobs and employers, changing locations, and leading busy lives—and the finite limits of time inevitably lead to an upper bound on the number of social relationships that an individual could possibly maitain (Dunbar, 1993, McFadyen & Cannella, 2004). Consequently, many social ties—including positive and rewarding relationships—end up neglected. Amid conversations on the strength, reciprocity, and the presence of a common third party significantly increase the possibility of tie persistence (Dahlander & McFarland, 2013) and decrease the likelihood of tie decay (Kleinbaum, 2017), we still lack understandings on how individuals' tendency to persist extant social ties differ as a consequence of career changes.

The first part of our theory concerns how individuals maintain persistent social relationships when they make intra-organizational moves. When employees change jobs, they inevitably use, adapt, and change the social relationships around them. Mobility and the need to reduce uncertainty tend to increase network diversity. Movers are encouraged to seek interaction with colleagues who have divergent perspectives, who provide non-redundant information, and who can help them make sense of, integrate across, and reconcile multiple interpretations (Morrison, 2002; Reagans & McEvily, 2003; Saint-Charles & Mongeau, 2009; Srivastava, 2015). Correspondingly, we expect both men and women to increase their network diversity and seek interactions with new colleagues when they experience job mobility. Despite the general tendency to establish new ties, a review of the literature on gender and social network structure suggests that the likelihood of persisting long-standing ties for women and men may differ. Herein we provide two major reasons to account for the gender difference.

First of all, there are structural differences between women's and men's networks that make women's network relations stronger, or in other words, more sustainable. A reading of the network literature highlights two types of structural difference that relate to gender, namely, homophily and embeddedness. Men and women tend to interact with different types networks, controlling for availability (Brass, 1985; Ibarra, 1992). Central to this observation is the principle of homophily: individuals prefer interacting with similar others (Lincoln & Miller, 1979). The availability of contact precedes and limits their possibility of differentiating social networks because contact between men and women in the work place is largely limited by the gender composition of the group and availability of opportunities (Blau, 1977). McPherson and Smith-Lovin (1987) suggest that both individual preferences for similar others and availability constraints would lead to gender segregation. In addition to the likelihood of establishing ties with other women, women are more likely to be embedded in cohesive groups where ties are densely connected with each other. A study on academic communication networks suggests that women are more likely to have higher network constraint than men, suggesting women's network contacts are more likely to contacts of one another (Rosen, 2009).

Given their embeddedness in cohesive social groups and connections with others who are likely to have similar network positions, women are in good positions to strategically maintain communication with their social contacts when they move. The commitment to a relationship and the persisence of it largely depend on the larger networks in which the relationship is embedded (Krackhardt, 1999). In other words, the persistence of a relationship depends on its embeddedness in a broader network of ties. For example, in a study of college dorms, Krackhardt's (1998) shows that ties are more ''sticky'' if the people in the relationship have mutual friends. Social cohesion around a relationship, in brief, tends to increase the willingness of individuals to invest their time and effort in maintaining those relations (Kleinbaum, 2017). As a result, women's ties are more sustainable than men's, and women's relative proportion of communication with newly established contacts will be correspondingly lower.

Second, women are more likely to seek and consume social support than men, who tend to seek advice and job-related information when facing uncertainty. Women oftentimes acquire different network resources from separate sources while men tend to mix different types of network resources together (Ibarra, 1992). To be effective at their jobs, women oftentimes attempt a network "division of labor" in the sense that they obtain social support from relationships with female colleagues but rely on ties to male colleagues to access professional or instrumental resources. Such division of social ties is positively associated with the advancement of women (Aldrich, 1989). Correspondingly, women are very likely to maintain two different social circles—ties for social support and ties for instrumental linkages—within organizations (Ibarra, 1995). When experiencing job mobility, ties for social support are sustained while ties for instrumental linkages tend to decay (Podolny & Baron, 1997). To cope with the uncomfortable feelings related to changes in careers, people immediately seek to interact with those who can help them to understand the situation, interpret what it means for them, and decide proper strategies in response (Srivastava, 2015; Saint-Charles & Mongeau, 2009).

The above two reasonings largely consider how the embeddedness and cohesion that women's networks typically exhibit could lead women to maintain a high proportion of persistent communication ties. In addition to the inadvertent structural consequences, it is also likely that women are able to strategically take advantage of their social capital at the workplace by maintaining ties to colleagues at the positions they leave. In an ongoing project examining MBA students' networking behaviors, Obukhova and Kleinbaum (2017) argue that women, when provided equal access to networking activities, tend to network more actively than men. In a very different setting, Ody-Brasier and Fernandez-Mato (2017) show that female grape growers are able to charge systematically higher price than do male grape growers because they can strategically develop and maintain social relations with each other. Both papers show that women are not just "constrained" by social structures, but that women can effectively leverage their social capital when provided opportunities to do so. Moving within the same organization is an opportunity through which individuals might create value by bridges colleagues at both jobs. Thus, we expect that female movers might maintain persistent communication ties as a surviving strategy when they move. Taken together, not only are women embedded in social support networks, but they would also be more motivated to exploit existing social relationships especially when they experience intra-organizational mobility. Thus, we hypothesize that:

Hypothesis 1: Women maintain a higher proportion of persistent contacts than men when experiencing intra-organizational mobility.

We proceed to argue that women can benefit from their high likelihood of retaining persistent communication ties when they experience intra-organizational mobility. The reasons are multifaceted. First, women get social support from their persistent ties when they move within an organization. A new job entails two fundamental types of activities: task-related activities (learning how to accomplish new tasks and adjust to changing work routines) and relational activities (seeking social support and managing the uncertainty or anxiety associated with moving). Task-related activities require forming new connections in the new role, potentially squeezing out the old contacts. Relational activities, in contrast, require leaning on close, old friends. Men tend to seek social support from their instrumental ties, and thus endure a period of transition in which they are forming new instrumental ties, but do not yet know those colleagues well enough to get much social support. By contrast, women have more differentiated networks, so they are able to continue to receive social support at precisely the time they need it the most (the difficult transition to a new role), even as they are busy forming new instrumental ties within the new job. In light of the work demonstrating that loss of social capital leads to major performance disruption (Groysberg et al., 2008), women's persistent ties provide social support and help them prepare for the challenges arising from job mobility (Ibarra, 1992).

Second, individuals generally obtain more benefits from persistent social ties than they do from newly formed ties. The individuals engaged in persistent social ties frequently communicate better with one another (Dahlander & McFarland, 2013; Marsden & Campbell, 2012; Uzzi, 1997). Persistent ties therefore could grant individuals all manner of benefits, such as easy and effective communication, relatively complete knowledge transfer, and great reciprocity in social exchanges (Katz, 1982). Additionally, the content of persistent relationships can enable actions that facilitate performance, as well as provide in-depth information about opportunities for new ways to create value (Podolny & Baron, 1997). In short, repeated communications could benefit female movers by allowing fewer startup costs, entailing greater certainty, and channeling information with better quality.

Third, persistent ties to prior colleagues elicit brokerage opportunities for the movers (Corredoira & Rosenkopf, 2010; Kleinbaum, 2012). A social network position that bridges otherwise disconnected parties can benefit the holder of this position by providing access to diverse sets of information that can be recombined into innovative ideas (Burt, 2004). Such a position can also enable control over the flow of information between the disconnected parties that can be parlayed into opportunities to profit from an intermediary role (Burt, 1992). In addition, persistent ties would provide greater returns on performance in terms of productivity and quality than did new ties (Dahlander & McFarland, 2013; Bidwell & Fernandez-Mateo, 2010). Correspondingly, we expect women, given their high likelihood of persisting social ties, are more likely to be brokers that bridge the groups they have worked in. These brokerage positions thus grant women opportunities to control information flow and create new values.

Moreover, although occupying brokerage positions itself might not be enough to guarantee returns and may even lead to penalty or perception biases (Brands & Kilduff, 2014; Quintane & Gianluca, 2016), we expect that retaining persistent communication ties to colleagues at prior jobs is less likely to be considered as a concern for female movers because of their gender stereotypes. Recent research points to the mismatch between stereotypes of women and expectations of business leaders as an important cause of gender inequality (Brands et al., 2015; Eagly & Diekman, 2005). Female professionals strategically asset male-typed characteristics associated with success. Yet because these are viewed as inconsistent with feminine stereotypes, such strategic self-presentation precipitates backlash from peers (Barbulescu & Bidwell, 2013). That is to say, women face a “double-bind” in organizations where the performance of their gender role can be viewed as violating their professional role, and vice versa (Eagly & Karau, 2002). Persistent communication ties, however, are consistent with female gender stereotypes. Gender literature typically agrees that women are social specialists (Ibarra, 1992), in part because such social activities map women’s prevailing stereotypes as communal and warm human beings (Spence & Buckner, 2000). Specifically, women are expected to be person-oriented, developing “functionally differentiated” information networks: separating their task-oriented networks from the networks of social support, while men to be more task-oriented and develop multi-complex social relations serving both functions (Eagly & Karau, 2002; Ibarra, 1992). Such a gendered differentiation in perceived networking styles oftentimes associates with disadvantages for women. The maintenance of persistent communication ties in the events of intra-organizational mobility offers a possibility to reconcile the perceived inconsistency between female stereotypes and their needs to advance their careers, and thus alleviate gender inequality in organizations. Taken together, we hypothesize:

> *Hypothesis 2a: Women will suffer less performance disruption arising from intra-organizational mobility than men.*
>
> *Hypothesis 2b: The proposed gender difference in moves’ post-move performance is mediated by the gender difference in their proportion of persistent contacts.*

METHOD

Empirical Setting

We investigate the intra-organizational mobility for women and men in Big Bank between Nov. 2014 and Apr. 2016. The individual-level data we collected is comprised of 102,841 monthly observations for 12,916 retails sales employees, including both individuals who were at Big Bank prior to the beginning of the observation period and those who joined during the window. In Nov. 2014, there were 7,486 retail salespeople, and since then has ranged from 7,568 to 7,760 monthly.

Employees in this department strive to provide products and services to customers and generate value for the bank. Examples of such products and services include residential mortgage loans, saving plans, investments, or the purchase of properties. The department computer automatically calculates the total amount of sales each employee makes by the end of each month. A retail sales department is an important and highly autonomous organizational context that operates in a relatively intensive environment. Retail sales employees are financially rewarded for their sales performance.

Each employee belongs to a local branch, where they co-locate and work with others. Employees are incentivized to work well individually. In the meantime, this context generates an atmosphere conducive to frequent communication and learning, which consequently could lead to possible performance externalities, including knowledge spillovers and shared tactics. Examples of knowledge in this setting include knowledge of the market, information on customers' appeal or preferences, and strengths and weakness of each product compared with those offered by competitors. Sales tactics, such as how to introduce a product to consumers or how to make small talk during waiting times, are also critical in driving sales. Essentially, retail sales employees seldom go out of the office to explore opportunities; they need to learn how to make most of the opportunities presented to them. Put differently, employees in retail sales departments, exhibiting certain degrees of autonomy in choosing how to perform their daily tasks, face resource limitations in terms of both available customers and internal support—limitations that require them to keep looking for efficient ways to boost productivity.

The needs for improvement and learning together highlight the importance of understanding the mechanisms underpinning individual performance. Finally, in retail sales groups, mobility is very common, and mobility plays a pivotal role in transferring and accumulating experience. Altogether, this context offers us a unique opportunity to examine the relationship between mobility, gender, and performance. Big Bank itself has been particularly interested in promoting equal opportunities in the workplace. In line with this goal, we utilize the granular data we have to provide a snapshot of gender diversity, with special attention to intra-organizational mobility and social networks.

Data

At Big Bank, we collected individual demographic information including gender, race, age, job role, job grade, organizational experience, role experience, supervisor, and local office location. We also collected monthly-updated performance of employees in the retail sales department. Individual performance was captured by the dollar value of retail products an employee sold by the end of each month. In addition, we collected all of the employees' meta email-communication variables including sender, receiver, timestamp, and the file size of each message. Indeed, email communication is only a partial representation of an employee's work-related behaviors; nonetheless, it is a powerful source of observations and is largely consistent with communication patterns through other means (Quintane & Kleinbaum, 2011; Srivastava, 2015). As a conservative representation of the intra-organizational communication network, we limit my analysis to one-to-one emails within the organization, excluding all one-to-many emails or emails sent to and received from external sources.

Descriptive Findings

We begin with an analytical description of hiring and intra-organizational mobility at Big

Bank. Employees are each assigned a job grade, which represents a range of performance expectations (and salaries). Job grade ranges from 8 to 22, with grade 8 being the lowest paid salaried employees, up to 22 being the highest. We averaged all the grades of employees in the retail sales department. We find that women are more likely to start with lower grades (as is shown in Figure 2.1, Panel A). Specifically, the starting levels for jobs that are dominated by women are, on average, lower than the ones for male employees. This provides some evidence of sex segregation in the types of jobs women and men start with. We find there is a significant correlation ($r = 0.059$, $p < 0.05$) between gender (male) and new hires' first-month performance within job grade (as is shown in Figure 2.1, Panel B). Although women predominantly start from jobs at a lower level, as they move up along the organizational career ladder, the performance gap between men and women does not exist (as is shown in Figure 2.1, Panel C).

[INSERT FIGURES 2.1 AND 2.2 HERE]

Opportunity for mobility within Big Bank is ample. Over the course of eighteen months, 5,945 employees have changed their jobs in some form, including supervisor change, promotion, and the changes in business units where they work. If we examine the breakdown by gender, we see a significant difference: women are less likely to change locations or supervisors than men, and women are slightly more likely to get promoted (though this difference is not significant). We plot the proportion of male movers (divided by all male employees) and the proportion of female movers (divided by all female employees) by the number of job changes in the form of supervisor change (Panel A), location change (Panel B), and promotion (Panel C), as is shown in Figure 2.2.

Measures

Individual Performance t+1. The dependent variable that we focus on is the log (performance) of individual retail sales employees (sales in dollar amounts). We are interested in an individual's performance in response to internal mobility in the form of changed job location in month t.

Location Change t. A binary variable for each individual-month observation, indicating whether or not the individual changes business units (working locations) in month t.

Supervisor Change t. A binary variable for each individual-month observation, indicating whether or not the individual changes supervisors in month t.

Grade Change t. A binary variable for each individual-month observation, indicating whether or not the individual receives a change in job level in month t. The grade change is always a positive change in this context, reflecting a promotion that an individual receives.

The Proportion of Persistent Communication Ties. The major independent variable that we explore is individuals' retaining of persistent communication ties. To quantify this construct, we calculate the percentage of individuals' persistent contacts (receivers who have received emails from the individual in month *t-2*, compared to all the individual's current email receivers in month *t*). That is, the independent variable measures the overlapped email receivers of ego between month t-2 and month t[5] divided by the total number of email receivers in month t, as is shown in Equation 1:

$$P_{t,i} = \frac{\sum \cap (R_{i,t-2}, R_{i,t})}{\sum R_{i,t}}$$

(Equation 1)

where P represents the proportion of persistent communication ties, which is the total number of overlapped email recipients between current month (R_t) and two months ago (R_{t-2}), divided by the total number of current email recipients (R_t).

[5] Results are robust to *t-3*, as is reported in Table A6.

Control Variables. We either control for or match on individuals' *organization tenure, job tenure, age, gender, race, job grade, primary market of focus*, and *group demographic characteristics*. These controls allow us to rule out some common alternative explanations. For example, it could be possible that the longer one works in the organization, the better performance one would deliver, regardless of whether one moves or not. The inclusion of organizational and role tenure controls away from this alternative explanation.

Sampling and Modeling Strategy

We conduct analyses on individual-month observations to answer our original question of the differential performance effects of intra-organizational mobility on men and women. Specifically, employees in our sample belong to the same department and work in the same job roles. While they may move for a variety of reasons, the fundamental drive for the intra-organizational movement is the need to improve performance (Bidwell, 2011). We focus our attention on changes of business units as the primary form of intra-organizational mobility, and control for job changes related to supervisor changes and promotions.

To estimate the effects of gender and intra-organizational mobility interaction on individuals' post-move performance, we adopt a ***differences-in-differences-in-differences*** (triple differences) approach. The basic differences-in-differences (diff-in-diff) analysis examines the outcomes of actors who are exposed to a treatment (in our case, treatment means moving within an organization) with that of those not exposed to the treatment (the control group of non-movers). With this approach, in our context, we seek to compare the trajectories of movers with a matched set of controls (observationally equivalent individuals who do not move). The diff-in-diff analysis basically controls away the average outcome in the control group (non-movers) from the average outcome in the treatment group (the movers), thereby eliminating confound effects arising from stable differences between groups and from the trend (Ashenfelter & Card, 1985).

Ideally, when the treaded actors are randomly picked or when the treatment is randomly assigned, we can interpret the estimated effects as causal (as opposed to simply correlational), but it seems impossible that voluntary job changes within an organization would occur at random. We therefore introduce an additional differencing into the diff-in-diff estimator to purge our results of factors correlated with moving, resulting in a triple differences approach (Rogan & Sorensen, 2014). This triple-differences approach can be understood as a two-step analyses: first estimating diff-in-diff for women and men separately and then comparing the effect sizes. In other words, how do female movers perform relative to similar female employees who remain not moved? And how do male movers perform relative to similar male employees who remain not moved? Together these differences provide an estimate of the effect of intra-organizational mobility, conditional on gender. The triple-differences analysis then represents differences between these differences, to arrive at an estimate of how the effect of intra-organizational mobility depends on gender. The analyses, therefore, net out the selection in who moves and focuses on variations in the effects of intra-organizational mobility as a function of gender.

To generate an appropriate comparison set (similar individuals who remain not moved), we construct a sample that matches the movers (cases) with a set of counterfactual movers (controls), movers who could have moved but that did not. For the movers, we followed a "Coarsened Exact Matching" (CEM) approach (Iacus, King, & Porro, 2012), choosing individuals from the complete employee lists that matched the movers on several observable characteristics including demographics, such as age and gender; tenure, such as the time one has spent in one's current job; geography, such as the primary market of focus; and job characteristics, such as one's job level in the organizational structure. The final matching sample includes 60,295 individual-month observations on 835 movers who have changed job locations and 4,073 observationally equivalent employees who remain not moved.

With the matching sample, we regress individual monthly performance with the treatment (mover or not), post-move indicator (set to 1 after the treatment for both movers and their control set of non-movers), and gender. Particularly, the effects of intra-organizational mobility, gender, and persistent communication ties are analyzed with three equations. The first model (as in Equation 2) sets out to examine the effects of the triple diff-in-diff estimator on job performance in the first month following the move. Performance is measured at the end of each month, so we perform multi-level regressions (where individuals are nested in business units) predicting performance in a subsequent month. The second model (as in Equation 3) estimates the effects of the same triple diff-in-diff estimator on an individual's proportion of persistent communication ties. We additionally analyzed the overall effect of the mobility and the proportion of persistent communication on an individual's job performance, as in Equation 4. The models are conditioned on the matching sets where one case is paired with several controls, thereby controlling for the characteristics of the movers and for the variables used in the CEM process. We cluster standard errors on the individual employee and month, as separate observations for the same employee or in the same month would be undoubtedly related. The models are presented as follow:

$$Y_{i,t+1} = \beta_0 + \beta_{11} M_i * PM_{i,t} + \beta_{12} G_i + \beta_{13} M_i * PM_{i,t} * G_i + \beta_{14} X_{i,t} + \varepsilon_{1i,t}$$

(Equation 2)

$$P_{i,t} = \beta_{20} + \beta_{21} M_i * PM_{i,t} + \beta_{22} G_i + \beta_{23} M_i * PM_{i,t} * G_i + \beta_{24} X_{i,t} + \varepsilon_{2i,t}$$

(Equation 3)

$$Y_{i,t+1} = \beta_{30} + \beta_{31} M_i * PM_{i,t} + \beta_{32} G_i + \beta_{33} M_i * PM_{i,t} * G_i + \beta_{34} X_{i,t} + \beta_{35} T_{i,t} * P_{i,t} + \varepsilon_{3i,t}$$

(Equation 4)

where Y represents the performance of individual i in month *t+1*, P represents the proportion of persistent communication ties of individual i in month *t+1*. The establishment of new ties and decay of prior ties are natural processes that take place as individual careers unfold. In months where the individual i does not experience any changes, we calculate this variable and use the value as a baseline to estimate the changes individual would incur when they make the moves. M is the "treatment" variable in the triple diff-in-diff estimation, set to 1 when individual i is a mover who has changed working locations during the observation period. M is set to 0 for the control group that consists of individuals who appear observational identical to the movers in month *t* based on the dimensions we have matched, but remain not moved during the entire observation period. PM is the "post-treatment (move)" indicator, representing whether or not the treatment has been applied. In our case, for both movers and the matched non-movers, PM becomes 1 after month t when the mover makes a move. G is the main independent variable, representing the gender of individual i. X represents all control variables that are included in the model, accounting for alternative explanations that we will explain in detail.

To test for the proposed mediated moderation, we adopt the extension in Muller, Judd, and Yzerbyt (2005) of the Baron and Kenny (1986) original approach. The sufficient conditions are checked accordingly and explained as follow: essentially, we estimate the above Equations 2, 3, and 4 and test for two conditions. The first condition is met when the moderation of the overall treatment effect exists ($\beta_{13} \neq 0$). The second condition is met when the moderation of the treatment effect in Equation 4 is smaller than the moderation of the overall treatment effect in Equation 2 ($\beta_{33} < \beta_{13}$). For the second condition to occur, the indirect paths from the diff-in-diff estimator via the mediator to the dependent variable must be moderated ($\beta_{35} \neq 0$).

We also examine the same estimations with a split sample approach. We split the sample by gender and report diff-in-diff estimations for men and women separately. The split sample approach could not only help eliminate the complexity in interpreting the coefficient of the three-way interaction, but also could reduce possible estimation errors due to the correction between the main effect (gender) and the mobility variables. We split the full matching sample into two sub-samples based on gender and estimate the effect of treatment (mover or not) and post-treatment indicator on individual performance separately. We expect the sign and the statistical significance level of the diff-in-diff estimator should remain constant between the two subsamples. We expect the magnitude of effect size on the dependent variable to be larger for men than for women.

MAIN RESULTS

Table 2.1 reports the descriptive statistics, including the maximum, minimum, means, standard deviation values and a correlation matrix, among all the variables. The pairwise correlations between the independent and control variables are, excluding multi-collinearity concerns, relatively low. We also report the summary statistics separately for the cases and the controls and for men and women. Besides all the categorical variables that are matched precisely, the matching process has effectively paired observationally equivalent controls to the movers.

[TABLES 2.1 AND 2.2 ABOUT HERE]

We provide the results in Table 2.2. The first model shows that there is an overall effect of diff-in-diff estimator (β_{11}= -0.402, $p < 0.001$), indicating that intra-organizational mobility in the form of changing job locations leads to a 40% decrease in individual performance after the location changes. As is shown in model 2, the overall effect of intra-organizational mobility depends on gender (β_{11}= -0.313 and β_{13}= -0.313, p < 0.001), suggesting the decrease is 62.6% for men and 31.3% for women. In the subsequent two models, we show that there is a negative effect of intra-organizational mobility in the form of changing job locations on the proportion of persistent communication ties (β_{21}= -0.495, p < 0.001), indicating that changing location leads to a 49.5% decrease in individual's proportion of persistent ties. This effect of intra-organizational mobility also depends on gender (β_{23}= -0.163, p < 0.01), suggesting the decrease in the proportion of persistent ties is 60.8% for men and 44.5% for women. In Model 5, the interaction effect size between intra-organizational mobility and gender is smaller than the interaction effect in Model 2 ($abs(\beta_{33}) = 0.287 < abs(\beta_{13}) = 0.313$). As seen in Model 5, which includes the proportion of persistent communication ties, the interaction between intra-organizational mobility and gender is no longer significant, and the indirect path from intra-organizational mobility and gender interaction via the proportion of persistent communication ties to the performance outcome is significant. Indeed, moderation of the intra-organizational mobility effect is observed along the path from the proportion of persistent communication ties to the performance outcome ($\beta_{35} = 0.073, p < 0.001$).

[TABLE 2.3 ABOUT HERE]

In Table 2.3, we separately estimate models 2, 4, and 5 in Table 2.2 with a subsample of men (models 1-3 in Table 2.3) and a subsample of women (models 4-6 in Table 2.3). All results remain robust. By comparing the effect size in model 1 and model 4 in Table 2.3, we can tell that male movers suffer a larger performance disruption than female movers. The gender difference can be explained by the inclusion of the proportion of persistent communication ties in the model (model 3 and model 6 in Table 2.3, respectively). One interesting observation from Table 2.3 is that women and men have demonstrated differential returns in maintaining persistent communication ties. Although women on average benefit from persistent communication ties, men could get greater returns by doing so.

ALTERNATIVE EXPLANATIONS

The main results support the hypotheses formulated above. Together, they suggest that women suffer a smaller performance disruption when making intra-organizational moves, and that the gender difference can be explained by women's high proportion of persistent communication ties. In this section, we assess the robustness of results to the business-unit level controls.

The social network is not the only mechanism that could generate an association between gender and the performance disruption that movers experience. Previous studies of mobility and its performance impact have highlighted the importance of organizational context in which the tasks are performed (for a review, see Dokko & Jiang, 2017). Thus, an alternative explanation is that the characteristics of the business unit drive individual performance. To separate the distinctive effects of business units, we include individual and matching group random effects, nested in business-unit locations, to account for the possibility that differences in various business units amounting to differences in individual performance. We also include controls for the main location-level determinants of individual performance. These controls are organized around the dominant explanations for group-level effects: demographic characteristics and social network characteristics. We control for demographic characteristics of the business units by including size, average organizational experience, average job role experience, total levels of hierarchy, and proportion of male employees.

[TABLE 2.4 ABOUT HERE]

Model 1 in Table 2.4 includes the controls on demographic characteristics of the business units. Comparing with model 2 in Table 2.2, all results remain robust. Models 2 and 3 separately estimate performance for women and men subsample. Model 4 replicates the estimation of the proportion of persistent ties as in model 4 in Table 2.2, with the controls. Model 5 further includes the estimation related to the proportion of persistent ties, and the result is consistent with model 5 in table 2.2. Thus, taken all together, both hypotheses are supported and remain robust to the broader set of control variables.

MECHANISM EXPLORATION

In this section, we conduct two sets of analyses to further understand the underlying mechanisms associated with the persistence of communication ties. The first set examines whether or not the persistence of communication ties permits individual movers to be able to be brokers and bridge between prior and current job positions. The second set examines the effect of gender on the likelihood of a tie being retained after the sender of the tie changes jobs from one business unit to another. This analysis aims to understand the dyadic-level variations across all the communication ties between the movers and their colleagues at prior job position.

The Effect of Persistent Communication Ties on Being Brokers. We herein conduct a similar set of analyses with our main triple diff-in-diff models as were explained in the prior section. Instead of estimating individual performance, we estimate individual betweenness score in this section. Betweenness score measures the extent to which individuals connect two other employees who are otherwise not able to connect (Freeman, 1977). Betweenness provides a way to qualify the extent to which the focal individual is a broker in a large network. Because we use the global betweenness score in the models, the measure is highly skewed (min = 0, max = 3,418,418), thus we use log (betweenness) as the dependent variable in the estimations.

[TABLES 2.5 ABOUT HERE]

We provide the results in Table 2.5. The first model shows that men are more likely to be brokers within organizations. There is no significant effect of the diff-in-diff estimator on individual betweenness score. The overall effect of the triple diff-in-diff estimator is significant (($\beta = -0.052$, $p < 0.05$), as is shown in the second model. Models 1 and 2 suggest that movers do not significantly increase their betweenness centralities compared with non-movers, but there is a significant gender difference in movers' change of betweenness centrality. Models 3 and 4 estimated movers' betweenness centrality by splitting the full matching sample into a women's sample and a men's sample. Model 3 suggests that female movers increase their betweenness centrality scores compared with female non-movers. Model 4 suggests that male movers decrease their betweenness centrality score compared with male non-movers. As the effects of the diff-in-diff estimator are in opposite directions, the overall effect in model 1 is not significant. Models 2, 3, 4, taken together, suggest that women gain brokerage opportunities by changing location whereas men do not. Model 5 includes the proportion of persistent ties to model 2. By comparing model 5 with model 2, we can tell that the significant effect of the triple diff-in-diff estimator no longer exists, suggesting women's increase in betweenness centrality can be partly explained by their high likelihood of maintaining persistent communication ties.

The Antecedents of Tie Persistence. We herein conduct a set of dyad-level analyses to estimate the factors that help explain the likelihood of a tie being retained after a move. To do so, we construct a sample of 5,683 communication ties between 1,017 movers who have changed working locations once and their colleagues working at movers' prior jobs. In this sample, we estimate the likelihood of a tie remaining persistent for three months after the mobility (persistent =1, decayed = 0) in a logistic regression. Particularly, we focus our attention on the sender's gender (main independent variable) and the sender-receiver relationship. We additionally cluster standard errors on the sender and the receiver of each tie, as separate observations for the same employee could be related.

[TABLES 2.6, 2.7, AND 2.8 ABOUT HERE]

Table 2.6 reports the descriptive statistics, including the maximum, minimum, means, standard deviation values and a correlation matrix, among all the variables. Table 2.7 reports the models estimating the likelihood of a tie being retained after the sender moves. Ties initiated by women are more likely to be retained after the movers change job locations (model 1). The effect of gender becomes less significant with the inclusion of homophily variables (model 2). Moreover, the effect of gender becomes less significant or insignificant when proxies of tie strength are included in the model. Particularly, tie symmetry (model 3), structural similarity (model 4), communication interval (the reverse of communication frequency, model 5), and the presence of at least one shared third party (simmelian tie, Krackhardt (1999), model 6) all help explain the likelihood of a tie being persistent.

Table 2.8 reports the effect of sender gender on the proxies of tie strength. Ties initiated by men are more likely be asymmetric (model 1), less structurally similar (model 2), less likely to be a simmelian tie (model 3), and exhibits a low level of communication frequency (model 4). Taken together, Tables 2.7 and 2.8 suggest that women's ties tend to be stronger in terms of mutual communication and embeddedness, which in turn increase the likelihood of tie persistence.

Taking the two sets of analyses together, we complement our main analyses by providing evidence suggesting that (1) women are able to increase their brokerage opportunities by strategically retaining persistent communication ties; and (2) women are able to maintain a high proportion of persistent communication ties because their communication ties to prior colleagues tend to be stronger than those of men. Specifically, women's communication ties to prior colleagues are more mutual, channeling more symmetric and frequent communications, and are more likely to be simmelian ties.

SUPPLEMENTAL ANALYSIS

Despite the matching approach we have adopted, there might be some inherent differences between movers and non-movers that have not been accounted for by the matching process and result in differential effects on performance. As a robustness check of the main results, we attempt to eliminate this concern by examining the performance with the unbalanced panel sample on movers. We run a complimentary multi-level analysis that investigates the performance variation across 15,866 individual-months of the 1,017 movers who have changed business units within the organization.

[TABLES 9 ABOUT HERE]

Results are presented in Table 2.9. Briefly, models in Table 2.9 demonstrates effects consistent with models in Table 2. Particularly, intra-organizational mobility leads to a performance disruption for movers ($\beta = -0.167$, $p < 0.01$ for the location change indicator), and the effect is more salient for male movers ($\beta = -0.159$, $p < 0.05$). Male movers suffer an additional 15.9% performance disruption compared to female movers. The inclusion of the proportion of persistent communication ties mediates the negative two-way interaction between the lagged location change indicator and gender on mover's performance in a subsequent month.

DISCUSSION AND CONCLUSION

Understanding the factors associated with tie persistence as career changes is particularly important to inform theory on how individual network differences come about and accumulate over time (Ahuja, Soda, and Zaheer, 2012; Kleinbaum, 2012; McEvilty, Soda and Tortoriello, 2014). Building on a theoretical foundation, we set out to extend our understandings on the gendered difference in individuals' likelihood to persist extant communication ties as they experience career mobility. Through a series of analyses, we demonstrate a systematic gender difference in how movers manage their portfolios of social ties, which in turn, affects movers' post-move performance.

Our paper offers three contributions to the literature. First, our attempt to investigate how women's and men's networks differ in response to intra-organizational mobility builds on and extends research that links social network and gender differences. Scholars studying gender differences increasingly acknowledge the critical role that social networks and social interactions play in organizations (Merluzzi, 2017; Ibarra, Kilduff, & Tsai, 2005). As women strive to pursue their professional goals by changing their networks, they are likely to experience the challenges associated with freeing themselves from the "super-strong and sticky" social relationships within which they were previously embedded (Krackhardt, 1998). Our results demonstrate that career mobility provides women the opportunities to transform these constraints to benefit their career outcomes, at least in the form of performance.

Second, our investigation also contributes to the question of how gender role stereotypes interact with characteristics of work to affect career advancement (Barbulescu & Bidwell, 2013; Merluzzi & Dobrev, 2015). According to the gender-stereotype literature, women who are seen to be in violation of gender role prescriptions elicit punishment such as hostility and antipathy from their peers (Eagly & Karau, 2002). Thus, where individuals perceive women as adhering to gender role prescriptions by refraining from male-type roles, the potentially disruptive effect of gender discrimination lies dormant. Indeed, when women are perceived to have a high level of brokerage within a group, the performance of the group actually decreases rather than increases

(Brands & Kilduff, 2014). By demonstrating that women could increase their bridging returns by maintaining persistent communication ties, our work contributes a new path through which women might be able to create value for themselves and their organizations.

Lastly, our research speaks to previous work on intra-organizational mobility and organizational hiring. Knowledge of how women may or may not be successful in their intra-organizational mobility is valuable for the efforts working to build a diverse environment and promote equal opportunities. For example, if the likelihood of hiring women into an organization is dependent on the ratio of women versus men at different levels (Cohen & Broschak, 2013; Cohen & Huffman, 2007), then understanding how women and men change jobs and make career advancements within the same organizations has far-reaching implications.

As with all single-firm studies, caution is necessary for generalizing these findings. Examining processes and mechanisms accounting for individual movers' performance changes requires detailed data that can be difficult to obtain from multiple organizations. Our results demonstrate that women can benefit more than men from intra-organizational mobility by retaining communication ties to their prior positions. It complements previous work examining gender diversity in firms (Merluzzi, 2017) by considering gender differences in the consequences of intra-organizational mobility.

The results of our project point to some interesting future directions. An interesting extension to the extant study would be to figure out *why* women retain persistent ties more than men do. It is possible that women maintain persistent social ties strategically or it is possible the exhibited gender difference is an inadvertent consequence of women sorting into embedded social networks. Although our data cannot clearly distinguish the two possibilities, the empirical finding that female movers tend to have higher betweenness scores than female non-movers suggests that women who are able to make intra-organizational career changes might have a strategic mindset.

It would be worthwhile to continue exploring the effect of career changes on mitigating gender-related inequality in the workplace. It is well recognized that women are confronted with greater challenges to perform well and advance their careers in organizations than their male peers (Baron, 1984; Catelyst, 2010; see England, 1984, 1994 for reviews). Despite the prevalence of this problem, the diversity literature has been mixed, with some practices leading to the advancement of a diverse workforce (Chatman et al., 1009; Leung & Lu, 2017), while others have been shown to exacerbate gender segregation and continue revealing challenges for women (Rubineau & Fernandez, 2015). The mixed evidence indicates a need to further investigate how women may be able to overcome the challenges they face in the workplace. Notably, Petersen and Saporta (2004) find that the gender gap between women and men reduces with tenure, and that women are promoted at a higher rate at higher levels in their context. More recently, Ming and Lu (2017) show that women could attain higher salaries at the expense of lower ratings by making "erratic" or "atypical" job movements within a large technology firm. These findings suggest that there may be potential career paths for women to take within an organization to ameliorate their starting disadvantages. Moreover, intra-organizational mobility provides a unique opportunity for the movers to take advantage of their social capital and expand their existing social networks. Given existing research has focused almost exclusively on mobility between organizations, this work suggests that internal labor market represents a fruitful avenue for future theory development.

RUNNING HEAD: EXPLORING THE EFFECTS OF NEWCOMERS ON INCUMBENTS

Chapter 3: Exploring the Effects of Newcomers on Incumbents: The Role of Social Comparison

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Abstract

Hiring high-performing newcomers is commonly seen as creating opportunities for incumbents to learn and improve. However, a high-performing newcomer may introduce unfavorable social comparison, which could demoralize low-performing incumbents. Using time-series data on a private financial institution's retail sales employees, I examine how a newcomer's performance influences the performance of incumbents. I argue that the introduction of a high-performing newcomer increases incumbents' performance on average; the positive effect, however, is not evenly distributed among the incumbents. Relatively low-performing incumbents could be adversely affected by a high-performing newcomer, and the negative impact is more pronounced when group performance ranking hierarchy is stable. A communication-network-related mechanism is proposed to explain this finding. This study provides insight into how incumbents are affected by newcomers and highlights the role of social comparison in understanding incumbents' performance fluctuations.

Keywords: learning by hiring, social comparison, communication network, mobility

INTRODUCTION

Recent years have seen a proliferation of employee mobility as a method through which organizations or groups enlarge their knowledge scopes and improve performance outcomes (Bidwell, 2011; Dokko & Rosenkopf, 2010; Groysberg, 2010). But is hiring high-performing employees, notwithstanding their direct contributions, beneficial for incumbent workers? The commonly held expectation is that the introduction of a high-performing newcomer benefits incumbents through the lens of learning. Hiring a high-performing employee provides incumbent members with “stretch opportunities” that allow them to interact with and learn from the newcomer. In academic research taking this view, incumbents have indeed been shown to reap several benefits, including acquiring externally developed knowledge (Song, Alemieda, & Wu, 2003), collaborating with newcomers (Singh & Agrawal, 2011), and drawing upon their knowledge or expertise for innovation (Slavova, Fosfuri, & De Castro, 2016; Tzabbar, 2009). The introduction of a high-performing newcomer is thus commonly understood as a benefit to incumbents.

Although prior research has begun to address the question of how hiring high-performing employees can affect the performance of incumbents, the associated outcomes have generally been assumed to be positive. The positive association builds on the assumption that incumbent group members are equally motivated to improve their performance, neglecting individual variations in their response to the introduction of the newcomer. In contrast to this positive view, it is also possible that the introduction of a high-performing newcomer will have no benefit or even negative effects for some incumbents. The introduction of a high-performing newcomer could, despite the positive influence through the lens of learning, result in social comparison, causing incumbents to reevaluate their perspectives, abilities, and performance (Festinger, 1954;

Kilduff, 1990). Such comparison, when the results appear to be unfavorable, is oftentimes associated with negative emotions (Edelman & Larkin, 2015), reduced self-esteem (Kuhnen & Tymula, 2012), and low effort provision (Flynn & Amanatullah, 2012; Greenberg, Ashton-James, & Ashkanasy, 2007). In this way, the introduction of a high-performing newcomer may be a source of unfavorable social comparison and consequent demoralization of low performing incumbents, which could undermine the incumbent members' willingness to learn or improve.

Integrating insights from the learning-by-hiring literature and social comparison theory, I argue that the introduction of high-performing newcomers, by facilitating knowledge acquisition, on average will improve incumbents' performance. Nonetheless, I expect that under a certain condition—namely, when the group performance-ranking hierarchy is very stable—hiring a high-performing newcomer could be detrimental to an incumbent. Stable performance rankings facilitate consensus on where members rank within the group, which consequently reinforces individuals' reliance on the performance hierarchy to assess individual competencies and status (Anderson & Kilduff, 2009; Bunderson & Reagans, 2011). In groups with a stable performance ranking, low-performing incumbents are more likely to experience unfavorable social comparisons and, thus, to interpret the arrival of a high-performing newcomer as a "threat" to their already low intra-group standing instead of an "opportunity to improve" (Scheepers, 2009). Low-performing incumbents might become demoralized, exhibit low willingness to improve, and become trapped in a vicious cycle in which their performance could worsen.

I tested my arguments in a retail sales department of a large US firm with multiple locations. Between November 2014 and April 2016, I collected individual monthly performance data in 1,327 retail sales groups across 784 branch locations that had hired at least one employee from other branches. The internal movements of sales employees allow me to observe newcomers' performance prior to their moves. Moreover, the dataset permits repeated observations on all incumbents group members that had recruited at least one newcomer at a time, providing a unique opportunity to investigate newcomer-induced peer effects. In addition, all employees' meta email data, including size and exact time of each message, were collected. The email data allows the examination of network related mechanisms. As the hiring decisions are typically made by supervisors at higher organizational levels, the arrival of newcomers is treated as exogenous to incumbent group members, and the focus is on communication patterns that emerge due to group membership mobility.

THE EFFECTS OF NEWCOMERS ON INCUMBENTS

The competitive advantage of a group typically resides in the knowledge and expertise of its members (Argote & Ingram, 2000). As such, group performance is likely to change based on membership mobility. Indeed, because significant tacit knowledge is embedded in human capital (Almeida & Kogut, 1999), hiring newcomers is particularly beneficial when a group wants to acquire externally developed expertise or tacit knowledge (Rao & Drazin, 2002; Song et al., 2003).

Such impacts of newcomers on group performance can be both direct and indirect. Because newcomers possess work-related knowledge, they can participate directly in the production process. Accordingly, upon the arrival of newcomers, groups can enjoy an immediate change of performance (i.e., Almerda & Kogut, 1999). Patent citations are oftentimes used as proxies for knowledge transfer when examing post-mobility learning effects (i.e., Song et al., 2003; Slavova et al., 2016). These studies consistently demonstrate that knowledge transfer through hiring benefits primarily the first channel—that is, the productive role of new hires and their direct contribution to organizational output. Newcomers also produce indirect effects on incumbent group members' performance (Mas & Moretti, 2009). If the indirect effect is positive, the return on hiring a top performer is actually larger than the mere productivity that the newcomer provides. By contrast, if the indirect effect is negative, incumbents' performance decreases as a result of the introduction of the newcomer, and the group reaps less than it potentially could.

To investigate the indirect impact of newcomers, a learning view is commonly used to explain the positive outcomes. Correspondingly, opportunities to introduce a newcomer are understood as means not only to acquire externally developed knowledge but also to spur learning and facilitate exploitation (Song et al., 2003; Tzabbar, 2009; Zucker, Darby, & Armstrong, 2002). In addition to human capital, newcomers carry social capital that can benefit the incumbent firm (Dokko & Rosenkopf, 2010). Moreover, the different perspectives, experiences, and practices that a newcomer brings to a group invite reflection and learning (Choi & Levine, 2004). The presence of a high-performing newcomer might prompt incumbents to benchmark their attitudes, performance, and behaviors against that high performer, thus motivating them to exert more effort and improve their performance (Max & Moretti, 2009; Slavova et al., 2016). These insights suggest that the introduction of high-performing newcomers, by facilitating knowledge acquisition and motivating incumbents to improve, on average will enhance incumbents' performance. Thus,

> *Hypothesis 1: Newcomers' prior performance will positively affect incumbent members' subsequent performance.*

In general, the literature to date has focused on incumbents' average performance (i.e., Slavova et al., 2016; Choi & Thompson, 2005). The positive newcomer effect implicitly assumes that incumbent group members are equally motivated to improve their performance, neglecting individual variations in their responses. Thus, the literature has not informed our understanding of the extent to which each incumbent could benefit from newcomers or of the conditions under which those benefits can be stronger or weaker. Addressing these two questions calls for an examination of the social-psychological mechanisms underpinning newcomer-induced peer effects.

THE ROLE OF SOCIAL COMPARISON

The arrival of newcomers can shape the social dynamics of incumbents and their performance. Despite its influence on knowledge access in general, the introduction of high-performing newcomers can result in social comparison, leading incumbents to reevaluate their perspectives, abilities, and performance (Festinger, 1954, Kilduff, 1990). The mechanism of social comparison represents the role that peers play in affecting individual behaviors (Tartari, Perkmann, & Salter, 2014).

The social comparison mechanism, representing the tendency of individuals to compare their perspectives, abilities, and performance with others, is an avenue by which employees affect each other (Festinger, 1954; Kilduff, 1990). A group performance ranking, as “an implicit or explicit rank order of individuals or groups with respect to a valued social dimension” (Magee & Galinsky, 2008), offers members a means of accessing the intra-group status hierarchy. Importantly, performance standards, by their nature, provide an assessment of status levels and perceptions of individual competence and accomplishment (Garcia, Tor, & Gonzalez, 2006). In this regard, the social comparison mechanism can serve an important role in motivating individuals’ contributions to groups when they believe their efforts will yield performance improvement (Halevy, Chou, & Galinsky, 2011; Magee & Galinsky, 2008). Conversely, however, employees who fail to meet performance criteria are likely to experience unfavorable social comparison, an individual’s feeling that she “lacks another’s superior quality, achievement, or possession" (Parrott & Smith, 1993). When expectations cannot be met through actual achievement, social comparison likely prompts negative emotions such as jealousy, demoralization, and frustration (Edelman & Larkin, 2015) or the feeling of being threatened due to potential loss of control over critical resources (Fiske et al., 2002; Jordan, Sivanathan, & Galinsky, 2011).

Although the arrival of a newcomer is commonly viewed as an opportunity for incumbents to learn and improve, such an assumption is more ideal than real. Social comparison motivates incumbents to exert more effort, learn, and improve their productivities only when a high-performing newcomer joins the group. Mere social comparison, however, does not necessarily entail a positively trending comparison process. In fact, unfavorable comparison is likely to generate a host of negative emotions or counterproductive behaviors (for a relevant review, see Greenburg et al., 2007). If unfavorable social comparison is the dominant mechanism induced by newcomers, incumbent members will likely suffer from negative influence and, consequently, lower their effort provision, which in turn will reduce their performance.

To the extent that the introduction of a high-performing newcomer is also a source of unfavorable social comparison, the presence of that person alone is not sufficient to guarantee incumbent members' willingness to learn or improve. In this chapter, I contend that the extent to which incumbents can benefit from newcomers depends on their prior performance as well as on the performance-ranking stability of the incumbent group. More specifically, I develop theories on how group ranking stability and newcomer-incumbent relative performance interact to affect the incumbents' subsequent performance. Figure 3.1 provides an overview of my expectations on the newcomer-incumbent peer effect. This chapter addresses the conditions under which an incumbent could or could not benefit from the arrival of a high-performing newcomer.

[FIGURE 3.1 ABOUT HERE]

The first variable of interest is the relative performance between the newcomer and the incumbent. The introduction of a newcomer is designated as a performance shock to an incumbent's intra-group standing. Incumbents pay attention to newcomers' performance, especially when the newcomers have demonstrated superior task accomplishments (Bunderson, Van der Vegt, & Sparrowe, 2014). When newcomers join focal groups, they bring with them a set of socially validated beliefs about the legitimate basis for their positions in the new groups. Newcomers are more likely to influence their new groups when they have been performing well and acknowledged as top performers (Hansen & Levine, 2009). Even when individual rankings based on objective task accomplishments are inconsistent with other established status positions (for example, gender or race), the established status order loses legitimacy, and members tend to be re-sorted based on relative performances (Berger et al., 1998). Given the salience of performance metrics in this context, I expect a relatively high-performing newcomer to challenge incumbents more than a relatively low-performing newcomer.

Specifically, consider the left column of Figure 3.1: when the difference in performance between the newcomer and the incumbent is very small or negative, or, said another way, the incumbent's prior performance is similar to or better than that of the newcomer. The incumbent member, in this case, has secured his or her intragroup ranking, and would not, thus, feel threatened or challenged. The incumbent member, then, would likely interpret the social comparison induced by the arrival of a newcomer as an opportunity to learn and improve. The incumbent's performance could remain the same or increase, depending on the application of knowledge brought in by the newcomer.

Alternatively, consider the right column of Figure 3.1: when the difference in performance between the newcomer and the incumbent is large and positive, the newcomer's prior performance is much better than the incumbent member's. The incumbent member, in this case, is very vulnerable to unfavorable social comparison and the consequent counterproductive effects, which in turn, limits the benefits the incumbent could reap from the arrival of the newcomer. In addition, the large performance gap between the newcomer and the incumbent could coincide with ability, experience, or expertise difference between them (Blau, 1977). Consequently, the incumbent might face challenges in absorbing and understanding the knowledge the newcomer provides. In brief, simply hiring high-performing new employees cannot guarantee that all incumbents will benefit, and indeed, low-performing incumbents may be negatively affected by the hire. Taken all together, I hypothesize that:

> *Hypothesis 2:* Relatively low (high)-performing incumbents will be adversely (positively) affected by the newcomer.

The second variable of interest is group ranking stability, which represents the consistency of the performance ranking of group members. A group with high performance-ranking stability is one for which the incumbents' relative performance rankings remain unchanged or highly correlated within the several months prior to the introduction of any newcomer. Even though an individual group member's objective performance could change month to month, a group with high performance-ranking stability is one in which the incumbents' performance rankings are, nonetheless, static. I expect that the disadvantages associated with low rankings are largely moderated by whether or not the performance rankings are stable or dynamic such that the aforementioned negative effect on low performers would be intensified in groups with high ranking stability.

How members perceive their intra-group rankings hinges on whether they believe that their position can change (Bunderson & Reagans, 2011; Van der Vegt et al., 2010) (see the top of figure 3.1). Stable performance rankings facilitate consensus on where group members rank, which consequently reinforces their reliance on the performance hierarchy to assess individual competencies and statuses (Anderson & Kilduff, 2009; Bunderson & Reagans, 2011). In groups with stable performance rankings, low-performing members are likely to believe that their position would difficult to improve. Such beliefs could lead them to experience greater unfavorable social comparison when a high-performing newcomer joins the group. Upon the arrival of high-performing newcomers, group members might experience this sting, which has been shown to induce perceptions of low status (Blanes i Vidal & Nossol, 2011), undermine the individual sense of self-esteem (Kuhnen & Tymula, 2012), and interfere with the application of effort to work (Greenberg et al., 2007). Relatively lower-performing employees may feel threatened because their odds of success are perceived to have diminished. The motivation to work hard and concentrate on tasks will likewise be diminished, undermining performance. When a newcomer joins groups with a stable performance-ranking hierarchy, low-performing incumbents are already liable to be making unfavorable social comparisons. In this case, then, the introduction of a new high-performing member tends to induce, from the low-performing incumbents, counterproductive responses that, in turn, further decrease their performance.

By contrast, high-performing incumbents in groups with a stable performance ranking are confronted with ranking uncertainties upon the arrival of a similarly high-performing newcomer. As a result, to defend their advantageous standings, high-performing incumbents will be more motivated to improve, and even competitive in seeking to improve, their performance (Bunderson & Reagans, 2011; Flynn & Amanatullah, 2012; Smith, 2000). Indeed, notions of competing and "winning" by outperforming peers are almost axiomatic for top performers. Festinger (1954) noted that "there is a value set on doing better and better which means that the higher the score on performance, the more desirable it is" (pp. 124–125). Accordingly, I expect that the relatively high-performing incumbents will, following the comparative process introduced by the high-performing newcomer, strive to maintain a high position in the competitive rankings.

The above arguments concern the incumbents in the top two quadrants of Figure 3.1, where group performance rankings remain stable. Contrastingly, in groups with dynamic performance rankings, members' intra-group standings are in flux and likely to change dramatically. In this case, all members, believing that their ranking positions can be improved, are less likely to link the dynamic performance rankings with their capabilities. In such groups, "falling behind" is less likely to be linked to a lack of competency and more likely to be interpreted as an "opportunity to improve." Indeed, when the group ranking hierarchy is dynamic, employees who temporarily fall behind tend to become proactive, goal-oriented, and willing to learn and innovate (Scheepers, 2009; Bunderson & Reagans, 2011). Additionally, individuals lower in the performance hierarchy are less stressed when the hierarchy is unstable than when it is stable (Sapolsky, 2005; Jordan et al., 2011). The introduction of the high-performing newcomer would, in this case, motivate incumbents to learn and improve. As a result of this motivation to improve, the performance of relatively low-performing incumbents could be less negatively affected or even increase.

To be clear, group ranking stability is a different construct than individual ranking stability within a group, albeit the two are correlated. In groups with stable performance ranking, individual rankings are likely to remain stable. The group-level construct, however, is distinct from individual rankings within the group. It is possible that an individual has a stable intra-group ranking in a group with dynamic performance rankings, meaning the individual would be likely to observe the changes in the relative performance of her colleagues. The consensus on where everyone ranks is a key that determines an individual's self-assessment within a group (Anderson & Kilduff, 2009; Kilduff, Willer, & Anderson, 2016). Put differently, the inherent ambiguity and uncertainty associated with dynamic performance hierarchy lead members to be less likely to experience unfavorable social comparison, even when their individual rankings remain relatively stable. I expect that the effects would be weaker in such cases.[6]

Taking these arguments together, I consider specifically those incumbents in the top right quadrant of Figure 3.1, who experience unfavorable social comparison and who tend to be demotivated to exert effort and improve. This quadrant represents a condition where unfavorable social comparison could dominate and produce a negative two-way interaction effect of the newcomer-incumbent performance gap and group performance ranking stability on the incumbent's subsequent performance. I hypothesize as follows:

> *Hypothesis 3:* Group ranking stability negatively moderates the effect of newcomer-incumbent relative performance on the incumbent's subsequent performance such that relatively low (high)-performing incumbents will be *more* adversely (positively) affected by the newcomer in groups where performance ranking is stable.

THE MEDIATING ROLE OF INCUMBENTS' COMMUNICATION BEHAVIOR

The impact of a newcomer on incumbents' performance hinges on the incumbents' variations in their responses to the newcomer's arrival. Since the relatively low-performing incumbents are the individuals who are most vulnerable to unfavorable social comparison and exhibit most variation, I focus my attention mainly on this group when I discuss the mediation effect. In groups with stable rankings, where unfavorable social comparison is the dominant mechanism, low-performing incumbents are likely to interpret the introduction of a high-

[6]Additional analyses confirm that individual ranking stability also negatively moderates the effect of newcomer-incumbent relative performance on the incumbent's subsequent performance, the effect size is smaller than that of group ranking stability, the analyses are reported in Table A7 in Appendix.

performing newcomer as “threat” or “challenge” to their already low intra-group standing. This is because the odds of achieving better standings could be decreased and the risk of losing the job could be increased. Alternatively, in groups with dynamic rankings, where incumbents are willing to learn and improve, low-performing incumbents are likely to interpret the introduction of a high-performing newcomer as an “opportunity” to learn. In brief, incumbents’ responses to the introduction of newcomers mediate the newcomer-induced peer effect.

The variation in response to a newcomer amongst incumbents can be investigated via incumbents’ communication behaviors, particularly the density of their communication networks (i.e., Smith at al., 2012). The density of an individual’s communication network represents who the individual communicates with (the alters) and how these colleagues communicate with each other. In detail, individual’s communication density is the number of connections that exist among the alters divided by the number of connections that could exist (Wasserman & Faust, 1994). Holding the size of communication network constant, high communication density represents a structure where the colleagues are close-knit (Barnes, 1969); whereas low communication density represents an open structure where these colleagues seldom communicate with one another. The individual is more likely to occupy a brokerage position in the latter case such that the individual bridges colleagues who are otherwise not able to communicate (Burt, 1992).

When incumbents under “newcomer threat” become demoralized, I argue that they will turn inward, winnowing their networks to a smaller and denser set of colleagues. The winnow response represents a high need for social support and low willingness to learn novel knowledge. This argument builds on the social psychology literature that states that individuals tend to reduce uncertainty in times of threat, such as organizational change (Shah, 2000; Srivastava,

2015) and job loss (Smith, Menon, & Thompson, 2012). Experiencing the newcomer's joining the group as a "threat" to their poor standings, low-performing incumbents would respond to the threat by reducing uncertainty or exposure to novel information. The winnowing response also has roots in research on unfavorable comparison that documents the occurrence of negative emotions (i.e., stress, anxiety, arousal) as a result of threat perception. These negative emotions have both cognitive and behavioral implications (Smith at al., 2012). The cognitive implications include restrictions in information processing, such as emphasizing prior experience and excluding novel information. The behavioral implications include low effort provision and increasing interactions with acquaintances. The implications of both accounts suggest a winnowing communication pattern.

Moreover, the literature on intra-group status hierarchy offers similar predictions. A performance-ranking hierarchy, when it is stable, oftentimes coincides with status hierarchy (Berger et al., 1998). The introduction of high-performing newcomers would inevitably introduce reflection and make the status difference salient to the incumbents. Individuals with a lower performance ranking or lower status likely perceive their groups to be less safe for social interaction (Bunderson & Reagans, 2011; Edmondson, 1999; Van der Vegt et al., 2010). Thus, they tend to behave in tentative and inhibited ways; low-performing individuals feel more constrained by their in-groups than their high-ranking peers and, therefore, are less willing to reach beyond their local networks (Galinsky, Gruenfeld, & Magee, 2003). Low-performing incumbents in groups with stable performance hierarchy would be likely to exhibit an "inhibition" behavior pattern (negative emotion and inhibited behavior) in contrast to an "approach" behavior pattern (positive emotion and uninhibited behavior) in response to their status disadvantages.

Thus, having synthesized the relevant literature, I expect that when a high-performing newcomer joins a group, relatively low-performing incumbents' responses to this perceived threat would have analogous repercussions for their communication networks. When a newcomer joins a group with a stable ranking hierarchy, the relatively low-performing incumbents are likely to experiencing unfavorable social comparison and feel threatened. Consequently, these low-performing incumbents become less likely to explore. To protect themselves from the uncertainties associated with less familiar colleagues, they are likely to winnow their communication networks. Altogether, I expect relatively low-performing incumbents to have lower communication density in groups where performance ranking is stable.

Although relatively low-performing incumbents winnow their networks due to unfavorable social comparison, the winnowing-network response can hurt rather than improve their performance. In fact, expanding one's communication network is the optimal response to the arrival of a high-performing newcomer, or to threat in general (Ancona & Caldwell, 1992; Smith et al., 2012). Communication with one's close colleagues might provide a supportive refuge, but it also coincides with fewer potential learning pathways to improved job performance. However, maintaining an open and diverse communication network is more difficult. Communication with receivers who are otherwise not talking with each other exposes an individual to divergent information and expertise as well as different perspectives on the work. Extensive interactions with colleagues otherwise not communicated with oftentimes builds bridges to those who possess disparate areas of expertise, which correspondingly increases the likelihood that an individual will become more accustomed to assessing and transforming work-related knowledge (Burt, 1992; Tortoriello, Reagans, & McEvily, 2012; Reagans & McEvily, 2003). Such a transformation is an essential part of improvement (Bechky, 2003). Broadly, the open and diverse networks might help incumbents to improve by increasing access to work-related information and spurring learning. Despite this, I expect that incumbents experiencing unfavorable social comparison would respond by limiting their communication to a smaller and denser set of colleagues, which in turn, would reduce their already low performance. I hypothesize as follows:

> *Hypothesis 4:* The incumbent's communication density mediates the negative interaction effect between newcomer-incumbent relative performance and group ranking stability on the incumbent's subsequent performance.

METHOD

Empirical Setting

I collected data from a U.S.-based private financial institution's retail sales department. Employees in this department strive to provide products and services to customers and generate value for the bank. Examples of such products and services include residential mortgage loans, saving plans, investments, or the purchase of properties. The department computer automatically calculates the total amount of sales each employee makes by the end of each month. A retail sales department is an important and highly autonomous organizational context that operates in a relatively intensive environment. Retail sales employees are financially rewarded for their sales performance.

Several features are unique in this empirical setting. First, each employee belongs to a local branch, where they co-locate and work with others. A hiring decision is typically made by colleagues in the human resource department and colleagues of higher job levels. Thus, the arrival of newcomers is exogenous to the incumbents in the local retail sales group.

Second, employees in the department work independently in selling products to their customers. The major proportion of their pay reflects the total number of their monthly sales.

The HR head at the firm stated that employees are both aware of and pay attention to the other employees' performance. Field observations at eight branches reinforce this statement; some groups even put everyone's performance on a whiteboard to reinforce in-group comparison. This incentive for employees to work well individually creates a competitive atmosphere wherein group members become vulnerable to unfavorable social comparisons if their performance cannot achieve the desired level of success.

Besides the intragroup competition, this context also generates an atmosphere conducive to frequent communication and learning, which consequently could lead to possible performance externalities, including knowledge spillovers and shared tactics. Examples of knowledge in this setting include knowledge of the market, information on customers' appeal or preferences, and strengths and weakness of each product compared with those offered by competitors. Sales tactics, such as how to introduce a product to consumers or how to make small talk during waiting times, are also critical in driving sales. Essentially, retail sales employees seldom go out of the office to explore opportunities; they need to learn how to make most of the opportunities presented to them. Put differently, employees in retail sales departments, having autonomy in choosing how to perform their daily tasks, face resource limitations in terms of both available customers and internal support—limitations that require them to keep looking for efficient ways to boost productivity.

The transparency of performance and the learning needs of the job together highlight the importance of understanding the social psychological mechanisms underpinning individual performance. Finally, in retail sales groups, mobility is very common, and plays a pivotal role in transferring and accumulating experience. Altogether, this context offers a unique opportunity to examine the relationship between mobility and performance.

Data and Sample

To investigate the influence of newcomers on incumbents, I performed an intra-group comparison only for the *same-title* and *same-level* employees within each Big Bank branch. Such groups are the basic job-related demographic units that employees often consider when they make social comparisons at the workplace; they also determine the number and nature of opportunities for interactions and knowledge sharing among peers (Ancona & Caldwell, 1992). Field observations in this financial institution have confirmed that, in this context, employees with different job titles and job levels are incomparable with one another. Employees at different job levels face different expectations, in the sense that higher-level employees are expected to generate more value than their lower-level peers. Furthermore, because of my interest in group ranking hierarchy and because it is difficult to assess or evaluate hierarchy with fewer than three members, I restricted the groups to those with at least three incumbents.

In the financial institution, I collected individual demographic information including gender, race, age, job role, job grade, organizational experience, role experience, supervisor, and branch. I also collected, for the November 2014-April 2016 period, the monthly-updated performance of employees in the retail sales department. Individual performance was captured by the dollar value of retail products an employee sold by the end of each month. In addition, I collected all of the employees' meta email-communication variables including sender, receiver, timestamp, and the size of each message. I examined individual behavioral responses to the arrival of newcomers, which, as I contend, would mediate the relationships among incumbents' intra-group ranking, group ranking stability, and individual performance, by analyzing changes in the individual communication patterns. Indeed, email communication is only a partial representation of an employee's work-related behaviors; nonetheless, it is a powerful source of observations and is largely consistent with communication patterns through other means (Quintane & Kleinbaum, 2011; Srivastava, 2015). As a conservative representation of the intra-organizational communication network, I limit my analysis to one-to-one emails within the organization, excluding all one-to-many emails or emails sent to and received from external sources.

The central interest of the analysis was to test the relationship between a newcomer's performance, group ranking stability, and incumbents' subsequent performance. Two empirical concerns are important in approximating an ideal experimental design in the field: (1) omitted variable bias, indicating that a low-performing incumbent might be one who cannot learn effectively due to unobservable reasons; and (2) selection bias, indicating that the incumbent-group association might not be random; groups exhibit certain structural characteristics due to unobserved characteristics of their members. I attempt to address both concerns by keeping the *incumbent-group* unit constant, observing the variance in the group ranking stability and the variance in the performance of incumbents over time. Fortunately, my field data allowed me to construct a sample that approximates this ideal design by investigating the same groups of incumbents when the group's ranking stability changes.

More specifically, because the analyses were conducted at both group and individual levels, I constructed an individual-level sample of 17,681 incumbent-month units and a group-level sample of 6,646 group-month units. The incumbents belonged to 1,327 same-role groups (the total number of incumbents varying between 3 and 15) across 784 branch locations. In essence, the sample of interest was all of the incumbents (including both high and low performers) working in groups that have had recruited at least one newcomer during the observation period.

Measures

Incumbent Performance. Incumbent performance is the main dependent variable of interest. Briefly, it represents the dollar value of an incumbent employee's sales by the end of a month. Newcomers are incorporated into a group over a moving window of two months. That is, I define newcomers as employees who joined the group between month *t* and month *t-1*. Incumbents are those members who joined the group prior to month *t-1*. I used a one-month lead (performance in month *t+1*) for this dependent variable after measuring my independent and control variables for each month. The time gap is reasonable for this setting, because retail sales delays tend to be relatively short. Using lagged independent variables (and a lead dependent variable, respectively) helped alleviate potential concerns about reverse causality.

Newcomer Performance. Newcomer performance measures the magnitude of impact on incumbents resulting from the arrival of newcomers. I operationalized it as the aggregated performance within *N* months prior to joining the new group, as shown in Equation 1.

$$Newcomer's\ Performance_t = \frac{1}{N}\sum_{t-N-1}^{t-1} Sales_i$$

(Equation 1)

where $t = 1, \ldots k$ represents the month when newcomers join the group, the dollar amount of sales has been divided into 9 performance categories by the institution, and categories with larger numbers represent higher sales. $Sales_i$ is the respective category value[7] of performance of newcomer *i*, and *N* indicates the total number of months prior to *t*. Using an *N*-month window helps to attenuate fluctuations, and, thus, better reflects individual propensity to generate a high dollar value of sales prior to hiring.[8]

[7] The categorical values provided by the bank and field observations confirm that people are more likely to remember and refer to them than to the precise numbers.
[8] An analysis of employees who have moved more than once in the financial institution during the observation

Newcomer-Incumbent Relative Performance. The difference of prior performance between the newcomer and incumbent measures the relative performance. I operationalized this as the gap between the aggregated performance within N months prior to the newcomer joining the incumbent's group, as is shown in Equation 2:

$$Performance\ Difference_t = \frac{1}{N}\sum_{t-N-1}^{t-1} Newcomer\ Sales_i - \frac{1}{N}\sum_{t-N-1}^{t-1} Incumbent\ Sales_i$$

(Equation 2)

where t = 1, …k represents the month when newcomers join the group. Similarly to Equation 1, $Sales_i$ is the respective category value of performance, and N indicates the total number of months prior to t. Newcomer i's prior performance is represented by his sales' dollar values within N months prior to joining the group.

Communication Network. In the present study, the ego-network analysis was performed because of the importance of the immediate social context of the ego.[9] The ego-network of an individual is composed of all *receivers* with whom the individual communicates and the communication relations among the receivers in month t. Receivers are included regardless of where they are physically located in the organization. The individual (either the incumbent or the newcomer of

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period suggests that the average length of time between jobs is six months; thus, N was set to five to measure a newcomer's average performance.

[9] Social network analysis frequently distinguishes between what are called "whole network" and "ego network" analyses. Ego-network analysis considers only the immediate social space of a given person/actor/ego. Whole-network analysis considers the linkage of many egos. However, in whole-network analysis of organizational structures, measures that involve calculating the properties of the entire graph could return non-useful results when ego network size is smaller than the diameter of the whole network (Carley, Morgan, & Behari, 2016). Alternatively, better results can be obtained by using the communication network around a given ego, which is the focus of my analysis.

interest in this case) is excluded from the network analysis. The *size*, *density*, and *clustering coefficient* of this network were calculated.

Communication Network Density. Receivers are colleagues to whom the ego has sent emails by the end of month *t*. Newcomers and leavers and all their ties are excluded from the list. Communication network density in month *t* is the measure of the total number of existing communication ties among all of the ego's receivers divided by the total number of possible ties among them. The main mediator, *individual's winnowing communication response*, is captured by *changes in individual's ego-network (communication) density*. Increasing communication density suggests that the ego communicates with a smaller and tighter set of email receivers who also communicate with one another; meanwhile, decreasing communication density suggests that the ego communicates with a larger and looser set of receivers.

Group Ranking Stability. Group ranking stability represents the persistence of ranking order amongst the *incumbents* in the few months before the newcomer is introduced. To measure group ranking stability, I use Kendall's correlation approach (Abdi, 2007; Kendall, 1938), which provides a pairwise correlation of incumbents' performance rankings in the *N* months prior to month *t* (incumbents are the group members that joined the group before month *t-1*). Ranking stability is simply the mean of month-to-month *Kendall's Tau*. That is,

$$Group\ Ranking\ Stability_{t-N,t-1} = \frac{1}{(N-1)} \sum\nolimits_{i \subseteq (t-N,t-2)} Tau_{i,i+1}$$

(Equation 3)

where *t* represents the month when newcomers join the group, and *N* indicates the total number of months prior to month *t* when incumbents' performance-ranking correlations are calculated. A Kendall's Tau is calculated between performance ranking in month *i* and month *i+1* (rankings in current and subsequent months). The higher this correlation, the more consistent the two ranking serials are. Then the group's ranking stability was calculated by averaging the pairwise performance correlations.

Control Variables. The main analyses are conducted with multi-level models. Thus, I include control variables at both levels to account for alternative explanations. At the individual level, I controlled for *organizational tenure, job tenure, job title, grade*, and *individual average prior performance* (three months prior to newcomer's arrival) before the newcomer arrival. I also controlled for individual ego-network *size* and *clustering coefficient* in order to examine individual ego-network density change. More specifically, the communication network *clustering coefficient* in month *t* is the measure of the total number of observed triads in the ego network divided by the total number of triples. A triad in the communication network indicates that three email receivers of an individual have communicated with one another. At the group level, I controlled for the *size of the group*, *total number of top performers*, the *total number of exits*, the *performance of leavers*, the *average organizational tenure of group members*, *average job tenure of group members*, the *total number of supervisors,* and *percentage of male members.*

Model

The relative performance change for each individual (H1, H2 and H3) and its mediation (H4) are estimated at the individual level. The sample, comprised of observations of each incumbent's performance and email communications over time, exhibits an unbalanced-panel structure. Given the data structure, I ran the analysis with a generalized linear regression on *incumbent's performance* (and *density of communication network*) at the incumbent-newcomer level, including *month* and *location* fixed effects. Additionally, I included individual-level random effects to account for those individual-level effects that are uncorrelated with the explanatory variables. Allowing the intercepts to vary by individuals is important, since increasing evidence suggests that formal job roles and individual personal differences can generate variations in behavior that are outside the social context (Burt, 2012; Sasovova et al., 2010). This random-effect model accounts for the possibility that observationally equivalent individuals differ on unmeasured characteristics (Hausman & Taylor, 1981). In addition, the Hausman test is not significant, indicating the random-effects model is preferred to fixed-effects model. The individual-level model is as follows:

$$P_{i,j,g,t+1} = \beta_0 + \beta_1 X1_{i,t-1} + \beta_2 X2_{g,t-1} + \beta_3 X3_t + \beta_4 M_{g,t-1} + \beta_5 R_{i,g,t-1} \times S_{g,t-1} + v_{1i} + \varepsilon_{i,g,t}$$

where $i = 1,\ldots.n$ incumbent group members and $g = 1,\ldots m$ incumbent groups. The dependent variable *P* represents the incumbent member's performance in month *t+1* (or incumbent member's communication density in the mediation analysis). *X1* consists of individual-level controls in month *t-1*. *X2* consists of group-level controls in month t-1. *X3* represents the fixed effects of *month t*. M represents the prior performance of the newcomer who joins group *g*. *R* represents the aggregated relative performance between the newcomer and incumbent *i* by month *t-1*. *S* represents incumbent group *g*'s ranking stability in the five months prior to month *t*. Main effects of *R*, and *S* are also included in the model, but are not spelled out here. v_{1i} is the individual-level random intercepts, and $\in_{i,g,t}$ is the residual error term.

MAIN RESULTS

The main hypothesis on an incumbent's performance and its mediation are analyzed at the individual level. Table 3.1 reports the descriptive statistics, including the maximum, minimum, means, standard deviation values, and a correlation matrix, among all of the variables at the individual level. The pairwise correlations between the independent and control variables are relatively low, excluding multicollinearity concerns.

Table 3.2 presents the main analytic results of the individual-level analyses. Model 1 shows a positive association between a newcomer's prior performance and the incumbent's performance in the subsequent month. This is consistent with hypothesis 1, that the prior performance of the newcomer positively affects an incumbent's subsequent performance. Model 2 in Table 2 further includes the newcomer-incumbent relative performance. The positive association between the newcomer's prior performance and incumbent's subsequent performance is robust to the inclusion of the relative performance. Model 2 also shows a negative association between the newcomer-incumbent relative performance and incumbent's subsequent performance. This is consistent with hypothesis 2: holding the newcomer's prior performance constant, the newcomer-incumbent prior relative performance negatively affects the incumbent's subsequent performance.

[TABLES 3.1AND 3.2 ABOUT HERE]

For hypothesis 3, I expected, and found, a negative two-way interaction between the newcomer-incumbent prior relative performance and group ranking stability with respect to the subsequent performance of incumbents. In model 3, the main effect of group ranking stability is added to model 2. The main effect of group ranking stability is not significant. In model 4, the two-way interaction terms are added, and the effect is negatively significant. As predicted, the most negative effect of a newcomer's performance on an incumbent's subsequent performance is observed when the gap of performance between the newcomer and the incumbent is large and group ranking stability is high. By contrast, the effect of a newcomer's performance on an incumbent's subsequent performance is most positive when the incumbent outperforms the newcomer and group ranking stability is low. The negative interaction is plotted in Figure 3.2. This result indicates that the performance of low-performing incumbents further suffers (improves) when a high-performing newcomer joins groups with a stable (dynamic) performance-ranking hierarchy, supporting hypothesis 3.

[INSERT FIGURE 3.2 ABOUT HERE]

Hypothesis 4 predicts that the negative interaction effect in model 4 is mediated by an incumbent's communication behavior such that relatively low-performing incumbents would respond to the introduction of a relatively high-performing newcomer by winnowing, instead of widening, their communication networks. The winnowing versus widening behavior is operationalized as the change of incumbent ego-network density, controlling for network size. Recall that density change represents the extent to which an individual communicates with a smaller and tighter set of email receivers. An increasing density suggests that individuals communicate with a smaller and tighter set of email receivers who also communicate with one another; a decreasing density, meanwhile, suggests that individuals communicate with a larger and looser set of receivers who might not know each other. As predicted, I observed the most positive effect of a newcomer's performance on an incumbent's communication density change when both the incumbent's prior intragroup ranking (high ranking represents low absolute performance, as is coded) and group ranking stability are high; the density of the relatively low-performing incumbents increases when a high-performing newcomer joins groups with a stable performance-ranking hierarchy, as is shown by model 5 in Table 3.2.

I include the dependent variable of model 5, the incumbent's communication network's density, in model 6 in Table 3.2, which examines the extent to which the incumbent communicates with a dense clique of colleagues who also communicate with each other. As is consistent with the conventional wisdom on social networks and performance (i.e., Burt, 1992), increasing communication density negatively correlates with performance in the subsequent month.[10] The negative and significant effect of the two-way interaction between the newcomer-incumbent relative performance and group ranking stability becomes not significant ($p > 0.1$) after including the *density of the incumbent's communication network*, as shown by model 6 in Table 3.2, supporting a mediation effect. Moreover, I performed a mediation analysis following the approach suggested by Imai, Keele and Yamamoto (2010) with models 5 and 6 in Table 3.2 with the package of "mediation" in R. The analysis results showed that the estimated mediation effect is significantly different from zero ($p < 0.000$), suggesting that the two-way interaction between the newcomer-incumbent performance gap increases the incumbent's communication density, which in turn decreases the incumbent's subsequent performance. The mediator explains the 18.94% variance between the two-way interaction and the dependent variable.

At the individual level, the selection of newcomers into groups is exogenous, as those in the group are not involved with its selection. Moreover, the models in Table 3.2 all include incumbent random intercepts, group random intercepts, and month fixed effects to control for fluctuations in the independent variable by individual, group, and year that are also correlated with incumbents' performance. As such, it helps to address the key source of reverse causality between incumbents' performance and the newcomer's prior performance.

ALTERNATIVE EXPLANATIONS

The main results support the hypotheses formulated above. Together they suggest that the introduction of a high-performing newcomer affects incumbents' performance through social comparison. Incumbents who experience unfavorable social comparison would respond to the

[10] The mediation effects are also estimated with *communication density* in $t+1$ and *performance* in $t+2$, the results are reported in Table A8. All results remain.

newcomer's advance with a winnowing communication behavior, which subsequently lowers their performance.

Nonetheless, unfavorable social comparison and its consequent social inhibition are not the only mechanisms that could generate an association between the two-way interaction of newcomer-incumbent relative performance and group ranking stability and individual network response. Previous studies of friendship networks have identified how leavers affect the morale and performance of incumbents (Krackhardt, 1999). It is possible that the winnowing effect of the communication network is partially driven by the effects of "exit," which sometimes occurs in parallel with the introduction of newcomers, as in the case of an employee who retires (the leaver) and then is replaced by a new hire. To differentiate the proposed unfavorable social comparison mechanism, I include measures on the total number of exits and their prior performance. In addition, I exclude the leavers along with all of their communication ties in constructing the incumbent's communication network within two months prior to their exits.

Another alternative explanation is that the winnowing effect of an incumbent's communication network is driven not by the incumbent's own initiative but, instead, by a newcomer's communication activity. That is, active newcomers may make incumbents' networks seem tighter than they actually are. For example, imagine two different groups of employees. All else being equal, suppose that newcomer M communicates with every colleague in Group A, whereas newcomer N does not communicate with anyone in Group B, and that an incumbent's communication network in Group A could be denser than an incumbent's communication network in Group B. The seemingly tighter network in Group A is not driven by the incumbent's behavior but, rather, by the fact that M is very active whereas N is not. If this is true, in groups where newcomers are active, incumbents' exhibit tighter communication networks. To rule out this possibility, I exclude the newcomer along with all of the communication ties of that newcomer in constructing the incumbent's communication network.

Finally, certain groups might allocate resources or tasks according to intra-group performance hierarchy. If these groups have other characteristics that limit low-performing incumbent's access to resources, then these characteristics could explain a positive association between the two-way interaction and the incumbent's communication networks. To address this concerns on unobserved variations at the group level, I include controls for the main group-month determinants of incumbent group members' networks. These controls include group demographic information and intragroup network characteristics. Moreover, I include group-specific random intercepts (Hausman & Taylor, 1981).

In Table 3.3, I present supplementary analyses at the individual level. I first assess the robustness of results to group and month fixed effects and a broader range of individual-level controls. These tests provide evidence of the robustness of the main results presented above and demarcate the limitations of the data used in this study. More specifically, model 1 reports the analysis controlling for individuals' age and experience, and model 2 reports the analysis controlling for group-level characteristics such as size, the total number of top performers, and turnover. As discussed in the theory section, it is possible that the departure of other colleagues could drive changes both in the incumbent's network and in his or her performance. To deal with this issue, model 2 includes two leaver-related variables: the total number of employees who leave (the variable "*Total Exits*") and the performance of leavers (the variable "*Performance of Exits*"). The correlation between newcomer's performance and leavers' average performance is low ($r = 0.162$, $p < 0.05$), indicating that the observed newcomer effects cannot be explained by attrition. I included the two variables in the models to account for leavers' impact. Model 3 reports the analysis controlling for other individual communication-network-related measures. Incumbents may try to increase the depth and strength of conversations by winnowing their communication network to a smaller and tighter set. I controlled away this alternative explanation by including the *average communication volume* between the incumbent and all his/her email receivers per month and the *average size of emails* an incumbent sent in model 3. Model 4 in Table 3.3 presents the analysis controlling for all the other predictors, and finds that all hypothesized effects at the individual level remain robust.

Model 5 in Table 3.3 reports the effect of the two-way interaction between newcomer-incumbent relative performance and group ranking stability on the mediator, incumbent's communication network density (Beat = 0.007, $p < 0.001$). Model 6 in Table 3.3 presents the effect of the two-way interaction after including the mediator. The two-way interaction remains significant in model 6, but the effect size decreases dramatically compared with model 4 where the mediator is not included. Thus, the mediation effect is supported. A mediation analysis with the "mediation" package in R further supports the significance of the mediation effect ($p < 0.001$).

[TABLES 3.3 ABOUT HERE]

SUPPLEMENTAL GROUP-LEVEL ANALYSES

The question of how the performance of incumbents is influenced by the arrival of a high-performing newcomer has group-level implications. The relatively low-performing incumbents will be caught, upon the arrival of a high-performing newcomer, in a vicious cycle between their prior performance and subsequent performance, because unfavorable social comparison tends to be the dominant mechanism, especially in groups where performance ranking is stable. As a result, low-performing incumbents tend to be less proactive within such groups. Their high-performing colleagues, however, are more likely to interpret the arrival of a high-performing newcomer as an opportunity to learn and to innovate. This mindset would further help improve their already high performance.

Building on the logic discussed above, the social comparison mechanism would imply that the relatively high-performing incumbents are motivated, but the relatively low-performing incumbents could get demotivated, resulting in an increase in dispersion of performance. The high-performance disparity is particularly problematic for organizational groups, because it can disrupt knowledge sharing and experimentation (Bunderson & Reagans, 2011), increase deception among group members (Edelman & Larkin, 2015), and leave the group more vulnerable to member turnover (Bunderson, Van der Vegt, & Sparrowe, 2014).

Moving from the individual-level effects to the group level, I expect that high-performing newcomers' prior performance is associated with wider dispersion in incumbents' performance within groups where the performance ranking is stable than in groups where performance ranking is dynamic. That is, when groups exhibit the same amount of performance increase on average, the performance distribution among the incumbent group members can vary depending on the incumbent group's ranking stability.

A panel generalized linear regression also was conducted at the group level. I included both group-specific and month-specific fixed effects as well as group-level random effects to account for the group-specific effect that is uncorrelated with the explanatory variables. Specifically, this model accounts for the possibility that observationally equivalent groups differ on unmeasured characteristics (Hausman & Taylor, 1981). The group-level model is as follows:

$$Y_{i,t+1} = \beta_1 + \beta_2 X_{i,t} + \beta_3 M_{i,t} \times S_{i,t} + \alpha_i + \epsilon_{i,t}$$

where $i = 1, \ldots n$ incumbent groups, and $t = 1, \ldots k$ months. The dependent variable Y represents the aggregated incumbent group members' performance, namely, the *average* and the *disparity*. X consists of group-level controls. M represents the main independent variable—*newcomer's performance*—the average prior performance rankings of newcomers who join the group in month t. This variable is set to 0 if there are no newcomers joining the group in the corresponding month. S represents the incumbent group's ranking stability in the five months prior to t. α_i is the group level random effect and $\in_{it}$ is the residual error term.

Table 3.4 reports the descriptive statistics, including the maximum, minimum, means, standard deviation values, and a correlation matrix, among all of the variables at the group level. The pairwise correlations between the independent and control variables are relatively low, excluding multicollinearity concerns. Particularly, the pairwise correlation between the independent variable (newcomer's prior performance) and the moderator (group ranking stability) is low (r = 0.014). To further assess the relationship between the two variables, I ran additional analyses estimating *groups' likelihood of hiring* and the *prior performance of their new hires* (contingent on hiring) with all group-month observations. As shown in Appendix Table A9, they also indicate that groups that have stable versus dynamic performance rankings do not significantly differ in their likelihood of hiring or the prior performance of the newcomers they hire.[11]

[TABLES 3.4 AND 3.5 ABOUT HERE]

Table 3.5 presents the main analytic results of the group-level analyses. In the simplest models, I control for group size and the total number of top performers (those who have a rank higher than 5 out of 9 categories). The two controls are critical to model the group average performance and performance disparity. More control variables are introduced in subsequent

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[11] Table A9 in the Appendix reports the estimations on *the likelihood of hiring* and the *performance of new hires* at the group level.

analyses. The dependent variable in model 1 in Table 5 is the average dollar amount of an incumbent member's performance in the subsequent month after newcomers join. Model 1 shows a positive association between newcomers' prior performance and the incumbents' performance in the subsequent month. This finding reaffirms hypothesis 1. I expect a positive effect of the newcomers' prior performance on the subsequent performance of incumbents; a positive and significant effect is found, holding group size and the total number of top performers constant.

Next, I test whether high-performing newcomers' prior performance is associated with wider gaps in incumbents' performance within groups where the performance ranking is stable. The average performance of incumbents is controlled in estimating the performance disparity (measured by standard deviation) of incumbents' performance. Models 2 and 3 in Table 3.5 include the main effects of newcomers' prior performance and group ranking stability. Although the introduction of high-performing newcomers reduces incumbents' performance disparity (β = -0.027, $p < 0.005$), model 4 includes the interaction effect and suggests that the reduction does not exist in groups with a stable performance ranking hierarchy. The two-way interaction between newcomers' prior performance and group ranking stability significantly increases the performance disparity of the incumbents ($\beta = 0.019$, $p < 0.01$). When groups exhibit the same amount of performance increase on average, the performance distribution among the incumbent group members can change in very different ways, depending on the incumbent group's ranking stability. More specifically, in groups where the performance ranking is stable, low-ranking incumbents will be less proactive in such groups. Their high-performing colleagues, however, are more likely to improve their already high performance. Thus, group performance disparity increases. The finding provides support for Hypothesis 3 at the group level.

There might be time variant, location-specific factors that explain both newcomer characteristics and incumbent's performance after the newcomer's arrival. An ideal empirical approach for testing the effect of newcomers involves random assignment of newcomers to groups and a subsequent analysis of performance. Unable to implement this approach, I sought to leverage the exogenous variation in newcomers' prior performance to estimate its effect on the outcomes of interest. To do so, I used *group's degree of expansion* (measured by the difference between average group size in the subsequent quarter and previous quarter) as an instrumental variable to identify the causal relationship between a newcomer's performance and incumbents' subsequent performance. On average and all else equal, my identifying assumption is that groups that expand are more likely to recruit top performers and good candidates compared with groups that are in urgent need to replace the exits. The degree of expansion, however, is independent of incumbents and their performance when market differences are controlled. This variation in the group's degree of expansion essentially inflates variation in the prior performance of the newcomers, allowing me to test the argument that it is the newcomer's performance that affects incumbents and not vice versa.

A valid instrumental variable must satisfy several additional statistical conditions (Wooldridge, 2002). I discuss some of those in the results section below but briefly mention a few conditions here. Namely, in this case, a group's degree of expansion must be correlated with the independent variable (i.e., newcomer's prior performance). As is shown in Table 3.5, the instrument variable and the independent variable (newcomer's prior performance) are significantly correlated ($r = 0.48$, $p < 0.05$). I expect that groups are more likely to find top performers when they seek to expand rather than seek a replacement. I ran an OLS to estimate this effect; the coefficient is positive and significant ($\beta = 0.636$, $p < 0.005$); thus, this condition is satisfied.

Results remain robust with instrument variable estimations, as is shown by models IV (1), IV (2), and IV (3) in Table 3.5. An ideal instrument influences the outcome of interest (i.e., the incumbent's performance) exclusively through its influence on the explanatory variable of interest (i.e., newcomer's prior performance). I cannot make this assumption because we know that membership turnover could affect incumbents; however, the inclusion of group-specific random intercepts helps eliminate some of this concern. The instrument variable influences the incumbent's performance through its effect on hiring top performers, conditional on group-specific variation that is common to all newcomers.

In Table 3.6, I present supplementary analyses at the group level that further test the theory. Models 1, 2, and 3 in Table 3.6 report the analyses on group's subsequent average performance, and models 4, 5, and 6 report the analyses on group's subsequent performance disparity, controlling for the average. I assess the robustness of results to a broader range of group-level controls, particularly, the controls on group demographics (model 1 and model 4, respectively) and group communication network structures (model 2 and model 5, respectively). These tests provide evidence of the robustness of the main result in hypothesis 5. In models 3 and 6 in Table 3.6, I include all predictors to show the robustness of the results, particularly for hypotheses 1 and 3.

EMPIRICAL CONCERNS

I attempted to address these methodological concerns by following the existing practice in the literature (i.e., Slavova et al., 2016). First, this paper demonstrates that the impact of a newcomer on incumbents' performance is mediated by the incumbents' communication behaviors. My regressions accounted for some time-varying controls. Nonetheless, controlling for all potential contextual factors is very difficult, and so spurious correlations might yet have biased my coefficients. Individual-fixed effects could partially address contextual or correlation biases. Even if some individual-level biases remain in the estimates of the effect of newcomers, I do not have theoretical reasons to believe that those are correlated with the moderators.

Second, the newcomer's self-selection effect could be a concern, in that newcomers self-select into a group wherein the incumbents perform poorly so that they can achieve a higher intra-group ranking. In this case, the effect of hiring high-performing newcomers on incumbents' average performance would biased downward. Nonetheless, in the relevant setting, individuals do not have incentives for such selections because group outcome as a whole partly affects each group member's bonus. Thus, the newcomer's self-selection effect should not be an issue for the theory. In addition, the newcomer's self-selection effect would only bias the estimation of the average incumbents' performance; it has little impact on each incumbent's performance and or the incumbent's performance disparity.

DISCUSSION AND CONCLUSION

Although an individual's past performance does predict future performance, the presence of newcomers in a group significantly affects incumbents' outcomes. I hypothesized and found that incumbents do not benefit equally from newcomers; instead, the extent to which incumbents can benefit hinges on their social context and their response to it. Results support a two-way interaction, indicating that when group hierarchy is stable and the newcomer-incumbent relative performance is large, the performance of the incumbent declines. When group hierarchy is dynamic, and the newcomer-incumbent relative performance is small or does not exist, the performance of the incumbent improves upon the arrival of a high-performing newcomer. Moreover, the effect of the two-way interaction is mediated by the extent to which incumbents exhibit a winnowing-network response (i.e., communicating with a smaller and tighter network of colleagues). Particularly, when a high-performing newcomer joins such groups, relatively low-performing incumbent members will exhibit a winnowing behavioral response (i.e., they will communicate with smaller and tighter subsets of their networks). Because of this winnowing communication response, the low-performing incumbents will be trapped in a vicious cycle in which their performance will worsen.

Theoretically, the paper adds to the learning-by-hiring literature by investigating the conditions under which unfavorable social comparison could dampen the anticipated learning benefits associated with hiring top performers (i.e., Slavova et al., 2016; Groysberg & Lee, 2008). In essence, the mere presence of a high-performing newcomer cannot guarantee learning or motivation to learn on the part of incumbents; a positive outcome, rather, depends on an incumbent's responses to the introduction of the newcomer. The focus on incumbents' behavioral responses (particularly, communication behavior) to the introduction of a newcomer allows me to detect and address the mechanisms through which newcomers affect incumbents. I argue that incumbents' behavioral responses are what explain how they benefit from newcomers, depending on whether unfavorable social comparison is dominant. To take full advantage of experienced newcomers, incumbent groups should attempt to activate internal knowledge sharing and learning processes. As is highlighted in this paper, a key to the learning process is the incumbents' willingness to learn and improve.

The examination of incumbents' networking responses to the introduction of a newcomer has clear implications for literature on individual networks. The network literatures on individual networks and the origin of network actions have been two separately lines of work. Literature on individuals' networks has largely focused on the consequences of individuals' personal network structure and its implications such as career success (Burt, 1992). There is much less understanding of the origins of network positions that individuals occupy, specifically on the individual differences that shape local network structure (Kilduff & Tsai, 2005; Vissa, 2012). Literation examining differences in actions that individuals take to shape their personal networks focuses solely on either existing (Obstfeld, 2005) or new ties (Shipilov et al., 2007). This paper, by examining the consequent density change in individual's networks, examines the joint effects related to forming new ties and managing existing ties and sheds light on the origin of network actions. This paper identifies incumbents' communication network as a distinct mechanism reflecting their behavioral responses to the introduction of newcomers.

By highlighting the conditions under which incumbent group members either benefit or suffer from high-performing newcomers, this study provides, to practitioners and contemporary organizations, field implications that allow them to strategically incorporate newcomers, manage hiring activities, and promote talent retention. My results caution organizations to be careful with group ranking hierarchies and to pay close attention to incumbents' responses to the readily available performance information of internal newcomers. Central to the literature on how different types of newcomers (internal and/or external) allow newcomers to achieve advances in the forms of both tangible and intangible rewards (i.e., Bidwell & Mollick, 2015) is information asymmetry between organizations and potential candidates. That is, organizations have significantly more information on their current employees than they do on potential candidates. Because organizations can observe how their employees performed in prior roles, they have an advantage in evaluating those candidates' abilities. That advantage will shape how organizations evaluate internal versus external candidates for a job and will make it more difficult for external newcomers, even if hired, to increase their job responsibilities and status relative to internal newcomers. Correspondingly, Bidwell and Mollick (2015) found that internal mobility tends to place newcomers into jobs with greater responsibilities and status than does external mobility, because knowledge of its own employees reassures an organization that they are capable of doing the job. However, prior knowledge of internal newcomers also enables incumbents to compare themselves with these newcomers. And in fact, my findings provide an example of a case in which having day-to-day performance information potentially hurts the performance of the employer's incumbent members via unfavorable social comparison.

Although I propose hypotheses about incumbents' responses to a newcomer on performance, I measure only one specific behavioral response, in the form email communications. Future research may measure individual responses precisely—including the willingness to learn, emotions, and stress—to directly capture the consequences of the newcomer-incumbent peer effect. Moreover, I limit groups to those who hire only one newcomer at a time and compare groups that hire one high-performing newcomer to those hire one low-performing newcomer. This design allowed me to cleanly demonstrate a newcomer-incumbent effect. But one might question whether we would observe the same dynamics in groups with greater mobility. For example, would incumbents pay attention to the top performer among many newcomers or all of them equally? This suggests a direction for future work. Additionally, the observations that guided the analysis suggest important contextual conditions. Within retail banking, sales employees are in positions of competing yet cooperating with one another, and employees' performances are made salient in their evaluations and made visible to their colleagues. These two contextual factors support my arguments on the relationship between newcomer and incumbents. The insights gained from this paper might not be portable to other settings that involve high dependency or subjective performance evaluation metrics.

This work highlights that workplace peer effects exist and play a role in affecting performance, even in a setting where everyone works independently. In groups with stable hierarchy, a high-performing newcomer results in a decline in a relatively low-performing incumbent's performance. By contrast, in groups with dynamic hierarchy, a high-performing newcomer results in an increase in a relatively low-performing incumbent's performance. The results indicate the double-edged nature of hiring top performers and illustrate the mechanisms underlying the newcomer-incumbent peer effect through the lens of the communication networks.

CONCLUSION

The three chapters of this dissertation, taken together, explore intra-organizational mobility by incorporating the role that social networks play. In all, the dissertation makes a significant contribution to our understanding of a consequential phenomenon—how individuals move within organizations—and enriches the research on careers and mobility.

Across organizational levels, intra-organizational mobility is shown to be benefitial (Bidwell and Keller, 2014). For organizations, internal hires are substantially less expensive and much less likely to fail in their new roles than external hires (Bidwell, 2011; Groysberg et al., 2008). Employees are also much more likely to advance their carerrs and enter jobs with greater responsibility through internal rather than external moves, suggesting that intra-organizational mobility is an important avenue for individual career advancement (Bidwell & Mollick, 2015). In light with these findings, studies on internal labor markets has provided tremendous insights such as who moves and how they move (promotion vs. transfer). But these investigations oftentimes take the perspective of mobility (either internal or external) as the outcome (i.e., Bode Singh, & Rogan, 2015), the consequences associated with how employees move between jobs within organizations have "remained a mystery" (Breaugh, 2013; Keller, 2017). This dissertation directly speaks to the need by developing theories on intra-organizational mobility and its performance concsequences, with the focus on network-related mechanisms.

Moreover, much of the current work on orgnaizational hiring (e.g., Bidwell et al., 2013; Breaugh, 2013; Cable and Yu, 2014; Brown, Setren, & Topa, 2016), as well as work examining the differences between job changes within and between organizations (e.g., Bidwell, 2011), have conceptualized intra-organizational mobility as a homogeneous process, unintentionally obscuring the social dyanamics and processes that could affect how employees select into their new jobs and how they subsequently perform their jobs. Yet from the very recent work we know that, the formal differentiation in the hiring processes, for example, posting open positions or slotting an employee into an open position without posting it, could lead to a substantial difference in the quality of hire (Keller, 2017). This dissertation takes one step further and demonstrates that even underlying a very standard hiring strategy (for example, posting open positions to both internal and external candidates simultaneously). Large organizations use a variety of internal hiring practices and there are hetergogenous processes underlying formal practices. Intra-organizational mobility is not homogeneous; and in fact, intra-organizational social networks substantially change not only how individuals find jobs within the organization, but also how they perform after they move.

The findings contribute to labor market literature by showing that performance for internal movers depend in part on the social networks where they are embedded within the organization. As a rich literature on organizational hiring has consistently demonstrated that variations in extant social relations used to identify and select job candidates shape not only who gets the jobs but also how well they perform after being hired (i.e., Sterling, 2015), the link between social networks and individual performance is not surprising. What is interesting is how the findings presented in this dissertation and other work (i.e., Keller, 2017) contrast with what we might have expected. Literature on the external labor market have largely found that the relation-based referral practices lead to positive outcomes (i.e., Brown et al., 2016; Castilla, 2005). If we had assumed the underlying mechanisms shaping post-move performance operate in the same way for moves both within and between organizations, we would expect the outcome to be positive. Nonetheless, this work demonstrates that the opposite could be true for intra-organizational movers, especially internal movers who move between proximate locations. My work highlight that social influence might be the dominant logic that leads them to make suboptimal decisions with respect to job performance.

This dissertaiton also contributes to the network literature by investigating the social networks and job changes within organizations. The dissertation explores the network dynamics associated with career changes. The preponderance of research takes networks as “given and static,” studying their consequences rather than how the networks evolve as career processes dynamically unfold. This dynamic view is particularly important because a career in organizations—as a “sequence of jobs occupied by an individual over time”—is inherently dynamic and mobile (Hall, 2002; McEvily, Soda, & Tortoriello, 2014). Speaking to the avid conversations on the link between networks and career attainment outcomes (i.e., Ahuja, Soda, & Zaheer, 2011; Granovetter, 1985; Podolny & Baron, 1997; Burt, 2005), the dissertation highlights the need to understand the dynamics of social relations as individual careers unfold.

This dissertation directly sheds lights on career management and mobility literature. It complements the extant research on the benefits of internal hiring by focusing on the corresponding challenges arising from mobility within an organization. For organizations, the work could potentially facilitate the design of internal hiring or transfer programs. Certainly, when designing such programs, organizations need to account for the experiences of both movers and incumbents and optimize the post-move outcomes for both parties. For employees looking to manage their careers, the research identifies contextual characteristics that enable them to gain relatively portable performance and effectively contribute to the new business unit.

Caution is necessary for generalizing findings in this dissertation. Examining intra-organizational mobility requires “tradeoffs between depths and generalizability” and calls for detailed internal data that can be difficult to obtain from multiple sites (Keller, 2017; Bidwell and

Keller, 2014). Although my observations with Big Bank did not reveal any reason to believe that Big Bank's intra-organizational networks are qualitatively different from those of other large organizations, Big Bank provides a unique context where individual employees work independently on similar knowledge-based tasks. Future research could test the generalizability of these findings and highlight the scope conditions.

It is also worth exploring how intra-organizational social networks may shape other outcomes of consequences, such as promotion and turnover in organizations. For example, moving relying on pre-existing social relationships leads to greater performance disruptions. Consequently, movers would fail to improve, which in turn, may lead to reduced motivation or attrition among the top performers who were initially trying to improve their performance. Alternatively, it is possible that moving relying on pre-existing social relations leads to improvement in subject evaluations, albeit at the expense of objective performance. In organizations where subject evaluations matter, movers might be able to get promotions and advance their careers more quickly.

Whether and how these social dynamics might help mitigate the gender inequalities in the organization is also an interesting question. Women and minorities are oftentimes found to enter the workforce with lower-level jobs and therefore have limited ability to build up their intra-organizational social networks, which are key to critical information about potential advancement opportunities (Ibarra, 1992; Podolny & Baron, 2997). Nonetheless, by providing opportunities to broaden social networks and providing open access to information, intra-organizational mobility might be able to facilitate the long-term advancement of women and other minority groups. Taken together, examine the outcomes other than performance and taking account long-term career effects would help to provide a complete understanding of intra-organizational mobility in contemporary internal labor markets.

By integrating research on careers with the social network and social psychology research, this dissertation also demonstrates the power of using social psychological literature to understand the macro-level phenomena, such as job changes in organizations and the associated implication. Future work could continue this direction; it would be valuable to supplement these empirical analyses with qualitative evidence or field experiments to address concerns about the endogeneity of hiring decisions. Altogether, the findings in this dissertation highlight the importance of considering organizational boundaries, and more importantly, the underlying mechanisms, for understanding how individuals move and how organizations hire. This dissertation reaffirms that internal labor market represents a fruitful avenue for future theory development.

APPENDIX

Social Networks and Intra-Organizational Mobility

Two related but distinct questions arise regarding intra-organizational mobility: who moves and where they move to. The first question is well documented in the literature. It is widely considered advantageous for an individual to maintain an extensive network—an idea expressed most succinctly in Lin's "extensity-of-ties" proposition—so that individuals may access information on career opportunities. Most recent work by Rider et al. (2017) further tests this proposition that individuals with more ties are more likely to access job opportunities and make career changes than individuals with fewer ties. Particularly, they find that NFL coaches with extensive ties to other teams' coaches (i.e., degree centrality) are more likely to change employers than their less-connected peers. In light of these studies, it is not surprising that individuals with more extensive ties to other business units are more likely to make intra-organizational moves.

Relatedly, regarding the second question, we also expect movers are more likely to move to the business units where they have greater PMC. PMCs within social networks significantly increase their odds of undertaking an internal move by bringing to their attention opportunities that become available at other business units (Feld, 1981). Above and beyond making employees aware of specific job openings, both mechanisms, information channeling and social influence channeling, predict that movers will likely join the business units where they have more PMCs. The information access provides movers with the job knowledge that is essential to their moving decision. It could also help to assuage their worry as well as instill confidence that the move will proceed smoothly. Because of the information channeled by PMCs, employees seeking to move have better knowledge about business units where they have direct social connections.

Meanwhile, with regard to social influence, homophily and favoritism arising from prior interactions likely enhance the perceived trustworthiness and cultural fit of a business unit. Peer pressure, moreover, increases the odds that the mover will accept a lateral job offer.

We replicate these findings with our data empirically, yet we choose not to theoretically hypothesize it because the findings are well established in the labor market literature and both network arguments (information and social influence) predict the effects in the same direction.

Social Networks and Who Moves. With the full sample that consists of 102,841 individual-month observations of 12,916 individuals, we run multi-level generalized linear regressions to estimate the effect of individual network characteristics on the individual's probability of moving within the organizations, getting promoted, and leaving the organizations with.

The main independent variable is the count of individual extensive ties (degree centrality, adopted from Rider et al., 2017). In the model, we also include individual global betweenness centrality, ego network density, and clustering coefficient.

We control for individual demographics, including age, gender, ethnicity, organizational experience, job role experience, and a binary indicator of whether or not the individual was originally hired from the same job family. We also control for demographics of the business units, including size, average organizational experience, average role experience, average performance in the prior quarter, the proportion of male employees, and total hierarchy. Moreover, the fixed effects on month, the market of focus, job role, and job grade (level) are controlled in the model. In addition, we include individual random intercepts to allow the probability to vary across different individuals.

[INSERT TABLES A1 AND A2 ABOUT HERE]

The descriptive statistics are presented in Table A1. And the results are reported in Table

A2. Specifically, model 1 in Table A2 reports the estimation of the lagged extensive social ties on the likelihood of intra-organizational mobility in the form of location change ($\exp(\beta) = 1.09$, $p < 0.05$). Model 2 reports the estimation of the lagged extensive social ties on the likelihood of getting a promotion in the subsequent month ($\exp(\beta) = 1.044$, $p < 0.001$). And model 3 reports the estimation of the lagged extensive social ties on the likelihood of leaving the organization ($\exp(\beta) = 0.721$, $p < 0.05$).

PMC and Where Movers Move to. We estimate the effect of PMCs on the likelihood of a mover joining a receiving business unit. Ideally, to model this relationship, one would have information on all of the possible business units considered both explicitly and implicitly by movers, but no such data exists. Employees who seek to move from one business unit to another might not even understand such information. To address this issue, we adopted a case-match design. Our case sample is the observed receiving business units that movers actually joined. The matched sample was constructed by pairing each actual receiving business unit with observationally equivalent business units that a mover could have joined but did not. By doing so, we take the perspective of the movers and assume individuals will consider observationally similar business units as their potential selection sets.

To select observationally equivalent business units, we adopt a coarsened exact matching (CEM) procedure (Iacus, King, & Porro, 2012). The matching process proceeded as follows. First, we identified a set of covariates, which we believed was required to ensure that the selected matching business units are equivalent to the business unit that the mover actually joined. We then created and populated strata to ensure that there is full coverage of the joint distribution of the covariates selected. For continuous covariates, we used the CEM's automatic algorithm (the "cem" command in the R "cem" package) to partition the movers' business-unit observations into coarsened groups. We then randomly selected a number of matches from these strata.

Our model uses business-unit months drawn at random from the population of potential business units in the *same geographic region*, in the same *quarterly sales* quartile (defined by the total dollar amount of sales that the branch makes in the previous quarter), and in the same *employee size* quartile. More specifically, for our main analysis, we matched on the following covariates: *month of moving*, *primary market of focus*, *quartile performance of business unit* (categorized according to aggregated unit sales into four categories: < 25%, 25%-50%, 50-75%, > 75%), *size of business unit* (measured by the total number of employees), and *total level of formal hierarchy*.

For each mover, from our original population of 2,830 business units across 36 unique markets, we constructed a case-matched sample. In particular, out of all 1,901,760 unit-month possibilities (672 movers * up to 2,830 business units in the month of moving), we matched 607 cases to 12,032 matched controls. As we constructed the case-match sample by matching the observed business units that movers actually joined to the possible business units that movers could have joined, the model adopted a within-mover comparison. Matching allows us to achieve balance on the selected covariates (Multivariable Imbalance Measure L1 = 0.000), achieving a "matched" sample that pairs the observed receiving business units with the observationally equivalent business units that movers could have joined.

Because business units essentially drive the hiring of employees, with movers saying yes or no to a particular job offer, we modeled the intra-organizational moving process as a logistic regression. We conditioned the estimation on the set of cases and matches, thereby controlling for the characteristics of the movers and the covariates on which the CEM was based.

Measures

Likelihood of a Mover Joining a New Unit. This is the dependent variable in the branch selection analysis. It is a binary variable that is set to one for the observed receiving business units and to zero for the observationally equivalent matches representing the business units that the mover could have joined but did not.

PMCs. The main independent variable is the total number of PMCs. To calculate the total number of movers' PMCs, we calculate the total number of unique email receivers working in the business units of interest. Particularly, a receiver is a person to whom the mover communicates within two months of moving. As ties persistence affects movers' subsequent performance (Castilla, 2005), in the main models that we report, we choose to calculate PMC by counting the total number of unique email receivers that a mover has communicated with and that the mover continues communicating with for at least two months after the move. A two-month window captures all of the unique pre-move email recipients that 95.2% of the movers communicate with. The other 4.7% of movers communicated with colleagues working at the receiving business units but did not continue the communication. By focusing on persistent email recipients, a two-month window could allow us to capture all unique persistent email recipients for all movers.

Geographic distance. Geographic distance measures the absolute distance in meters between a mover's prior working unit and the receiving (or controlled) business unit. For each business unit, we use the R package "geosphere" to obtain the precise point distance between the two zip codes. The distance between two business units located in the same zip code is therefore zero.

Control Variables. The CEM processes account for most of the observational variation among the actual business units and the control group; thus, we include only a few more control variables on business units' characteristics that are not quite transparent to employees, including *average organizational tenure of retail sales employees*, *total attrition, total number of unique supervisors*, *proportion of male employees*, and *average role tenure of retail sales employees*.

Our first model examined the effect of PMCs on the likelihood of moving. Table A3 reports the descriptive statistics of the branch-level variables, including the maximums, minimums, means, standard deviation values, and a correlation matrix among all variables for all business units.

[INSERT TABLES A3 AND A4 ABOUT HERE]

With the first sample summarized in Table A4, we examined the effect of PMCs on the probability that the individual mover joins the receiving group. The dependent variable, *moved*, is dichotomous and set to one for the observed mover and to zero for the controlled matches. Model 1 in Table 3 reports the effects of all control variables; models 2 and 3 report the effects of PMCs without any control variables; model 4 includes all linear predictors and suggests that PMCs positively increase the mover's likelihood of joining the business unit ($\exp(\beta) = 2.768$, $p < 0.05$). Model 5 suggests the effect of PMC on the likelihood of joining the business unit is nonlinear ($\exp(\beta) = 12.871$ and $\exp(\beta^2) = 0.759$, $p < 0.001$). Comparing models 4 and 5 to models 2 and 3, including the control variables leads the effect size to be larger in both cases.

The nonlinearity effect in model 5 partly comes from a ceiling effect: that probability cannot increase at the same rate when approaching 1. Above and beyond the ceiling effect, the nonlinearity of PMC also speaks to the two mechanisms that social networks can channel. If information is the dominant mechanism, we should be able to observe a stronger curvilinear effect as the marginal increase of one more PMCs decreases in "value" in terms of channeling information. Alternatively, if social influence is the dominant mechanism, we should be able to observe a weaker curvilinear effect, because the marginal increase of one more PMC increases for social influence. Model 6 tests this speculation by including the interaction between PMCs and geographic distance. The results suggest that the curvilinear effect is indeed stronger when the distance associated with mobility is greater (exp $(\beta_{PMC} + \beta_{dist*PMC})$ = 15.120 and exp $(\beta^2_{PMC} + \beta^2_{dist*PMC})$ = 0.698, $p < 0.05$ for both). Taken together, these results support Hypothesis 1; moreover, they indicate that social influence is likely to be the dominant mechanism in the context of intra-organizational mobility.

Robustness Checks of the Time Window in Calculating PMC

Robustness checks of the time window used in defining PMC are presented in this section. Specifically, a pre-move communication contact is an email recipient that the mover has communicated prior to the move and continued communication for *n* months after the move. In the main analyses reported in chapter 1, *n* is set to 2. We vary n and test the effects with the same models, with all the controls included. The comparisons of key coefficients are reported in Table A5, where model 1 has n= 1, model 2 has n =3, and model 3 has n=4. All interpretations remain.

[INSERT TABLE A5 ABOUT HERE]

Robustness Checks of the Time Window in Calculating Persistent Social Ties

Robustness checks of the time window used in calculating persistent social ties are presented in this section. Specifically, in chapter 2 Equation 1, the proportion of persistent communication ties is measured by the percentage of individuals' persistent contacts (receivers who have received emails from ego in month t-2, compared to all current email receivers in month t). We report results with the same proportion measured with email recipients in month t-3 here. Results remain robust. Women are more likely to maintain higher proportion of persistent ties, which can help explain the gender difference in performance disruption female and male movers exhibit. All interpretations remain.

[INSERT TABLE A6 ABOUT HERE]

Robustness Checks of the Effects of Newcomers on Incumbents' Performance

Robustness checks of the main results evaluating the effects of newcomers on incumbents' performance in the subsequent months are presented in this section. Specifically, models 1-2 in Table A5 check the robustness of the construct of group rankings stability.

The results estimated with individual ranking stability within groups are reported in Models 1-3 in Table A5. My theory suggests that social comparison effect is a group phenomenon, but *individuals' ranking stability* (measured by calculating the variation of individual's past proportional standings in the group, from month *t-6* to *t-1*, reversely coded) within the group should predict similar with *group ranking stability*, albeit its effects might be much weaker. Particularly, model 2 reports the interaction effect, and model 3 additionally includes the mediator (individual communication density). The main effects on performance remain but the mediation effect no longer exists with *individuals' ranking stability*. Interpretations of the proposed theories remain. Models 4-5 in Table A7 report the estimations with a smaller but more specific subsample which only include observations in the months when groups have hired the newcomers (not the others). All results remain robust.

Another robustness check is performed to check the time lag, especially the time lag used in testing the mediation effect. The main models report estimations on performance in the subsequent month. I also vary the time lag by testing the effects of the main independent variable on mediator in the subsequent month and the performance in two months. The results are reported in models 1-4 in Table A8. All results remain robust.

[INSERT TABLE A7 AND A8 ABOUT HERE]

Estimating Groups' Likelihood of Hiring

To eliminate the concerns that groups that hire newcomers significantly differ from groups that do not hire, I run additional estimations to evaluate groups' likelihood of hiring (DV set to 1 when groups have newcomers in month *t* and 0 otherwise) and the prior performance of groups' new hires with the full sample on all groups. The all-group sample includes 8,820 group-month observations on 1,895 groups with more than 3 incumbents. Results are reported in Table A9. Models 1-2 in Table A9 report the likelihood of hiring, and models 3-4 in Table A9 reports the prior performance of newcomers in the groups that have hired. Analyses suggest that group ranking stability or group performance do not affect groups' likelihood of hiring or the prior performance of groups' new hires. Exits and turnover do affect groups' hiring activities, suggesting replacing leavers is an important reason why groups hire, thus exits are controlled in the main models.

[INSERT TABLE A9 ABOUT HERE]

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LIST OF TABLES

Table 1.1: Descriptive Statistics of 10,042 Individual-Months Observations of 672 Movers

	Varnames	Mean	Std	Min	Max	1	2	3	4	5
1	Individual Monthly Performance Z score	0	1	-0.9	14.55					
2	Org Experience (years)	4.24	6.23	0	44.9	0.21 *				
3	Role Experience (years)	1.1	1.21	0	11.7	0.29 *	0.34 *			
4	PMC (count)	1.03	1.81	0	16	0.15 *	0.01	0.09 *		
5	Distance (meters)	57261.32	208162.56	0	1803086.75	0.04 *	-0.03 *	-0.02 *	-0.08 *	
6	Network Size	40.82	53.28	0	2447	0.35 *	0.16 *	0.23 *	0.14 *	-0.01
7	Density	0.13	0.06	0	1	-0.35 *	-0.16 *	-0.2 *	-0.04 *	-0.05 *
8	Clustering Coef	0.48	0.15	0	1	-0.12 *	-0.05 *	-0.07 *	0.11 *	-0.02 *
9	Betweenness Centralization	0.31	0.13	0	1	0.24 *	0.13 *	0.12 *	0.05 *	0.06 *
10	Dept Size	12.5	30.12	1	1305	0.09 *	0.01	0.04 *	0.08 *	-0.01
11	Dept Hirarchy	5.76	3.48	1	25	0.22 *	0.07 *	0.1 *	0.19 *	0
12	Avg Dept Org Tenure	5.61	3.79	0.03	36.9	0.08 *	0.43 *	0.16 *	0.08 *	-0.06 *
13	Avg Dept Role Tenure (years)	1.94	1.21	0.01	9.21	0.13 *	0.23 *	0.26 *	0.08 *	-0.06 *
14	Avg Dept Prior Performance (years)	5.58	1.78	0	9	0.3 *	0.13 *	0.12 *	0.06 *	0.02 *

		6	7	8	9	10	11	12	13	14
7	Density	-0.3 *								
8	Clustering Coef	-0.13 *	0.68 *							
9	Betweenness Centralization	0.07 *	-0.47 *	-0.43 *						
10	Dept Size	0.06 *	-0.06 *	-0.02 *	0.04 *					
11	Dept Hirarchy	0.14 *	-0.09 *	0.04 *	0.09 *	0.55 *				
12	Avg Dept Org Tenure (years)	0.06 *	-0.03 *	0.02 *	0.08 *	0.16 *	0.31 *			
13	Avg Dept Role Tenure (years)	0.07 *	-0.06 *	0	0.08 *	0.12 *	0.33 *	0.68 *		
14	Avg Dept Prior Performance	0.09 *	-0.18 *	0	0.1 *	0.01	0.13 *	0.16 *	0.18 *	

Note: $^{*}p<0.05$

Table 1.2: Intra-Organizational Mobility and PMC on Job Performance

	Dependent variable: Performance Z Score (t+1)						
	panel linear			*linear mixed-effects*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Location Change	-0.073^{***}		-0.043^{*}	-0.107^{***}	-0.108^{***}	-0.080^{***}	-0.062^{**}
	(0.019)		(0.020)	(0.021)	(0.021)	(0.021)	(0.021)
Time Since Move		0.006^{**}	0.010^{**}	0.011^{*}	0.011^{**}	0.010^{**}	0.011^{*}
		(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.005)
PMC Z * Location Change					-0.039^{*}		-0.049^{*}
					(0.019)		(0.020)
PMC Z * Time Since Move						-0.006^{*}	-0.010^{*}
						(0.003)	(0.005)
Distance Z Score				0.031^{**}	0.018	0.018	0.010
				(0.014)	(0.017)	(0.018)	(0.018)
PMC Z Score				0.083^{***}	0.104^{***}	0.156^{***}	0.160^{***}
				(0.013)	(0.018)	(0.021)	(0.023)
Org Experience	0.105^{**}	0.084^{*}	0.022^{***}	0.014^{***}	0.015^{***}	0.020^{***}	0.022^{***}
	(0.034)	(0.041)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)
Role Experience	-0.061^{**}	-0.044^{*}	0.096^{***}	0.110^{***}	0.055^{***}	0.060^{***}	0.069^{***}
	(0.020)	(0.019)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)
Hired from Same Job Family				0.062^{***}	0.057^{*}	0.109^{***}	0.138^{***}
				(0.022)	(0.022)	(0.022)	(0.023)
Constant				-0.781^{*}	-0.563	-0.885	-0.308
				(0.466)	(0.595)	(0.659)	(0.155)
Observations	10,042	10,042	10,042	10,042	10,042	10,042	10,042
Individual Fixed Effects	Yes	Yes	Yes	No	No	No	No
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects	No	No	No	Yes	Yes	Yes	Yes
Random Intercepts	No	No	No	Yes	Yes	Yes	Yes
Random Slopes	No	No	No	Yes	Yes	Yes	Yes
Age, Gender, Race	No	No	No	Yes	Yes	Yes	Yes
R^2	0.005	0.004	0.024				
Adjusted R^2	0.004	0.003	0.024				
AIC				22,460.010	22,468.920	22,870.170	21,307.150
Note:	*p<0.05;**p<0.01;***p<0.001						

Table 1.3: Intra-Organizational Mobility and PMC on Job Performance by Geographic Distance

	Dependent variable: Performance Z Score (t+1)							
	Distance <= Median			Distance > Median			Same City	Same State
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Location Change	−0.090**	−0.108***	−0.120***	−0.041	−0.056	−0.058	−0.120**	−0.089***
	(0.029)	(0.027)	(0.028)	(0.033)	(0.032)	(0.032)	(0.034)	(0.022)
Time Since Move	0.007*	0.004*	0.004*	0.008	0.007*	0.006	0.007*	0.007*
	(0.003)	(0.002)	(0.002)	(0.005)	(0.004)	(0.005)	(0.003)	(0.003)
PMC Z * Location Change	−0.043*		−0.064*	−0.019		−0.029	−0.050*	−0.057**
	(0.025)		(0.027)	(0.030)		(0.031)	(0.025)	(0.021)
PMC Z * Time Since Move		−0.014*	−0.013*		−0.001	−0.003	−0.012*	−0.011*
		(0.007)	(0.005)		(0.006)	(0.007)	(0.005)	(0.005)
Distance Z Score	−0.027	−0.041	−0.038	0.003	0.001	−0.0001	0.021	0.011
	(0.026)	(0.024)	(0.023)	(0.025)	(0.023)	(0.023)	(0.023)	(0.017)
PMC Z Score	0.142***	0.111***	0.145***	0.120***	0.091**	0.103***	0.177***	0.135***
	(0.028)	(0.029)	(0.028)	(0.026)	(0.029)	(0.030)	(0.026)	(0.023)
Org Experience	0.014**	0.011*	0.012**	0.022***	0.016**	0.016**	0.023***	0.015***
	(0.005)	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)	(0.008)	(0.004)
Role Experience	0.056**	0.045*	0.049**	0.102***	0.088***	0.087***	0.109***	0.050***
	(0.019)	(0.019)	(0.018)	(0.023)	(0.023)	(0.023)	(0.017)	(0.015)
Hired from Same Job Family	0.086**	0.057	0.038	0.196***	0.125***	0.123***	0.109***	0.072**
	(0.031)	(0.032)	(0.031)	(0.034)	(0.035)	(0.035)	(0.024)	(0.025)
Constant	−0.890	−0.726	−0.846	−0.484**	−0.729***	−0.731***	−0.582***	−0.723
	(0.685)	(0.617)	(0.602)	(0.181)	(0.171)	(0.172)	(0.084)	(0.582)
Observations	5,063	5,063	5,063	4,979	4,979	4,979	2,792	8,685
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Random Intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Random Slopes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age, Gender, Race	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	11,398.820	11,059.440	11,042.330	10,082.930	9,867.764	9,872.473	6,359.211	19,331.400
Note:	*p<0.05;**p<0.01;***p<0.001							

Table 1.4: Intra-Organizational Mobility and PMC on Job Performance Controlling for Alternative Explanations

	Dependent variable: Performance Z Score (t+1)				
	Full Sample			Proximate Moves	Distant Moves
	(1)	(2)	(3)	(4)	(5)
Location Change	−0.061**	−0.065**	−0.058**	−0.062*	−0.056
	(0.022)	(0.021)	(0.022)	(0.030)	(0.039)
Time Since Move	0.010*	0.011*	0.010*	0.010	0.005
	(0.004)	(0.005)	(0.005)	(0.005)	(0.008)
PMC Z * Location Change	−0.063**	−0.061**	−0.070***	−0.088**	−0.050
	(0.020)	(0.020)	(0.021)	(0.027)	(0.038)
PMC Z * Time Since Move	−0.011**	−0.016***	−0.013***	−0.018***	−0.001
	(0.003)	(0.004)	(0.004)	(0.005)	(0.008)
Network Size	0.003***		0.002***	0.003***	0.003***
	(0.0002)		(0.0002)	(0.001)	(0.0002)
Density	−1.088***		−1.072***	−0.900***	−1.063***
	(0.114)		(0.118)	(0.168)	(0.182)
Clustering Coef	0.574***		0.495***	0.295*	0.657***
	(0.082)		(0.084)	(0.116)	(0.132)
Betweenness Centralization	0.418***		0.422***	0.207*	0.652***
	(0.072)		(0.074)	(0.100)	(0.114)
Dept Size z score		−0.021	−0.015	−0.007	−0.069*
		(0.012)	(0.013)	(0.015)	(0.033)
Dept Hirarchy		0.019***	0.018***	0.013*	0.042***
		(0.004)	(0.004)	(0.005)	(0.008)
Avg Dept Org Tenure		−0.014**	−0.014**	−0.017**	−0.008
		(0.005)	(0.005)	(0.006)	(0.009)
Avg Dept Role Tenure		0.006	0.009	0.031	−0.016
		(0.014)	(0.014)	(0.019)	(0.026)
Avg Dept Performance (t-4,t-1)		0.052***	0.049***	0.058***	0.043***
		(0.006)	(0.006)	(0.008)	(0.009)
Distance Z Score	−0.001	0.007	−0.007	−0.033	−0.036
	(0.017)	(0.017)	(0.016)	(0.023)	(0.022)
PMC Z Score	0.143***	0.166***	0.136***	0.157***	0.073*
	(0.021)	(0.021)	(0.020)	(0.029)	(0.034)
Org Experience	0.013***	0.019***	0.014***	0.013**	0.010*
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Role Experience	0.060***	0.059***	0.059***	0.042*	0.134***
	(0.014)	(0.014)	(0.014)	(0.018)	(0.025)
Hired from Same Job Family	0.200***	0.260***	0.196***	0.227***	0.154***
	(0.026)	(0.026)	(0.027)	(0.038)	(0.038)
Constant	−0.470***	−0.570***	−0.705***	−0.633**	−1.006***
	(0.136)	(0.133)	(0.138)	(0.228)	(0.184)
Observations	10,042	10,042	10,042	5,063	4,979
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects	Yes	Yes	Yes	Yes	Yes
Random Intercepts	Yes	Yes	Yes	Yes	Yes
Random Slopes	Yes	Yes	Yes	Yes	Yes
Age, Gender, Race	Yes	Yes	Yes	Yes	Yes
AIC	20,767.390	20,751.340	19,425.270	10,224.640	9,673.384
Note:	*p<0.05;**p<0.01;***p<0.001				

Table 1.5: Comparison of the Main Model with the Robustness-Check Models

	Dependent variable: Performance Z Score (t+1)					
	Main Model	Closed Business Units	IV	M1	M2	M3
Location Change	-0.058^{**}	-0.054	-0.060^{**}	-0.061^{**}	-0.059^{**}	-0.061^{**}
	(0.022)	(0.069)	(0.022)	(0.022)	(0.022)	(0.022)
Time Since Move	0.010^{*}	0.030^{*}	0.008^{*}	0.010^{*}	0.010^{*}	0.010^{*}
	(0.005)	(0.015)	(0.003)	(0.004)	(0.004)	(0.004)
PMC * Location Change	-0.070^{***}	-0.093^{*}				
	(0.021)	(0.052)				
PMC * Time Since Move	-0.013^{***}	-0.017^{*}				
	(0.004)	(0.008)				
2SLS * Location Change			-0.161^{***}			
			(0.022)			
2SLS * Time Since Move			-0.111^{**}			
			(0.035)			
High Volume Ties * Location Change				-0.044^{*}		
				(0.020)		
High Volume Ties * Time Since Move				-0.009^{*}		
				(0.003)		
Symmetric Ties * Location Change					-0.055^{**}	
					(0.021)	
Symmetric Ties * Time Since Move					-0.009^{**}	
					(0.003)	
Simmelian Ties * Location Change						-0.057^{**}
						(0.022)
Simmelian Ties * Time Since Move						-0.007^{*}
						(0.004)
Note:	$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$					
Observations:	10,042 indivdual-months, 672 movers					

Table 2.1: Summary Statistics of the Matching Sample

		Full Sample				Women		Men		Movers		Controls	
	Varnames	Mean	Sd	Min	Max	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
1	log(Performance)	10.13	2.28	0	13.61	10.22	2.14	9.82	2.73	9.49	2.8	10.26	2.14
2	log(Betweenness)	8.99	2.37	0	15.04	9.02	2.34	8.9	2.47	8.77	2.52	9.04	2.34
3	Proportion of Persistent Ties	0.41	0.21	0	1	0.41	0.21	0.38	0.22	0.38	0.23	0.41	0.21
4	Org Tenure (years)	7.81	9.67	0	49.8	9.11	10.2	2.8	4.56	3.77	6.35	8.6	10
5	Role Tenure (years)	1.08	0.77	0	9.79	1.3	0.76	0.87	0.7	1.09	0.73	1.07	0.74
6	Age	34.43	11.08	18	74	37.22	13.15	32.49	10.14	34.39	11.8	34.41	11.09
7	Dept Size	11.17	31.8	1	1911	10.57	27.83	13.48	43.83	12.23	39.43	10.97	30.1
8	Avg Dept Org Tenure (years)	6.22	4.12	0.1	36.9	6.72	4.22	4.29	2.98	5.33	3.85	6.39	4.15
9	Avg Dept Role Tenure (years)	2.03	1.23	0.1	9.93	2.15	1.26	1.58	1.01	1.86	1.23	2.07	1.23
10	Proportion of Male	0.3	0.2	0	1	0.26	0.18	0.47	0.19	0.33	0.21	0.3	0.2
11	Avg Dept Performance (Prior Quarter, Ranked)	5.73	1.77	0	9	5.79	1.74	5.48	1.84	5.41	1.89	5.79	1.74
12	Dept Hirarchy	5.39	3.06	1	25	5.46	2.87	5.09	3.68	5.37	3.42	5.39	2.98
		1	2	3	4	5	6	7	8	9	10	11	12
1	log(Performance)												
2	log(Betweenness)	0.4 *											
3	Proportion of Persistent Ties	0.17 *	-0.04 *										
4	Org Tenure (years)	0.25 *	0.16 *	0.09 *									
5	Role Tenure (years)	0.35 *	0.18 *	0.16 *	0.49 *								
6	Age	0.23 *	0.13 *	0.07 *	0.64 *	0.45 *							
7	Dept Size	-0.02 *	0.01 *	-0.01	-0.01 *	-0.01	-0.03 *						
8	Avg Dept Org Tenure (years)	0.16 *	0.09 *	0.09 *	0.56 *	0.35 *	0.38 *	0.08 *					
9	Avg Dept Role Tenure (years)	0.14 *	0.09 *	0.07 *	0.33 *	0.38 *	0.26 *	0.07 *	0.71 *				
10	Proportion of Male	-0.07 *	-0.04 *	-0.07 *	-0.25 *	-0.23 *	-0.23 *	0.08 *	-0.41 *	-0.29 *			
11	Avg Dept Performance (Prior Quarter, Ranked)	0.51 *	0.22 *	0.1 *	0.2 *	0.25 *	0.19 *	-0.01	0.23 *	0.25 *	-0.11 *		
12	Dept Hirarchy	0.11 *	0.12 *	0.03 *	0.14 *	0.13 *	0.1 *	0.45 *	0.26 *	0.33 *	0.05 *	0.18 *	

Note: *p<0.05

Table 2.2: The Effect of Gender, Location Change, the Proportion of Persistent Communication Ties on Individual Subsequent Performance (with the Matching Sample)

	Dependent variable:				
	log(Performance)		Persistent Ties (z score)		log(Performance)
	(1)	(2)	(3)	(4)	(5)
Male	−0.162	−0.180	−0.116***	−0.130***	−0.140
	(0.093)	(0.097)	(0.024)	(0.027)	(0.094)
Mover or not	0.078*	0.059	0.093***	0.069***	0.028
	(0.033)	(0.039)	(0.017)	(0.020)	(0.036)
Post-move Indicator	0.144***	0.121***	0.013	0.007	0.074***
	(0.016)	(0.017)	(0.010)	(0.011)	(0.017)
Mover or not * Post-move Indicator	−0.402***	−0.313***	−0.495***	−0.445***	−0.287***
	(0.039)	(0.047)	(0.024)	(0.029)	(0.045)
Male * Mover or not		0.071		0.079*	0.030
		(0.072)		(0.037)	(0.067)
Male:Post-move Indicator		0.124**		0.032	0.073
		(0.039)		(0.025)	(0.038)
Male * Mover * Post-move Indicator		−0.313***		−0.163**	−0.117
		(0.083)		(0.051)	(0.080)
Persistent Ties (z score)					0.079***
					(0.007)
Persistent Ties (z score) * Post-move Indicator					0.073***
					(0.013)
Promotion	−2.144***	−2.140***	−0.163***	−0.162***	−1.345***
	(0.033)	(0.033)	(0.021)	(0.021)	(0.033)
Supervisor Change	−0.621***	−0.621***	−0.214***	−0.214***	−0.372***
	(0.024)	(0.024)	(0.015)	(0.015)	(0.023)
Org Tenure	0.044***	0.044***	0.009***	0.009***	0.032***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.004)
Prior Job is Same Role	0.246***	0.245***	0.233***	0.233***	0.153***
	(0.025)	(0.025)	(0.015)	(0.015)	(0.024)
Constant	10.628***	10.625***	0.027	0.029	10.678***
	(0.343)	(0.343)	(0.103)	(0.103)	(0.335)
Observations	60,295	60,295	60,295	60,295	60,295
Matching Group Fixed Effects	Yes	Yes	Yes	Yes	Yes
Job Grade Fixed Effects	Yes	Yes	Yes	Yes	Yes
Moving Months Fixed Effects	Yes	Yes	Yes	Yes	Yes
Log Likelihood	−116,721.900	−116,719.300	−79,633.140	−79,635.000	−106,422.300
Note:	*p<0.05; **p<0.01; ***p<0.001				

Table 2.3: The Effect of Gender, Location Change, the Proportion of Persistent Communication Ties on Individual Subsequent Performance with a broader range of controls (with the Matching Sample)

	Women Subsample			Men Subsample		
	log(performance)	Persistent Ties (z score)	log(performance)		Persistent Ties (z score)	log(Performance)
	(1)	(2)	(3)	(4)	(5)	(6)
Mover or not	0.074*	0.072***	0.040	0.134	0.143***	0.090
	(0.036)	(0.020)	(0.033)	(0.069)	(0.031)	(0.064)
Post-move Indicator	0.118***	0.005	0.075***	0.246***	0.049*	0.144***
	(0.016)	(0.011)	(0.015)	(0.045)	(0.022)	(0.042)
Mover or not * Post-move Indicator	−0.368***	−0.461***	−0.305***	−0.503***	−0.550***	−0.299***
	(0.043)	(0.029)	(0.042)	(0.087)	(0.043)	(0.084)
Persistent Ties (z score)			0.055***			0.162***
			(0.007)			(0.019)
Persistent Ties (z score) * Post-move Indicator			0.056***			0.142***
			(0.014)			(0.036)
Promotion	−1.869***	−0.146***	−1.194***	−2.823***	−0.183***	−1.789***
	(0.035)	(0.024)	(0.035)	(0.078)	(0.040)	(0.079)
Supervisor Change	−0.545***	−0.206***	−0.319***	−0.787***	−0.232***	−0.501***
	(0.025)	(0.017)	(0.024)	(0.058)	(0.029)	(0.055)
Org Tenure	0.034***	0.008***	0.022***	0.229***	0.038***	0.206***
	(0.005)	(0.002)	(0.004)	(0.019)	(0.006)	(0.017)
Prior Job is Same Role	0.296***	0.234***	0.216***	0.070	0.201***	−0.055
	(0.027)	(0.017)	(0.026)	(0.064)	(0.030)	(0.061)
Constant	10.275***	0.069	10.408***	10.707***	0.001	10.441***
	(0.331)	(0.100)	(0.320)	(0.656)	(0.151)	(0.698)
Observations	47,981	47,981	47,981	12,314	12,314	12,314
Matching Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Job Grade Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Moving Months Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	−88,238.850	−63,600.570	−80,483.490	−26,784.580	−16,156.680	−24,324.280
Note:	*p<0.05; **p<0.01; ***p<0.001					

Table 2.4: The Effect of Gender, Location Change, the Proportion of Persistent Communication Ties on Individual Subsequent Performance with a broader range of controls (with the Matching Sample)

	Full Sample	Women	Men	Full Sample	
		log(Performance)		Persistent Ties (z score)	log(Performance)
	(1)	(2)	(3)	(4)	(5)
Male	−0.162			−0.107***	−0.136
	(0.084)			(0.028)	(0.082)
Mover or not	0.059	0.071*	0.104	0.069***	0.033
	(0.036)	(0.033)	(0.064)	(0.020)	(0.034)
Post-move Indicator	0.107***	0.106***	0.214***	0.007	0.064***
	(0.017)	(0.015)	(0.042)	(0.011)	(0.016)
Mover or not * Post-move Indicator	−0.266***	−0.319***	−0.479***	−0.440***	−0.252***
	(0.045)	(0.041)	(0.082)	(0.029)	(0.043)
Male * Mover or not	0.047			0.078*	0.016
	(0.067)			(0.037)	(0.063)
Male * Post-move Indicator	0.115**			0.032	0.065
	(0.038)			(0.025)	(0.036)
Male* Mover or not * Post-move Indicator	−0.246**			−0.160**	−0.074
	(0.079)			(0.051)	(0.076)
Persistent Ties (z score)					0.066***
					(0.007)
Persitent Ties (z score) * Post-move Indicator					0.065***
					(0.013)
Dept Size (z score)	−0.089***	−0.106***	−0.062	0.0001	−0.080***
	(0.016)	(0.016)	(0.041)	(0.007)	(0.014)
Avg Dept Job Tenure	−0.088***	−0.088***	−0.082	−0.004	−0.069***
	(0.016)	(0.016)	(0.049)	(0.009)	(0.015)
Avg Dept Org Tenure	−0.019**	−0.016**	−0.033	0.003	−0.019***
	(0.006)	(0.006)	(0.018)	(0.003)	(0.006)
Proportion of Male	−0.081	−0.103	−0.147	−0.119**	−0.048
	(0.069)	(0.075)	(0.161)	(0.040)	(0.064)
Dept Hirarchy	0.027***	0.031***	0.032*	−0.001	0.025***
	(0.006)	(0.006)	(0.013)	(0.003)	(0.005)
Avg Dept Performance (Prior Quarter)	0.435***	0.391***	0.552***	0.034***	0.395***
	(0.005)	(0.005)	(0.013)	(0.003)	(0.005)
Promotion	−1.973***	−1.727***	−2.582***	−0.155***	−1.241***
	(0.031)	(0.033)	(0.074)	(0.021)	(0.031)
Supervisor Change	−0.559***	−0.498***	−0.680***	−0.209***	−0.332***
	(0.022)	(0.024)	(0.054)	(0.015)	(0.022)
Org Tenure	0.040***	0.030***	0.174***	0.007***	0.030***
	(0.004)	(0.004)	(0.017)	(0.002)	(0.003)
Prior Jobs is Same Role	0.207***	0.254***	0.034	0.222***	0.133***
	(0.024)	(0.025)	(0.061)	(0.015)	(0.023)
Constant	7.995***	7.967***	7.258***	−0.124	8.254***
	(0.284)	(0.280)	(0.563)	(0.106)	(0.277)
Observations	60,291	47,981	12,314	60,291	60,291
Matching Group Fixed Effects	Yes	Yes	Yes	Yes	Yes
Job Grade Fixed Effects	Yes	Yes	Yes	Yes	Yes
Moving Months Fixed Effects	Yes	Yes	Yes	Yes	Yes
Log Likelihood	−113,231.300	−85,641.440	−25,975.560	−79,588.740	−103,255.700
Note:	*p<0.05; **p<0.01; ***p<0.001				

Table 2.5 The Effect of Gender, Location Change, the Proportion of Persistent Communication Ties on Individual Betweenness Score in the intra-organizational Network

	Dependent variable: log(betweenness)				
	Full Sample		Women	Men	Full Sample
	(1)	(2)	(3)	(4)	(5)
Male	0.017	0.134^{*}			0.047
	(0.066)	(0.070)			(0.066)
Mover or not	0.159^{***}	0.228^{***}	0.196^{***}	−0.016	0.167^{***}
	(0.031)	(0.037)	(0.037)	(0.060)	(0.033)
Post-move Indicator	0.042^{*}	0.041	0.017	0.071	0.025
	(0.024)	(0.026)	(0.027)	(0.057)	(0.023)
Mover or not * Post-move Indicator	−0.038	0.084	0.120^{*}	-0.190^{*}	−0.008
	(0.055)	(0.066)	(0.058)	(0.095)	(0.059)
Male * Mover or not		-0.241^{***}			-0.217^{***}
		(0.068)			(0.060)
Male * Post-move Indicator		−0.0003			−0.003
		(0.060)			(0.054)
Male * Mover or not * Post-move Indicator		-0.329^{***}			−0.160
		(0.118)			(0.106)
Persistent Ties (z score)					-0.230^{***}
					(0.009)
Persistent Ties (z score) * Post-move Indicator					0.097^{***}
					(0.019)
Dept Size	-0.071^{***}	-0.070^{***}	-0.087^{***}	0.010	-0.061^{***}
	(0.010)	(0.010)	(0.012)	(0.026)	(0.009)
Avg Dept Job Tenure	-0.024^{**}	-0.024^{**}	0.002	0.081^{**}	−0.015
	(0.012)	(0.012)	(0.013)	(0.034)	(0.011)
Avg Dept Org Tenure	-0.015^{***}	-0.015^{***}	-0.018^{***}	-0.044^{***}	-0.019^{***}
	(0.004)	(0.004)	(0.004)	(0.012)	(0.003)
Proportion of Male	-0.276^{***}	-0.278^{***}	-0.229^{***}	−0.129	-0.224^{***}
	(0.058)	(0.058)	(0.068)	(0.124)	(0.051)
Dept Hirarchy	0.075^{***}	0.075^{***}	0.073^{***}	0.031^{***}	0.076^{***}
	(0.004)	(0.004)	(0.005)	(0.009)	(0.004)
Avg Dept Performance (Prior Quarter)	0.182^{***}	0.182^{***}	0.133^{***}	0.177^{***}	0.131^{***}
	(0.006)	(0.006)	(0.006)	(0.012)	(0.005)
Promotion	-0.755^{***}	-0.753^{***}	−0.034	-0.521^{***}	-0.459^{***}
	(0.035)	(0.035)	(0.033)	(0.067)	(0.032)
Supervisor Change	-0.340^{***}	-0.342^{***}	-0.079^{**}	-0.569^{***}	-0.095^{***}
	(0.035)	(0.035)	(0.040)	(0.071)	(0.031)
Org Tenure	0.007^{***}	0.007^{***}	0.006^{***}	0.017^{***}	0.008^{***}
	(0.002)	(0.002)	(0.002)	(0.006)	(0.001)
Prior Job is Same Role	0.526^{***}	0.524^{***}	0.303^{***}	0.763^{***}	0.417^{***}
	(0.029)	(0.029)	(0.027)	(0.054)	(0.026)
Constant	6.726^{***}	6.693^{***}	7.639^{***}	7.749^{***}	7.143^{***}
	(0.082)	(0.083)	(0.074)	(0.147)	(0.075)
Observations	60,295	60,295	47,981	12,314	60,295
Matching Group Fixed Effects	Yes	Yes	Yes	Yes	Yes
Job Grade Fixed Effects	Yes	Yes	Yes	Yes	Yes
Moving Months Fixed Effects	Yes	Yes	Yes	Yes	Yes
Log Likelihood	−132,764.600	−132,747.200	−96,698.050	−27,395.650	−122,717.600
Note:	*p<0.05; **p<0.01; ***p<0.001				

Table 2.6: Summary Statistics for the Dyadic Level Analyses

		Full Sample				Women		Men			
	Varnames	Mean	Sd	Min	Max	Mean	Sd	Mean	Sd	.1	.2
1	Persist or not	0.12	0.32	0	1	0.12	0.32	0.12	0.32		
2	Distance	71428.59	253135.84	0	1727926.53	78985.13	266157.45	59260.81	230153.95	-0.02 *	
3	Sender Job Tenure	0.94	1.31	0	10.7	0.98	1.4	0.89	1.15	0.08 *	-0.05 *
4	Sender Org Tenure,	4.75	6.46	0.03	44.4	5.64	7.35	3.3	4.32	0	-0.04 *
5	Receiver Eigenvector	0.14	0.19	0	0.82	0.14	0.19	0.13	0.18	0.09 *	-0.02
6	Job Tenure Difference	-1.25	2.86	-22.31	8.91	-1.28	2.98	-1.2	2.68	0.04 *	-0.02
7	Org Tenure Difference	-1.99	9.79	-44.82	43.03	-1.41	10.56	-2.9	8.37	-0.01	-0.01
8	Same Role or not	1.19	0.39	1	2	1.2	0.4	1.19	0.39	0.08 *	-0.01
9	Same Gender or not	1.57	0.5	1	2	1.69	0.46	1.37	0.48	0	-0.02
10	Asymmetry (Sender to Receiver - Receiver to Sender)	0	1	-39.09	27.02	0.02	0.85	-0.03	1.21	-0.08 *	0.01
11	Structural Similarity	0	1	-1.31	4.46	0.05	1	-0.08	1	0.09 *	-0.03 *
12	Sender Sending Email Internval	0	1	-1.26	0.8	-0.06	1.01	0.1	0.97	-0.25 *	-0.01
13	Simmelian Tie or not	0.43	0.5	0	1	0.46	0.5	0.39	0.49	0.23 *	-0.01
		3	4	5	6	7	8	9	10	11	12
4	Sender Org Tenure,	0.38 *									
5	Receiver Eigenvector	-0.05 *	-0.05 *								
6	Job Tenure Difference	0.41 *	0.1 *	-0.06 *							
7	Org Tenure Difference	0.2 *	0.57 *	-0.1 *	0.47 *						
8	Same Role or not	-0.05 *	-0.1 *	-0.09 *	0.18 *	0.05 *					
9	Same Gender or not	0.02	0.07 *	0.01	-0.03	-0.02	0				
10	Asymmetry (Sender to Receiver - Receiver to Sender)	0	-0.01	-0.12 *	0.01	0.02	0.03 *	-0.01			
11	Structural Similarity	-0.11 *	-0.08 *	0.03 *	0.02	0	0.21 *	0.05 *	0		
12	Sender Sending Email Internval	0.08 *	0.03 *	-0.22 *	0.02	0.02	-0.11 *	-0.04 *	0.04 *	-0.32 *	
13	Simmelian Tie or not	-0.06 *	-0.02 *	0.26 *	-0.01	-0.03 *	0.1 *	0.02	-0.07 *	0.38 *	-0.74 *

Note: $^{*}p<0.05$

Table 2.7: The Effect of Gender on the Likelihood of a Tie Being Persist

	Dependent variable:					
	The Likelihood of a Tie Being Retained After The First Quarter Since Moving					
	(1)	(2)	(3)	(4)	(5)	(6)
Male	−0.257**	−0.218*	−0.134	−0.218*	−0.106	−0.151
	(0.092)	(0.099)	(0.104)	(0.102)	(0.106)	(0.105)
Distance	−0.045	−0.048	−0.020	−0.068	−0.066	−0.064
	(0.049)	(0.051)	(0.053)	(0.053)	(0.055)	(0.054)
Sender changed Roles	0.135	0.083	0.183	0.065	0.172	0.158
	(0.140)	(0.147)	(0.155)	(0.151)	(0.158)	(0.155)
Sender is Promoted	0.361*	0.394**	0.439*	0.408**	0.291	0.305
	(0.145)	(0.150)	(0.171)	(0.156)	(0.161)	(0.159)
Receiver Eigenvector	1.798***	1.983***	0.839***	2.055***	1.243***	1.149***
	(0.205)	(0.220)	(0.251)	(0.228)	(0.239)	(0.238)
Sender Job Tenure	0.025	0.062	0.039	0.070	0.101*	0.095*
	(0.039)	(0.044)	(0.049)	(0.045)	(0.047)	(0.046)
Sender Org Tenure	−0.005	−0.015	−0.019	−0.009	−0.012	−0.012
	(0.008)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)
Role Tenure Difference		−0.025	−0.016	−0.025	−0.031	−0.034
		(0.021)	(0.023)	(0.021)	(0.022)	(0.022)
Org Tenure Difference		0.006	0.006	0.003	0.003	0.004
		(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
Same Role		0.471***	0.395***	0.268*	0.374***	0.413***
		(0.103)	(0.113)	(0.107)	(0.110)	(0.109)
Same Gender		0.054	0.0001	0.001	0.049	0.058
		(0.091)	(0.100)	(0.093)	(0.097)	(0.096)
Symmetry			0.048***			
			(0.003)			
Structural Similarity				2.654***		
				(0.258)		
Email Interval (z score)					−0.934***	
					(0.053)	
Simmellian Tie						1.771***
						(0.107)
Constant	−3.661***	−3.968***	−6.783***	−4.470***	−4.356***	−5.169***
	(0.499)	(0.525)	(0.855)	(0.537)	(0.539)	(0.539)
Observations	5,683	5,683	5,683	5,683	5,683	5,683
Sender Job Grade Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Sender Job Role Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	−1,964.877	−1,802.087	−1,469.394	−1,733.042	−1,612.228	−1,641.136

Note: *p<0.05; **p<0.01; ***p<0.001

Table 2.8: The Effect of Gender on Proxies of Tie Strength

	Dependent variable:			
	Asymmetry	Strctural Similarity	Interval	Simmelian Tie
	normal	*normal*	*normal*	*logistic*
	(1)	(2)	(3)	(4)
Sender is Male	-0.095^{**}	-0.103^{***}	0.164^{***}	-0.298^{***}
	(0.032)	(0.028)	(0.029)	(0.060)
Sender Role Tenure	0.002	-0.045^{***}	0.034^{**}	-0.067^{*}
	(0.015)	(0.013)	(0.013)	(0.027)
Sender Org Tenure	-0.008^{*}	-0.012^{***}	0.001	0.002
	(0.003)	(0.003)	(0.003)	(0.006)
Receiver Eigenvector	-0.625^{***}	0.177^{*}	-1.147^{***}	2.986^{*}
	(0.079)	(0.070)	(0.071)	(0.173)
Role Tenure Difference	−0.008	−0.0002	−0.004	0.032^{*}
	(0.007)	(0.006)	(0.006)	(0.013)
Org Tenure difference	0.005^{*}	0.005^{*}	0.001	-0.013^{**}
	(0.002)	(0.002)	(0.002)	(0.004)
Same Role	0.037	0.506^{***}	-0.151^{***}	0.138^{*}
	(0.035)	(0.031)	(0.032)	(0.065)
Same Gender	−0.028	0.068^{*}	−0.022	−0.033
	(0.031)	(0.027)	(0.028)	(0.057)
Constant	0.197^{*}	0.105	-0.166^{*}	0.851^{***}
	(0.080)	(0.070)	(0.072)	(0.152)
Observations	5,683	5,683	5,683	5,683
Log Likelihood	−8,589.793	−7,752.332	−7,975.851	−3,882.875
Note:	*p<0.05; **p<0.01; ***p<0.001			
Note:	Standard errors were clustered on senders and receivers			

Table 2.9: The Effect of Gender, Location Change, the Proportion of Persistent Communication Ties on Individual Subsequent Performance (the Mover Sample)

	Dependent variable:				
	log(Performance (t+2))		Persistent Ties z score (t+1)		log(Performance (t+ 2))
	(1)	(2)	(3)	(4)	(5)
Male	0.029	0.081	−0.058*	−0.043	0.004
	(0.060)	(0.079)	(0.028)	(0.031)	(0.056)
Location Change (t)	−0.167**	−0.172*	−0.266***	−0.328***	−0.111
	(0.061)	(0.070)	(0.037)	(0.041)	(0.067)
Male * Location Change (t)		−0.159*		−0.027*	0.043
		(0.077)		(0.013)	(0.084)
Persistent Ties z score (t+1)					0.085***
					(0.012)
Dept Size z score	−0.046	−0.069*	−0.021	−0.011	−0.050
	(0.031)	(0.028)	(0.013)	(0.012)	(0.030)
Avg Dept Role Tenure	0.067*	0.019	−0.009	0.002	0.059*
	(0.028)	(0.026)	(0.014)	(0.014)	(0.027)
Avg Dept Org Tenure	−0.014	−0.021*	0.004	0.003	−0.014
	(0.010)	(0.009)	(0.005)	(0.005)	(0.009)
Proportion of Male	−0.182	−0.208	−0.069	−0.030	−0.081
	(0.121)	(0.116)	(0.064)	(0.063)	(0.115)
Dept Hirarchy	0.021*	0.056***	0.001	−0.003	0.024**
	(0.009)	(0.008)	(0.005)	(0.004)	(0.009)
Avg Dept Performance (Prior Quarter)	0.112***	0.094***	0.038***	0.032***	0.100***
	(0.010)	(0.009)	(0.006)	(0.005)	(0.009)
Promotion	−0.522***	−0.086	−0.031	0.203***	−0.334***
	(0.061)	(0.049)	(0.040)	(0.025)	(0.061)
Org Tenure	0.035***	0.046***	0.002	0.006*	0.031***
	(0.006)	(0.008)	(0.003)	(0.003)	(0.005)
Supervisor Change	−0.074	−0.090	−0.216***	−0.246***	−0.032
	(0.048)	(0.052)	(0.030)	(0.030)	(0.048)
Job Tenure	0.194***	0.072*	0.068***	0.120***	0.188***
	(0.026)	(0.028)	(0.012)	(0.012)	(0.024)
Prior Job is Same Role	−0.033	−0.362***	0.082**	0.016	−0.058
	(0.045)	(0.040)	(0.026)	(0.019)	(0.044)
Constant	6.146***	7.032***	−0.825*	0.418*	5.804***
	(0.581)	(0.629)	(0.324)	(0.181)	(0.622)
Observations	15,866	15,868	15,868	15,868	15,868
Individual/Location Randome Intercepts	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects	Yes	Yes	Yes	Yes	Yes
Job Grade Fixed Effects	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Race Fixed Effects	Yes	Yes	Yes	Yes	Yes
Job Role Fixed Effects	Yes	Yes	Yes	Yes	Yes
Log Likelihood	−28,751.980	−29,899.140	−22,065.400	−22,145.150	−26,712.590
Note:					*p<0.05; **p<0.01; ***p<0.001

Table 3.1: Individual-Level Descriptive Statistics

	Varnames	Mean	Sd	Min	Max	1	2	3	4	5	6	7	8	9
1	Individual Performance (Z score)	0	1	-0.77	18.68									
2	Newcomer's Prior Performance	0.17	1.03	0	9	0.05 ∗								
3	Newcomer-Incumbent Relative Performance	-4.82	2.91	-9	9	-0.33 ∗	0.31 ∗							
4	Group Ranking Stability	0.42	0.32	-0.96	1	0	0.01	0.07 ∗						
5	Incumbent's Network Density	0.58	0.25	0.01	2	-0.31 ∗	-0.03 ∗	0.25 ∗	0.02 ∗					
6	Age (Z score)	0	1	-1.42	3.6	0.12 ∗	0.01	-0.12 ∗	0.01	-0.08 ∗				
7	Role Experience	0.91	0.85	0	12.1	0.19 ∗	-0.01 ∗	-0.25 ∗	-0.05 ∗	-0.16 ∗	0.24 ∗			
8	Org Experience	2.95	5.17	0.02	41.5	0.23 ∗	0.02 ∗	-0.25 ∗	-0.01	-0.16 ∗	0.47 ∗	0.35 ∗		
9	Group Size	4.08	1.21	3	15	0.12 ∗	0.16 ∗	-0.02 ∗	-0.01 ∗	-0.07 ∗	-0.01	-0.04 ∗	0.01 ∗	
10	Total Newcomers	0.15	0.39	0	4	0.02 ∗	0.43 ∗	0.15 ∗	0.01	-0.03 ∗	-0.02 ∗	-0.05 ∗	-0.03 ∗	0.26 ∗
11	Total Leave	0.15	0.38	0	4	0.01	0.08 ∗	0.04 ∗	0.01 ∗	-0.01	-0.02 ∗	-0.03 ∗	-0.04 ∗	0.02 ∗
12	Avg Org Experience	2.95	3.41	0.09	28.8	0.23 ∗	0.02 ∗	-0.2 ∗	-0.01 ∗	-0.14 ∗	0.35 ∗	0.26 ∗	0.66 ∗	0.02 ∗
13	Avg Role Experience	0.91	0.59	0.09	6.79	0.17 ∗	-0.02 ∗	-0.17 ∗	-0.07 ∗	-0.09 ∗	0.19 ∗	0.69 ∗	0.25 ∗	-0.05 ∗
14	Proportion of Male	0.36	0.27	0	1	0.11 ∗	0.02 ∗	-0.04 ∗	-0.02 ∗	-0.05 ∗	-0.09 ∗	0.04 ∗	-0.13 ∗	0.08 ∗
15	Total Unique Supervisors	1.12	0.41	1	5	0.07 ∗	-0.01	0.04 ∗	0.01 ∗	-0.09 ∗	0.08 ∗	0.12 ∗	0.06 ∗	0.3 ∗
16	Total Top Performers	1.38	1.48	0	10	0.41 ∗	0.1 ∗	-0.44 ∗	-0.01	-0.2 ∗	0.07 ∗	0.12 ∗	0.19 ∗	0.41 ∗
17	Incumbent's Network Size	16.64	28.54	0	2118	0.22 ∗	0.01 ∗	-0.12 ∗	-0.01	-0.37 ∗	0.04 ∗	0.12 ∗	0.07 ∗	0.05 ∗
18	Incumbent's Network Reciprocity	0.85	0.11	0	1	-0.06 ∗	0	0.06 ∗	-0.01	0.36 ∗	0	-0.07 ∗	-0.01 ∗	-0.03 ∗
19	Incumbent's Network Clustering Coef	0.65	0.2	0	1	-0.12 ∗	0	0.1 ∗	-0.01 ∗	0.48 ∗	-0.04 ∗	-0.07 ∗	-0.08 ∗	-0.01
20	Betweenness Centralization	0.33	0.2	0	1	0.18 ∗	0.02 ∗	-0.15 ∗	0.01	-0.39 ∗	0.05 ∗	0.06 ∗	0.12 ∗	0.02 ∗
21	Incumbent's Avg Email Frequency	0	1	-0.37	79.29	0.03 ∗	0	-0.02 ∗	0	-0.03 ∗	-0.01 ∗	0.01	0	0.02 ∗
22	Incumbent's Avg Email Size	0	1	-0.11	157.75	0.03 ∗	0	-0.01	0	-0.02 ∗	0.01	0.02 ∗	0.01	0

		10	11	12	13	14	15	16	17	18	19	20	21	22
11	Total Leave	0.14 ∗												
12	Avg Org Experience	-0.05 ∗	-0.06 ∗											
13	Avg Role Experience	-0.07 ∗	-0.04 ∗	0.38 ∗										
14	Proportion of Male	0.03 ∗	0.06 ∗	-0.2 ∗	0.06 ∗									
15	Total Unique Supervisors	-0.02 ∗	0.01 ∗	0.1 ∗	0.18 ∗	0.08 ∗								
16	Total Top Performers	0.02 ∗	0	0.29 ∗	0.18 ∗	0.09 ∗	-0.02 ∗							
17	Incumbent's Network Size	0.01	0.01	0.07 ∗	0.13 ∗	0.07 ∗	0.11 ∗	0.09 ∗						
18	Incumbent's Network Reciprocity	-0.01	-0.01	0	-0.05 ∗	-0.04 ∗	-0.04 ∗	-0.03 ∗	-0.38 ∗					
19	Incumbent's Network Clustering Coef	-0.02 ∗	0.01	-0.08 ∗	-0.03 ∗	-0.02 ∗	-0.07 ∗	-0.05 ∗	-0.1 ∗	0.19 ∗				
20	Betweenness Centralization	0.01 ∗	0	0.12 ∗	0.03 ∗	-0.01	0.03 ∗	0.13 ∗	-0.05 ∗	0.1 ∗	-0.65 ∗			
21	Incumbent's Avg Email Frequency	0	0	0	0.01	-0.01	0.03 ∗	0.02 ∗	0.03 ∗	0.02 ∗	0.03 ∗	0		
22	Incumbent's Avg Email Size	0	0	0.01	0.02 ∗	0.02 ∗	0.02 ∗	0.01	0.03 ∗	-0.01	-0.01	0.01 ∗	0	

Note: *p<0.05
Note: Observations: 17,681
Note: Individual's performance in dollar amount and age are standadized, as requested by the firm

Table 3.2: Individual-Level Analyses: The Effect of Newcomers on Incumbents' Subsequent Performance

	Dependent variable					
	Performance(t+1)				Density	Performance(t+1)
	(1)	(2)	(3)	(4)	(5)	(6)
Newcomer's Prior Performance	0.001	0.069***	0.069***	0.069***	−0.014***	0.069***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.001)	(0.007)
Newcomer-Incumbent Relative Performance		−0.067***	−0.067***	−0.060***	0.010***	−0.060***
		(0.003)	(0.003)	(0.005)	(0.001)	(0.005)
Group Ranking Stability			−0.004	−0.082*	0.028***	−0.067
			(0.025)	(0.046)	(0.010)	(0.049)
Relative Performance * Group Ranking Stability				−0.016**	0.006***	−0.013
				(0.008)	(0.002)	(0.008)
Incumbent's Network Size					−0.003***	0.001***
					(0.0001)	(0.0003)
Incumbent's Network Density						−0.375***
						(0.035)
Constant	−0.079	−0.295***	−0.292***	−0.256***	0.657***	−0.054
	(0.055)	(0.076)	(0.077)	(0.079)	(0.009)	(0.083)
Individual Random Intercepts	Yes	Yes	Yes	Yes	Yes	Yes
Group Random Intercepts	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,681	17,681	17,681	17,681	17,681	17,681
Log Likelihood	−25,940.840	−21,429.520	−21,397.250	−21,399.160	4,657.587	−20,190.510
AIC.	51,895.670	42,875.040	42,812.500	42,818.320	−9,293.174	40,405.030

Note: *p<0.1;**p<0.05;***p<0.01

Table 3.3: Individual-Level Analyses: the Effect of Newcomers on Incumbents' Subsequent Performance, Controlling for Alternative Explanations

	Performance (t+1)				Density	Performance (t+1)
	(1)	(2)	(3)	(4)	(5)	(6)
Newcomer's Prior Performance	0.062***	0.059***	0.072***	0.056***	−0.007***	0.055***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.001)	(0.007)
Newcomer-Incumbent Relative Performance	−0.055***	−0.052***	−0.061***	−0.048***	0.005***	−0.047***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.001)	(0.005)
Group Ranking Stability	−0.069	−0.099**	−0.087*	−0.101**	0.037***	−0.088*
	(0.046)	(0.046)	(0.050)	(0.049)	(0.008)	(0.049)
Relative Performance*Group Stability	−0.013*	−0.021***	−0.017**	−0.020**	0.007***	−0.018*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.001)	(0.011)
Incumbent's Network Density						−0.356***
						(0.043)
Age	0.036***			0.041***	−0.001	0.041***
	(0.011)			(0.011)	(0.002)	(0.011)
Role Experience	0.014			0.018	−0.004	0.017
	(0.013)			(0.015)	(0.003)	(0.015)
Org Experience	0.014***			0.007***	−0.001**	0.007***
	(0.002)			(0.002)	(0.0005)	(0.002)
Group Size		−0.023*		−0.026**	0.002	−0.026**
		(0.012)		(0.013)	(0.002)	(0.012)
Total Newcomers		0.045**		0.046**	−0.012***	0.041**
		(0.019)		(0.020)	(0.003)	(0.020)
Total Leave		0.029*		0.031*	−0.005*	0.029
		(0.017)		(0.018)	(0.003)	(0.018)
Leaver's Quarterly Performance		-0.046		-0.046	0.005	-0.041
		(0.036)		(0.036)	(0.004)	(0.036)
Group Avg Org Experience		0.044***		0.031***	−0.002***	0.030***
		(0.005)		(0.005)	(0.001)	(0.005)
Group Avg Job Experience		−0.028		−0.040	0.022***	−0.032
		(0.025)		(0.029)	(0.005)	(0.028)
Prop of Male		0.311***		0.322***	−0.012	0.321***
		(0.046)		(0.047)	(0.008)	(0.047)
Total Unique Supervisors		0.043		0.046	−0.012**	0.046
		(0.031)		(0.032)	(0.005)	(0.032)
Total Top Performers		0.055***		0.071***	−0.008***	0.071***
		(0.009)		(0.009)	(0.002)	(0.009)
Incumbent's Network Size			0.002***	0.002***	−0.001***	0.001***
			(0.0003)	(0.0003)	(0.00005)	(0.0003)
Incumbent's Network Reciprocity			−0.097	−0.089	0.611***	0.142*
			(0.076)	(0.076)	(0.013)	(0.081)
Incumbent's Network Clustering Coef.			−0.042	−0.037	0.298***	0.064
			(0.050)	(0.050)	(0.008)	(0.051)
Bewteenness Centralization			0.283***	0.271***	−0.289***	0.171***
			(0.047)	(0.047)	(0.008)	(0.048)
Incumbent Avg Email Freq			0.019	0.020	-0.220	0.022
			(0.018)	(0.019)	(0.181)	(0.019)
Incumbent Avg Email Size			0.014	0.014	0.005	0.018
			(0.019)	(0.019)	(0.009)	(0.019)
Constant	−0.294***	−0.478***	−0.272**	−0.487***	0.016	−0.499***
	(0.080)	(0.099)	(0.106)	(0.122)	(0.017)	(0.121)
Individual Random Intercepts	Yes	Yes	Yes	Yes	Yes	Yes
Group Random Intercepts	Yes	Yes	Yes	Yes	Yes	Yes
Location Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
AIC	42,751.210	42,710.470	40,206.360	40,073.270	−17,430.360	40,012.010

Note: *p<0.1; **p<0.05; ***p<0.01

Note: Observations: 17,681

Table 3.4: Group-Level Descriptive Statistics

	Varnames	Mean	Sd	Min	Max	1	2	3	4	5	6
1	Avg Performance	0	1	-1.01	12.06						
2	Performance Disparity	0	1	-0.89	14.84	0.75 *					
3	Group Ranking Stability	0	1	-4.22	1.75	-0.01	0.04 *				
4	Newcomer's Prior Performance	0.17	1.03	0	9	0.05 *	0.01	0.01			
5	Group Size	0	1	-0.9	11.55	0.1 *	0.09 *	-0.02	0.17 *		
6	Total Leave	0	1	-0.4	9.86	0	0	0.01	0.06 *	-0.01	
7	Avg Org Experience	0	1	-0.81	7.32	0.3 *	0.2 *	-0.01	0.02	-0.03 *	-0.07 *
8	Avg Role Experience	0	1	-1.37	9.64	0.22 *	0.12 *	-0.07 *	-0.03 *	-0.11 *	-0.06 *
9	Proportion of Male	0	1	-1.32	2.36	0.13 *	0.12 *	-0.01	0.02	0.08 *	0.06 *
10	Total Unique Supervisors	0	1	-0.29	10.96	0.13 *	0.15 *	0.01	-0.01	0.16 *	-0.01
11	Total Top Performers	0	1	-0.96	6.67	0.49 *	0.33 *	0	0.06 *	0.35 *	-0.02
12	Group Network Size	0	1	-0.86	19.91	0.38 *	0.32 *	-0.02	0.03 *	0.21 *	0
13	Group Network Density	0	1	-1.12	10.18	-0.13 *	-0.09 *	-0.02 *	0.03 *	0.06 *	0.03 *
14	Group Network Reciprocity	0	1	-1.36	2.06	0.21 *	0.19 *	-0.03 *	0.05 *	0.17 *	0.03 *
15	Group Clustering Coef	0	1	-0.93	6.07	-0.02	-0.02	-0.04 *	0.03 *	0.31 *	-0.02
16	Group Betweenness Centralization	0	1	-1.27	4.25	0.15 *	0.16 *	-0.01	0.04 *	0.07 *	0.05 *
17	Group Degree Centralization	0	1	-1.39	2.43	0.07 *	0.09 *	-0.01	0.04 *	0.05 *	0.06 *

		7	8	9	10	11	12	13	14	15	16
8	Avg Role Experience	0.38 *									
9	Proportion of Male	-0.2 *	0.06 *								
10	Total Unique Supervisors	0.1 *	0.17 *	0.08 *							
11	Total Top Performers	0.29 *	0.18 *	0.07 *	0						
12	Group Network Size	0.15 *	0.14 *	0.18 *	0.17 *	0.32 *					
13	Group Network Density	-0.05 *	-0.07 *	0.05 *	-0.14 *	0.02	0.09 *				
14	Group Network Reciprocity	0.1 *	-0.01	0.11 *	-0.01	0.27 *	0.56 *	0.65 *			
15	Group Clustering Coef	-0.02 *	-0.11 *	0.02	-0.13 *	0.19 *	0.2 *	0.66 *	0.62 *		
16	Group Betweenness Centralization	0.06 *	-0.01	0.12 *	-0.02	0.18 *	0.54 *	0.56 *	0.89 *	0.45 *	
17	Group Degree Centralization	0	-0.01	0.14 *	-0.07 *	0.16 *	0.54 *	0.69 *	0.87 *	0.52 *	0.92 *

Note: $^{*}p<0.05$

Note: Observations: 6,646

Table 3.5: Group-Level Analyses: The Effect of Newcomers on Incumbents' Performance (Average and Disparity)

	Dependent variable						
	Average Performance (t+1)		Performance Disparity (t+1)				
	(1)	IV(1)	(2)	(3)	(4)	IV(2)	IV(3)
Newcomer's Prior Performance	0.023***		−0.027***	−0.027***	−0.029***		
	(0.007)		(0.007)	(0.007)	(0.007)		
Predicted IV by instrument		0.163***				−0.097***	−0.040***
		(0.029)				(0.029)	(0.008)
Group Ranking Stability				0.013	0.011	0.013	0.014
				(0.009)	(0.009)	(0.009)	(0.009)
Newcomer's Performance*Stability					0.019**		
					(0.008)		
Predicted IV by Instrument*Stability							0.020**
							(0.009)
Group Average Performance			0.828***	0.828***	0.828***	0.829***	0.829***
			(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Size	−0.069***	−0.106***	0.047***	0.050***	0.050***	0.065***	0.054***
	(0.013)	(0.015)	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)
Total High Performers	0.227***	0.224***	−0.068***	−0.069***	−0.070***	−0.068***	−0.070***
	(0.014)	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Constant	−0.026	−0.054	0.005	0.003	0.003	0.016	−0.002
	(0.083)	(0.083)	(0.034)	(0.035)	(0.035)	(0.035)	(0.034)
Group Random Intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,646	6,646	6,646	6,646	6,646	6,646	6,646
Log Likelihood	−6,972.368	−6,959.587	−6,433.711	−6,388.151	−6,389.423	−6,387.814	−6,384.429
AIC.	13,960.740	13,935.170	12,885.420	12,796.300	12,800.850	12,795.630	12,790.860
Note:	*p<0.1;**p<0.05;***p<0.01						

Table 3.6: Group-Level Analysis: The Effect of Newcomers on Incumbents' Average Performance and Performance Disparity, controlling for Alternative Explanations

	Dependent variable					
	Average Performance (t+1)			Performance Disparity (t+1)		
	(1)	(2)	(3)	(4)	(5)	(6)
Avg Performance				0.831***	0.805***	0.829***
				(0.011)	(0.011)	(0.011)
Group Ranking Stability	0.004	−0.002	0.003	0.009	0.010	0.009
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Newcomer's Prior Performance	0.017**	0.013*	0.021***	−0.028***	−0.023***	−0.028***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)
Newcomer's Prior Performance*Group Stability				0.019**	0.018**	0.019**
				(0.008)	(0.008)	(0.008)
Group Size	−0.046***		−0.058***	0.035***		0.034***
	(0.013)		(0.014)	(0.011)		(0.012)
Total Leave	0.027		0.022	0.005		0.002
	(0.021)		(0.021)	(0.020)		(0.020)
Avg Org Experience	0.240***		0.204***	−0.012		−0.012
	(0.020)		(0.019)	(0.014)		(0.014)
Avg Role Experience	0.051***		0.056***	−0.050***		−0.051***
	(0.018)		(0.017)	(0.013)		(0.013)
Proportion of Male	0.104***		0.092***	0.008		0.004
	(0.014)		(0.014)	(0.011)		(0.011)
Total Supervisors	0.018		0.016	0.039***		0.041***
	(0.013)		(0.013)	(0.011)		(0.011)
Total Top Performers	0.182***		0.177***	−0.055***		−0.058***
	(0.015)		(0.015)	(0.013)		(0.013)
Group Network Size		0.053***	0.056***		0.004	0.001
		(0.013)	(0.013)		(0.012)	(0.013)
Group Communication Density		−0.057***	−0.055***		−0.006	−0.009
		(0.018)	(0.017)		(0.017)	(0.017)
Group Communication Reciprocity		0.894***	0.697***		−0.077	−0.040
		(0.104)	(0.102)		(0.095)	(0.096)
Group Clustering Coef.		−0.031**	−0.025*		0.010	0.005
		(0.013)	(0.013)		(0.013)	(0.013)
Betweenness Centralization		−0.080	0.091		0.184	0.114
		(0.176)	(0.175)		(0.170)	(0.170)
Degree Centralization		−0.045	−0.287*		0.027	0.118
		(0.150)	(0.147)		(0.132)	(0.133)
Constant	−0.024	−0.316***	−0.207**	0.0003	−0.020	−0.048
	(0.084)	(0.081)	(0.087)	(0.036)	(0.044)	(0.046)
Group Random Intercepts	Yes	Yes	Yes	Yes	Yes	Yes
Location Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,646	6,646	6,646	6,646	6,646	6,646
AIC.	13,660.270	13,892.620	13,576.980	12,814.440	12,861.180	12,848.070
Note:	*p<0.1;**p<0.05;***p<0.01					

Table A1: Descriptive Statistics in the Intra-organizational Mobility Analysis

	Varnames	Mean	Sd	Min	Max	1	2	3	4	5	6
1	Location Change	0.01	0.12	0	1						
2	Promotion	0.09	0.29	0	1	0.11 *					
3	Attrition	0.03	0.18	0	1	-0.01 *	-0.01 *				
4	Extensive Ties Z Score	0	1	-0.92	64.38	0.01 *	-0.01 *	-0.04 *			
5	Density	0.13	0.06	0	1	0.01 *	0.01 *	0.04 *	-0.36 *		
6	Clustering Coef	0.47	0.16	0	1	0.01 *	0.02 *	0	-0.1 *	0.64 *	
7	Betweenness Z Score	0	1	-0.37	162.47	0	-0.01 *	-0.02 *	0.64 *	-0.22 *	-0.09 *
8	Org Experience (years)	4.69	7.23	0	49.8	-0.02 *	-0.01 *	-0.06 *	0.15 *	-0.18 *	-0.03 *
9	Job Experience (years)	1.14	1.26	0	14.9	0	0.02 *	-0.03 *	0.3 *	-0.23 *	-0.05 *
10	Performance in Prior Month	5.49	2.9	0	9	-0.01 *	-0.14 *	-0.06 *	0.24 *	-0.38 *	0
11	Department Size Z Score	0	1	-0.21	27.61	0	-0.01 *	-0.01 *	0.08 *	-0.05 *	-0.04 *
12	Avg Dept Org Experience (years)	5.73	3.81	0	36.9	-0.01	0	-0.04 *	0.07 *	-0.06 *	0.01 *
13	Avg Dept Role Experience (years)	1.96	1.17	0	12.3	0	0.03 *	-0.03 *	0.09 *	-0.08 *	0
14	Avg Dept Performance (Prior Quarter)	5.48	1.81	0	9	-0.01 *	-0.25 *	-0.04 *	0.14 *	-0.2 *	0.01 *
15	Proportion of Male	0.32	0.2	0	1	0.01 *	-0.01 *	0.02 *	0.07 *	-0.04 *	-0.05 *
16	Dept Hirarchy	5.72	3.53	1	25	-0.01 *	-0.03 *	-0.02 *	0.2 *	-0.12 *	0.01 *

		7	8	9	10	11	12	13	14	15	16
8	Org Experience (years)	0.1 *									
9	Job Experience (years)	0.17 *	0.4 *								
10	Performance in Prior Month	0.12 *	0.29 *	0.23 *							
11	Department Size Z Score	0.05 *	0.02 *	0.05 *	-0.04 *						
12	Avg Dept Org Experience (years)	0.07 *	0.45 *	0.2 *	0.11 *	0.13 *					
13	Avg Dept Role Experience (years)	0.07 *	0.25 *	0.27 *	0.12 *	0.08 *	0.71 *				
14	Avg Dept Performance (Prior Quarter)	0.07 *	0.18 *	0.14 *	0.62 *	-0.06 *	0.18 *	0.19 *			
15	Proportion of Male	0.02 *	-0.16 *	-0.02 *	-0.03 *	0.06 *	-0.32 *	-0.19 *	-0.05 *		
16	Dept Hirarchy	0.13 *	0.11 *	0.15 *	0.09 *	0.43 *	0.35 *	0.36 *	0.14 *	0.07 *	

Note: $^{*}p<0.05$

Table A2: The Effect of Extensive Ties on Intra-organizational Mobility

	Dependent variable:The Likelihood		
	Location Change	Promotion	Attrition
	(1)	(2)	(3)
Extensive Ties	0.087^{***}	0.044^{**}	-0.326^{***}
	(0.018)	(0.016)	(0.051)
Density	-2.020^{***}	-2.934^{***}	0.172
	(0.449)	(0.194)	(0.221)
Clustering Coef	1.839^{***}	2.128^{***}	−0.052
	(0.306)	(0.127)	(0.145)
Betweenness	−0.030	−0.017	0.013
	(0.025)	(0.018)	(0.040)
Male	0.206^{**}	−0.021	0.161^{***}
	(0.066)	(0.031)	(0.042)
Org Experience	-0.020^{**}	-0.023^{***}	-0.047^{***}
	(0.007)	(0.003)	(0.006)
Role Experience	0.076^{**}	0.214^{***}	0.127^{***}
	(0.026)	(0.012)	(0.021)
Hired from Same Job Famility	−0.108	1.268^{***}	0.056
	(0.068)	(0.030)	(0.045)
Prior Performance	0.002	0.181^{***}	-0.065^{***}
	(0.016)	(0.007)	(0.010)
Department Size	−0.087	-0.061^{***}	−0.012
	(0.065)	(0.014)	(0.024)
Avg Unit Org Experience	0.014	0.041^{***}	−0.010
	(0.013)	(0.006)	(0.009)
Avg Unit Job Experience	0.040	0.079^{***}	-0.063^{*}
	(0.037)	(0.016)	(0.026)
Avg Dept Performance	-0.043^{*}	-0.475^{***}	−0.014
	(0.021)	(0.009)	(0.013)
Proportion of Male	0.191	0.316^{***}	−0.021
	(0.165)	(0.077)	(0.105)
Dept Hirarchy	-0.024^{*}	-0.053^{***}	−0.003
	(0.012)	(0.005)	(0.007)
Constant	2.269^{*}	1.330	-6.072^{***}
	(1.138)	(1.011)	(1.028)
Observations	102,841	102,841	102,841
Month Fixed Effects	Yes	Yes	Yes
Market Fixed Effects	Yes	Yes	Yes
Random Intercepts	Yes	Yes	Yes
Age, Gender, Race	Yes	Yes	Yes
AIC	13,905.070	43,643.510	28,825.240
Note:	*p<0.05; **p<0.01; ***p<0.001		

Table A3: Descriptive Statistics in the Business Unit Selection Analysis

	Var Names	Mean	Std	Min	Max	.1	.2	.3	.4	.5	.6	.7	.8	.9
1	PMC	0.238	1.08	0	23									
2	PMC Z score	0	1	-0.286	4.817	0.86 *								
3	PMC^2	1	4.038	0.082	23.204	0.88 *	0.95 *							
4	Distance Z score	0	1	-0.536	10.994	-0.07 *	-0.09 *	-0.08 *						
5	Total Alternatives with the Same PMC	165.583	25.951	0	172	-0.9 *	-0.97 *	-0.97 *	0.08 *					
6	Total Attrition	0.152	0.391	0	3	0.05 *	0.06 *	0.06 *	-0.01	-0.06 *				
7	Avg Role Experience	1.184	0.763	0.01	10.18	0.05 *	0.02 *	0.02 *	0.01	-0.03 *	-0.04 *			
8	Avg Org Experience	4.721	5.054	0.09	41	0.02	0.01	0.01	0.01	-0.01	-0.08 *	0.37 *		
9	Total Supervisors	1.261	0.482	1	4	0.08 *	0.07 *	0.06 *	0.03 *	-0.07 *	0.01	0.31 *	0.08 *	
10	Proportion of Male	0.33	0.306	0	1	0	0	0	-0.02	0	0.04 *	-0.01	-0.28 *	0.13 *

Note: $^{*}p<0.05$

Table A4: The Effect of PMCs on the Likelihood of Moving to a Business Unit

	Dependent variable: The Likelihood of Joining a Business Unit					
	(1)	(2)	(3)	(4)	(5)	(6)
PMC Z score		0.999***	1.924***	1.018***	2.555***	2.517***
		(0.034)	(0.085)	(0.036)	(0.582)	(0.582)
PMC Z Scoreˆ2			−0.226***		−0.276***	−0.280***
			(0.018)		(0.046)	(0.047)
DistanceZ * PMC Z						0.199**
						(0.099)
Distance Z * PMC Zˆ2						−0.079*
						(0.042)
Distance Z Score	0.009			0.012	0.025	0.005
	(0.057)			(0.057)	(0.054)	(0.069)
Total Alternatives with the Same PMC	−1.087***			−1.833***	0.422	0.373
	(0.037)			(0.178)	(0.419)	(0.419)
Total Attrition	1.180***			1.179***	1.175***	1.174***
	(0.096)			(0.096)	(0.096)	(0.096)
Avg Role Experience	−0.177*			−0.180*	−0.156*	−0.156*
	(0.076)			(0.075)	(0.073)	(0.072)
Avg Org Experience	0.007			0.007	0.007	0.007
	(0.012)			(0.012)	(0.011)	(0.011)
Total Supervisors	−0.216			−0.242*	−0.182	−0.189
	(0.114)			(0.113)	(0.110)	(0.111)
Proportion of Male	−0.151			−0.132	−0.141	−0.142
	(0.171)			(0.170)	(0.167)	(0.167)
Constant	−3.569***	−3.640***	−3.604***	−3.581***	−3.452***	−3.437***
	(0.164)	(0.067)	(0.068)	(0.163)	(0.160)	(0.161)
Observations	12,639	12,639	12,639	12,639	12,639	12,639
Matching Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	−1,581.297	−1,697.751	−1,629.524	−1,571.969	−1,555.139	−1,553.414
AIC	3,180.595	3,401.502	3,267.047	3,163.938	3,132.278	3,132.829
Note:	*p<0.05; **p<0.01; ***p<0.001					

Table A5: Robustness Checks on the Time Window in Calculating PMC

	Dependent variable: Performance Z Score (t+1)			
	Main Model	1	2	3
Location Change	−0.058**	−0.061**	−0.060**	−0.055**
	(0.022)	(0.022)	(0.022)	(0.020)
Time Since Move	0.010*	0.011*	0.010*	0.013*
	(0.005)	(0.003)	(0.004)	(0.005)
PMC (t+2) * Location Change	−0.070***			
	(0.021)			
PMC (t+2) * Time Since Move	−0.013***			
	(0.004)			
PMC (t+1) * Location Change		−0.065***		
		(0.022)		
PMC (t+1) * Time Since Move		−0.011*		
		(0.005)		
PMC (t+3) * Location Change			−0.074***	
			(0.023)	
PMC (t+3) * Time Since Move			−0.015**	
			(0.004)	
PMC (t+4) * Location Change				−0.081*
				(0.034)
PMC (t+4) * Time Since Move				−0.016**
				(0.006)
Observations	10,042	10,042	9,321	8,871
Note:	*p<0.05; **p<0.01; ***p<0.001			

Table A6: Robustness Checks on the Time Window in Calculating Persistent Ties

	Dependent variable:				
	Persistent Ties			log(Performance)	
	(1)	(2)	(3)	(4)	(5)
	Full	Women	Men	Women	Men
Male	-0.138^{***}				
	(0.028)				
Mover or not	0.090^{***}	0.091^{***}	0.150^{***}	0.034	0.079
	(0.020)	(0.020)	(0.030)	(0.033)	(0.064)
Post-move Indicator	-0.007	-0.009	-0.006	0.076^{***}	0.157^{***}
	(0.011)	(0.011)	(0.022)	(0.015)	(0.042)
Mover or not * Post-Move Indicator	-0.544^{***}	-0.459^{***}	-0.620^{***}	-0.284^{***}	-0.292^{**}
	(0.028)	(0.028)	(0.042)	(0.043)	(0.085)
Male * Mover or not	0.063				
	(0.037)				
Male * Post-Move Indicator	-0.011				
	(0.024)				
Male * Mover or not * Post-move Indicator	-0.128^{*}				
	(0.050)				
Persistent Ties (t-3/t)				0.109^{***}	0.202^{***}
				(0.007)	(0.020)
Persistent Ties (t-3/t) * Post-move Indicator				0.041^{**}	0.106^{**}
				(0.014)	(0.037)
Constant	-0.203	-0.185	-0.067	10.453^{***}	10.472^{***}
	(0.114)	(0.113)	(0.156)	(0.321)	(0.698)
Observations	60,295	47,981	12,314	47,981	12,314
All Controls	Yes	Yes	Yes	Yes	Yes
Matching Group Fixed Effects	Yes	Yes	Yes	Yes	Yes
Job Grade Fixed Effects	Yes	Yes	Yes	Yes	Yes
Moving Months Fixed Effects	Yes	Yes	Yes	Yes	Yes
Log Likelihood	$-78{,}082.190$	$-62{,}479.020$	$-15{,}803.140$	$-80{,}383.410$	$-24{,}313.080$
Note:	*p<0.05; **p<0.01; ***p<0.001				

Table A7: Robustness Checks on the Effects of Newcomers on Incumbents (Individual Ranking Stability & Subsample with Only Months when Newcomers Joined)

	Full Sample		Newcomer > 0 Subsample		
	Performance (t+1)	Density	Performance(t+1)		Density
	(1)	(2)	(3)	(4)	(5)
Newcomer's Prior Performance	0.068***	−0.014***	0.068***	0.116***	−0.018***
	(0.006)	(0.001)	(0.007)	(0.010)	(0.003)
Relative Performance	−0.071***	0.014***	−0.070***	−0.098***	0.019***
	(0.003)	(0.001)	(0.004)	(0.011)	(0.002)
Individual Ranking Stability	0.014	0.010	0.016		
	(0.030)	(0.007)	(0.031)		
Relative Performance * Individual Ranking Stability	−0.008*	0.001	−0.011*		
	(0.003)	(0.001)	(0.005)		
Group Ranking Stability				0.017	0.014
				(0.096)	(0.008)
Relative Performance*Group Ranking Stablity				−0.030*	0.003**
				(0.013)	(0.001)
Incumbent's Network Density			−0.411***		
			(0.033)		
Constant	−0.290***	0.628***	−0.044	−0.461***	0.678***
	(0.077)	(0.009)	(0.080)	(0.102)	(0.015)
All Controls	Yes	Yes	Yes	Yes	Yes
Individual Random Intercepts	Yes	Yes	Yes	Yes	Yes
Group Random Intercepts	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	17,681	17,681	17,681	2,632	2,632
Log Likelihood	−21,427.890	3,568.069	−20,211.880	−3,033.476	610.385

Note: *p<0.05; **p<0.01; ***p<0.001

Table A8: Robustness Checks on the Effects of Newcomers on Incumbents (Two-month Lag)

	Dependent variable:			
	Performance(t+2)		Density(t+1)	Performance(t+2)
	(1)	(2)	(3)	(4)
Newcomer's Prior Performance	0.064^{***}	0.064^{***}	-0.007^{***}	0.066^{***}
	(0.007)	(0.007)	(0.002)	(0.007)
Relative Performance	-0.052^{***}	-0.042^{***}	0.007^{***}	-0.042^{***}
	(0.003)	(0.005)	(0.001)	(0.005)
Group Ranking Stability	−0.034	-0.146^{**}	0.013	-0.161^{**}
	(0.028)	(0.051)	(0.013)	(0.055)
Relative Performance * Group Ranking Stability		-0.023^{**}	0.005^{*}	-0.024^{**}
		(0.009)	(0.002)	(0.009)
Density (t+1)				-0.437^{***}
				(0.036)
Constant	-0.212^{*}	−0.160	0.601^{***}	0.099
	(0.085)	(0.087)	(0.010)	(0.090)
All Controls	Yes	Yes	Yes	Yes
Individual Random Intercepts	Yes	Yes	Yes	Yes
Group Random Intercepts	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Observations	14,507	14,507	14,507	14,507
Log Likelihood	−17,559.820	−17,560.230	2,569.157	−16,312.610
Note:	*p<0.05; **p<0.01; ***p<0.001			

Table A9: Estimating Groups' Likelihood of Hiring and the Prior Performance of the New Hires

	Dependent variable:			
	The Likelihood of Hiring(t+1)		Newcomer's Prior Performance	
	liner binomial mixed-effects		*linear mixed-effects*	
	(1)	(2)	(3)	(4)
Avg Incumbents' Prior Performance	0.033	0.040	0.034	0.029
	(0.046)	(0.049)	(0.018)	(0.019)
Group Ranking Stability	−0.019	−0.015	−0.007	−0.005
	(0.038)	(0.039)	(0.014)	(0.014)
Group Size	-0.201^{***}	-0.200^{***}	−0.023	−0.031
	(0.055)	(0.050)	(0.016)	(0.017)
Total Leave	0.998^{***}	0.974^{***}	0.220^{***}	0.214^{***}
	(0.083)	(0.080)	(0.036)	(0.037)
Avg Org Experience	-0.128^{*}	-0.136^{*}	0.021	0.017
	(0.052)	(0.053)	(0.017)	(0.017)
Avg Role Experience	-0.288^{***}	-0.283^{***}	-0.057^{***}	-0.059^{***}
	(0.056)	(0.055)	(0.016)	(0.017)
Proportion of Male	0.053	0.018	0.004	−0.005
	(0.040)	(0.041)	(0.015)	(0.015)
Total Supervisors	0.018	0.051	0.008	0.012
	(0.042)	(0.044)	(0.015)	(0.015)
Total Top Performers	0.202^{***}	0.192^{***}	0.063^{***}	0.058^{**}
	(0.052)	(0.053)	(0.019)	(0.019)
Group Network Size		−0.012		0.013
		(0.057)		(0.021)
Group Communication Density		0.047		0.011
		(0.071)		(0.027)
Group Communication Reciprocity		0.168		0.230
		(0.412)		(0.155)
Group Clustering Coef.		−0.00005		−0.006
		(0.057)		(0.021)
Betweenness Centralization		−0.148		−0.282
		(0.759)		(0.292)
Degree Centralization		0.981		0.133
		(0.553)		(0.209)
Constant	-2.032^{***}	-2.418^{***}	0.155^{***}	0.081
	(0.067)	(0.148)	(0.043)	(0.063)
Group Random Intercepts	Yes	Yes	Yes	Yes
Location Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Observations	8,820	8,820	6,646	6,646
Log Likelihood	−2,316.481	−2,316.481	−8,711.875	−8,718.226
Note:	*p<0.05; **p<0.01; ***p<0.001			

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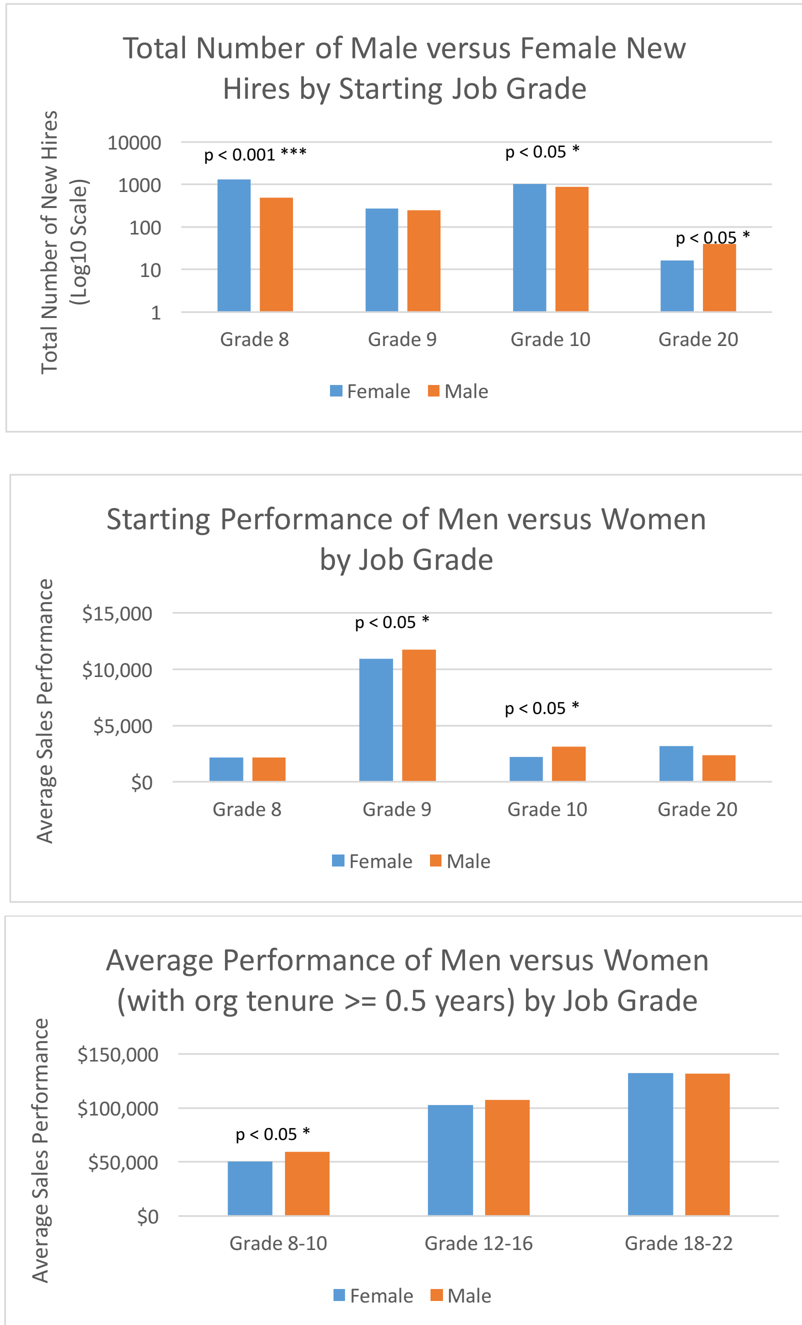

Figure 2.1: Starting Level, Starting Performance, and Average Performance by Gender

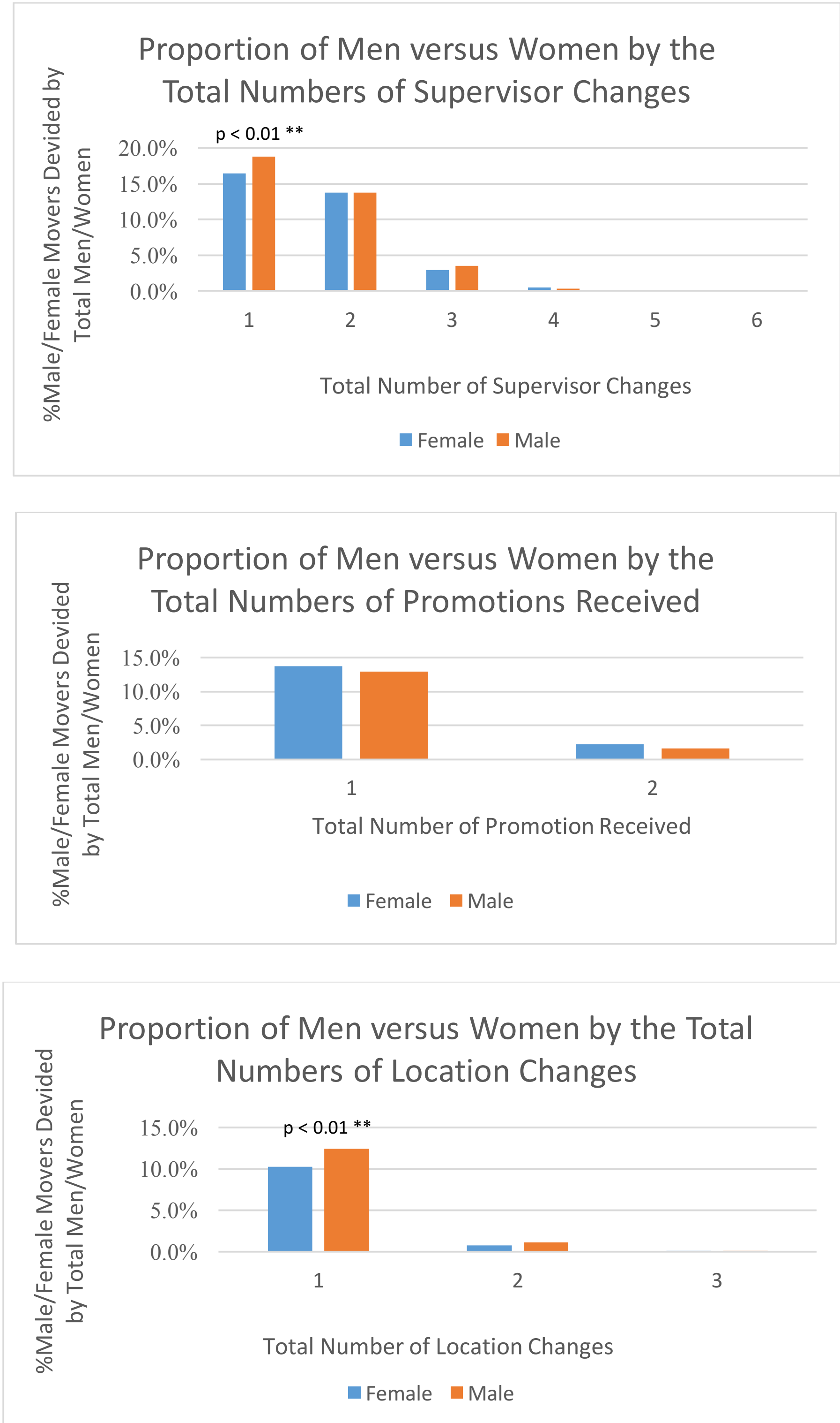

Figure 2.2: Proportion of Men and Women by the Number of Job Changes Experienced

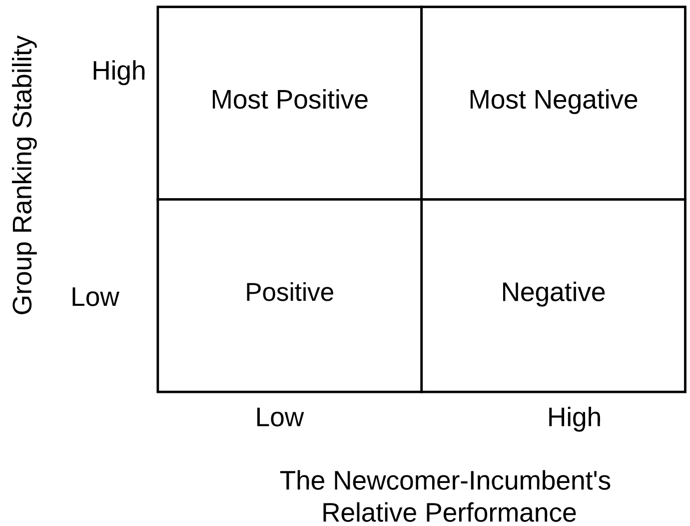

Figure 3.1: Impact of a Newcomer on an Incumbent’s Subsequent Performance

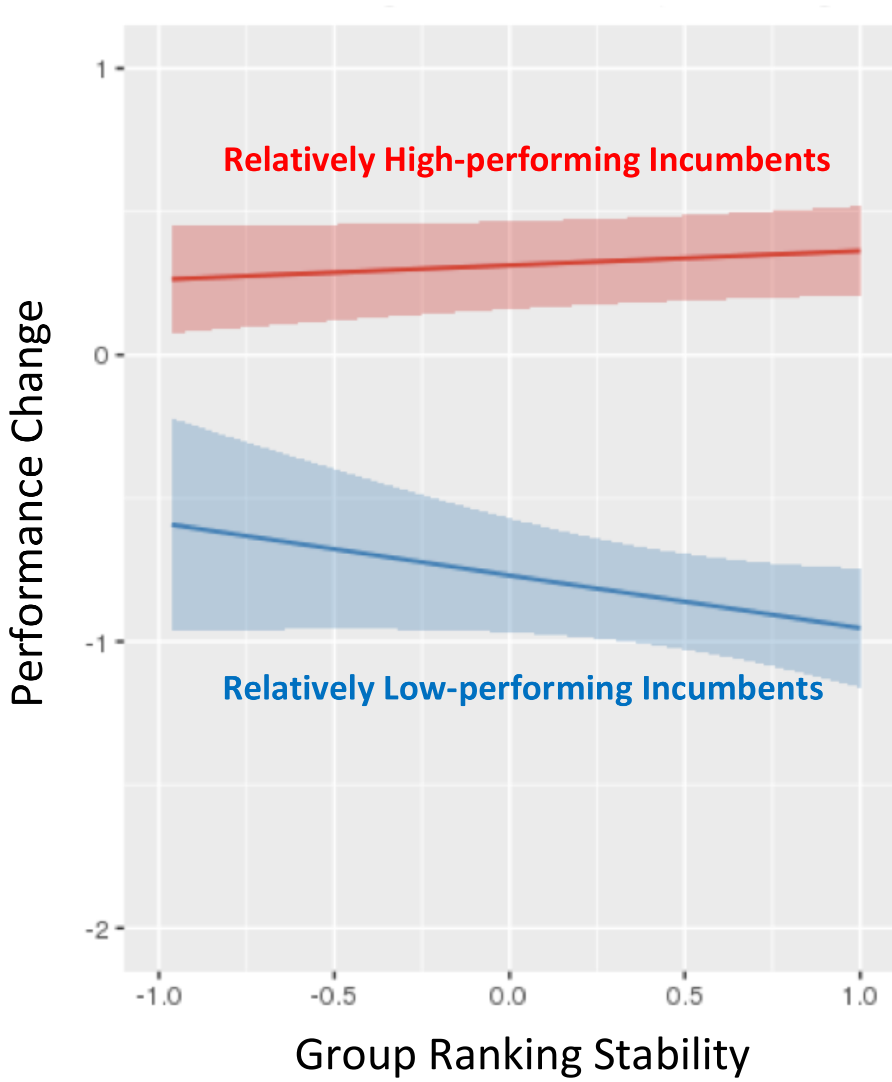

Figure 3.2: Impact of Group Ranking Stability and Newcomer-Incumbent Relative Performance on an Incumbent's Subsequent Performance