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Shifting Modalities: Social Networks, Intra-Organizational Lateral Mobility, and Performance

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INTRODUCTION

In the U.S., tens of millions of people find new jobs every year, and estimates vary—from double-digits to the majority of jobs—regarding how often social networks are at play in the jobs that people secure (Granovetter, 2005; Rubineau and Fernandez, 2013; Lazear and McCue, 2018; see also Franzen and Hangartner 2006 for rates in other countries).[1] For scholars, the question has been largely why social networks appear to have such a prevalent role in the movement of people across organizations and jobs during careers (e.g. see Marsden and Gorman, 2001; Castilla, Lan, and Rising, 2013 for reviews). And studies indicate that a primary explanation for this phenomenon is that social networks are anticipated to influence how individuals perform *after* they are hired (Castilla, 2005; Yakubovich and Lup, 2006; Burks et al., 2015). Either because at the applicant stage, individuals on either side of the organization-labor market interface are expected to have information that leads to better selection (Granovetter, 1973; Simon and Warner, 1992) or because those hired through social networks can become better through post-hire social interactions, such as by receiving insights about the norms and values of the organization (Fernandez, Castilla, and Moore, 2000) or who to associate with (Sterling, 2015), the foregoing explanation in the literature, as well as what may be at the forefront of managers' minds as they make hiring decisions, are reasons why job candidates with connections to employees *ought* to perform better once they are hired than those without the equivalent social connections.[2]

Nevertheless, the evidence that those hired through social network connections *indeed do* perform better is somewhat mixed. While some studies suggest there is a positive effect of social

[1] See the JOLTS survey of the Bureau of Labor Statistics
https://www.bls.gov/news.release/archives/jolts_03162018.htm
[2] For example, see recommendations by The Society for Human Resource Management.
https://www.shrm.org/resourcesandtools/hr-topics/talent-acquisition/pages/employee-referrals-remains-top-source-hires.aspx

ties on employee performance, others suggest that the effects are somewhat limited and may only adhere to a subset of workers, while still other studies cast doubt that such effects exist at all (Castilla, 2005; Breaugh, 2013; Shwed and Kalev, 2014; Burks et al., 2015; Merluzzi and Sterling, 2017). But even with this mix of evidence in tow, theory by and large emphasizes that social networks should lead to *higher* post-move performance for employees. However, an examination of theory has occurred in the absence of, empirically-speaking, a test of the counterfactual. When circumscribing the effects of social connections on mobility and performance, scholars have studied effects at the cross-section of employees and their social ties *after moves*. With such estimates, we do not know what would have been an individual's performance if he or she had moved with (or without) social ties, nor do we have a comparison of individual's performance before or after moves transpire. This leads to the possibility that we have not only theoretically given weight to positive expectations of the effects of networks on mobility, but that we have also systematically over or under-estimated these effects. This would be the case if unobserved aspects of candidates that affect performance also cohere to candidates having social connections (see discussions in Mouw, 2003; 2006, Obukhova and Lan, 2013).[3]

One reason why theories of mobility anticipate positive performance outcomes is that they lean on networks as arbiters of uncertainty. Studies of networks, mobility, and performance have focused on either inter-organizational mobility, wherein individuals change employers and jobs, or vertical mobility within organizations, wherein people expand (or shrink) their job responsibilities through promotions (demotions). In both forms of mobility, high levels of

[3] Scholars have noted the particular difficulties of studying networks in lab experiments to inform actual workplace outcomes and behaviors, and some have studied network formation outside of the lab, such as Hasan and Bagde (2015). Such studies have not focused on mobility and networks in tandem. In the context of mobility research, Obukhova and Lan (2013) suggest a methodological improvement, which is to use within-individual fixed effect models to see how, for the same individual, mobility is affected by networks. For slightly different reasons, we also implement a within-individual fixed approach here, with a pre-post comparison we elaborate on below.

uncertainty exist. In inter-organizational mobility, uncertainty revolves around whether prospective employees will be well-matched not only to a job but to the organization. This uncertainty also leads candidates to seek out information from their social contacts employed at the firm, including information about what jobs will entail, and difficult-to-understand aspects of organizations, such as their norms and culture (Goldberg et al., 2016). Employers attempt to glean information about the relative fit or match of candidates before moves occur through employees that are socially-tied to the candidates. Likewise, in vertical mobility, individuals have uncertainty about how they will perform in the context of a new role, because they have new tasks, responsibilities, and span-of-control, which leads them to seek out information about their readiness from others. In parallel, managers have not seen individuals in action performing these jobs, prompting them to retrieve information about an individual's skills and abilities from others (Briscoe and Kellog, 2011; Mizruchi, Stearns, and Fleischer, 2011; Correll et al., 2019).

Although prior work has focused on networks as a means to reduce uncertainty, broader networks research suggests that other modalities beyond information may be conferred through social ties and may surface in mobility of another type. Specifically, while studies have focused on information with respect to mobility, less attention has been paid to social influence as a modality. Social influence is the process by which individuals are affected by the perspectives, beliefs, and desires of those with whom they are connected for varied reasons, including obligations, attachments, and "histories of interaction" that may be imbued with sentiment in social ties. This modality presents a countervailing force to the positive performance outcomes brought about simply by informational exchange in network ties. These aspects of networks could influence people to take jobs, as well as prompt others to encourage their associates to take jobs, for reasons unrelated to expectations of post-hire performance. These aspects can also hinder performance, akin to dynamics and behavior seen for networks at the inter-organizational level (Uzzi, 1997; Gulati, Nohria, and Zaheer, 2000; Beckman, Haunschild, and Phillips, 2004; Sorenson and Waguespack, 2006; Sytch and Tatarynowicz, 2014). While drawing attention to social influence aspects of networks is not new (c.f. Granovetter, 2005), its effects and the potential downsides of social networks on mobility have rarely been examined theoretically and empirically (see a recent discussion in Castilla, Lan, and Rissing, 2013:1006). Thus, it is important to understand when this side of networks comes to the fore and which contextual aspects might contribute to it.

One type of mobility that could provide traction to our understanding of the aspects of social influence for networks and their effects is lateral mobility. Intra-organizational lateral mobility refers to moves wherein people remain in the same job and organization but move internally across units or geographic regions (Anderson, Milkovich, and Tsui, 1981; Bidwell, 2011). In many organizations, intra-organizational lateral moves have now become a common practice that is argued to break down bureaucratic silos within organizations. This is because employees may share new information and routines that they learned while working in their previous units. (Bidwell and Keller, 2013). This particular type of mobility is different from inter-organizational or inter-job mobility for a host of reasons, but one difference arguably at or near the top is the level of uncertainty between potential movers and the business units that could receive them; it is less than it is for inter-organizational and vertical moves. In intra-organizational lateral moves, the tasks and skill-sets required for jobs are, by and large, the same, and prospective movers have already learned first-hand about the firm. While there might be differences in norms and cultures across business units, these differences are arguably less stark than those found across firms (Carroll and Harrison, 1998; Goldberg et al., 2016).

Building on theories on social networks and inter and intra-organizational mobility, we develop and test theories about the influence of social relationships on lateral mobility and performance. While existing theory of other types of mobility lead to an expectation that social networks a) increase the likelihood of a move to a location of a social contact and b) improve performance in the presence of social ties, we develop theoretical arguments that are consistent with respect to the former but *divergent with respect to the latter*. More pointedly, we develop theories about how social networks instigate lateral mobility to certain opportunities, which in turn can have negative consequences on performance. We also explicate conditions where aspects of social influence flowing through social relationships are apt to be the highest, i.e. owing to the physical proximity and rank of the social contacts and thereby leading to the biggest performance decrements. While we focus squarely on lateral mobility, we believe that by surfacing when and how social influence in networks may negatively influence performance, that we shed light on equivocal findings in prior research.

In order to test our theory, we gathered data from the retail sales department of a large US-based financial institution (hereafter, Big Bank), which is well-suited for examining the effects of social networks on intra-organizational mobility. Employees at Big Bank move to the same job, but often to different business units or geographic locations. We collect monthly data for the 672 employees who made lateral moves between November 2014 and April 2016. Using data on a few million email exchanges to indicate social network relationships, we investigate how prior relationships to employees in subunits affect the likelihood of moving as well as their post-move performance. Fortuitously and key to our choice of this setting, retail employees at Big Bank sell similar products to consumers and are independent contributors in the financial retail sales department. We are able to gather objective sales performance data and use it to address some of the aforementioned thorny empirical issues. For the same individual, we obtain data on how they perform *before and after a move,* in order to ascertain a pre/post-comparison, thus improving our ability to make inferences about the effects of networks on mobility and post-move performance.

NETWORKS AND INTRA-ORGANIZATIONAL LATERAL MOBILITY

The preponderance of research on networks and mobility has taken place in the context of external labor markets, wherein people change jobs and employers (see Marsden and Gorman, 2002; Granovetter, 2005; and Castilla, Lan, and Rissing, 2013 for reviews). Studies indicate that both the candidates and employers in labor markets make common use of social networks. On the candidate side, individuals receive information about job opportunities and potential employers that can surface from neighbors (Granovetter, 1973; Bayer, Ross, and Topa, 2008; Topa, 2011), prior co-workers (Rider, 2012), and friends (Sterling, 2014; Bond, Labuzova, and Fernandez, 2018) as candidates look for work. On the employer side, networks yield employers richer and more fine-grained information than they would otherwise receive when screening for candidates (Rees and Schulz, 1970; Simon and Warner, 1992).

In labor market mobility studies, both employer and candidate accounts center around the expectation that job candidates who share social relationships to one or more employees of a particular employer will have a greater likelihood of moving to that employer, all else equal, than applicants without such relationships in place. This assumption highlights the inherent uncertainty of mobility for both candidates and employers predicated upon each side's lack of information regarding the other in external markets. The logic then being that pre-existing social relationships between candidates and employees of a potential employer—what we refer to as pre-move contacts (PMCs)—help to offset this information asymmetry by facilitating the transfer of pertinent and often crucial information. From a candidate's perspective, PMCs might share private aspects about the employer and provide privileged access to job opportunities (Petersen, Saporta, and Seidel, 2000; Obukhova and Lan, 2013). By detailing what the candidate can expect, PMCs can improve the candidate's understanding of the new position, such that she can enter it with 'eyes wide open' (Wanous, 1980). Moreover, it is assumed that PMCs will aid the candidate by smoothing out transitional challenges and accelerating her organizational learning and integration (Fernandez, Castilla, and Moore, 2000; Beckman and Haunschild, 2002; Castilla, 2005). From the employer's vantage point, PMCs are also expected to benefit the hiring manager through the initial selection and then subsequent socialization of candidates. Whether through greater information sharing by the PMCs, or the anticipation of improved learning through social interaction, employers tend to have higher expectations about the performance of candidates connected to PMCs than candidates without PMCs. These expectations foster a preference to hire candidates who have pre-existing social connections in the hiring area over those lacking connections.

Contemporaneously, mobility is a salient aspect of careers, not only because individuals change employers or jobs externally (Hollister, 2004; Fernandez-Mateo, 2009; Bidwell et al., 2013), but because as previously intimated, a substantial amount of mobility takes place within organizations and within jobs (Anderson, Milkovich, and Tsui, 1981; Cappelli and Keller, 2014). Intra-organizational lateral mobility—i.e. movement within the same organization to positions with the same titles, tasks, and responsibilities—is becoming increasingly common (Bidwell, 2011; Bidwell and Keller, 2013; Keller, 2018). Although these lateral movements do not result in changes to the individual's tasks or role expectations, they often entail shifts to new organizational subunits, including to new work groups and departments, geographic regions, and co-workers. These lateral moves are known to appeal to employees because they get a change of pace and context, while retaining the core aspects of their jobs.

While to our knowledge no studies directly examine the effects of social ties on intra-organizational lateral mobility, the ubiquity of social networks and their importance for various organizational processes suggest that social ties may affect lateral movement. Organizations inform the emergent patterns of social networks (Feld, 1981; Kleinbaum, Stuart, and Tushman, 2013; McEvily, Soda, and Tortoriello, 2014), and social networks also affect an array of organizational outcomes related to vertical mobility such as promotions (Burt, 1992; Podolny and Baron, 1997) and pay (Mizruchi, Stearns, and Fleischer, 2011; Greenberg and Fernandez, 2016), as well as other outcomes such as employee performance (Mehra, Kilduff, and Brass, 2001), and turnover (Krackhardt and Porter, 1985). In organizations, employees can get to know employees in other parts of the organization, including those in other subunits, geographic regions, and work groups through job assignments, workforce reorganization, and other means. As social networks are consequential for the mobility of individuals across organizations and jobs, there is reason to believe they may also be significant for lateral moves within them.

In alignment with the external labor market and vertical mobility literature, we anticipate that in the context of lateral mobility, PMCs may provide advantages to the employee and hiring manager in a business unit, leading to a greater propensity for these employees to make moves to that unit. Employees with social contacts in other parts of the organization may be more likely to move to these units than those without such connections. Further, greater numbers of PMCs in a particular area of the organization will likely amplify this gravitational pull towards a position. Greater numbers of social ties between the employees considering a move and employees in the hiring unit should increase the confidence that these lateral moves should occur. Additionally, increases in the number of PMCs between the movers and the hiring units lead to increased expectations for the types of behaviors that are seen after inter-organizational mobility, such as socialization, integration, and learning that we reviewed previously. We predict the following:

> <u>*Hypothesis 1*</u>*: The likelihood of an employee joining a particular unit increases with the total number of PMCs that the employee has to that specific unit when employees move within organizations.*

A SOCIAL INFLUENCE APPROACH TO MOBILITY AND PERFORMANCE

Social influence is the process through which a person's behavior is affected by others through intentional or unintentional means. Social influence occurs for numerous reasons, such as compliance to the expectations of high-status individuals, conforming to the norms of socially desirable groups, and reliance on social proof or obligations of reciprocity (Krackhardt and Porter, 1985; Ibarra and Andrews, 1993; Rider, 2012). While social influence can be overt and explicit, it is a process that is most often subtle, indirect, and outside the awareness of individuals (Cialdini and Goldstein, 2004). Social influence is exerted in relationships and has been found to augment a variety of positive behaviors (e.g., Hasan and Bagde, 2013; 2015), but also negative ones, such as bullying and corruption (e.g., Aven, 2015).

Considering social influence in addition to information as a social network modality promises more nuanced insights when considering outcomes *after moves*. While the informational and social influence aspects of networks are largely aligned in their predictions about lateral mobility, the same may not be true concerning post-mobility performance. In external labor markets, prior research has largely cast search for prospective candidates and employers as difficult and costly because information asymmetry is high. In such settings, third parties in the form of social contacts are argued to smooth over search and information challenges, which in turn leads to expectations of better post-mobility performance outcomes.

However, empirical evidence for the effects that relationships play in post-mobility performance are far from conclusive. For example, Pallais and Sands (2016) find that relationships have a positive effect on candidate performance, whereas Castilla's (2005) study suggests that the benefits are only temporary. Still, other studies find that relationships might, in fact, hinder the performance of the incoming candidate (Breaugh, 2013; Shwed and Kalev, 2014). Perhaps one explanation for these inconsistencies in performance outcomes stems from extant scholarship not adequately considering the social influence modalities of social relationships.

Employment at a firm simultaneously decreases the need for third party social contacts as sources of information, and concomitantly increases the extent to which employees may become more susceptible to one another's social influence. In terms of the former, an employee already possesses information about expectations for his or her job, knowledge about organizational reporting structures, and skills to complete requisite tasks. In addition, the employee has also experienced the organization's culture first-hand. At the same time, managers can ascertain the employee's skills and abilities, as well as how the employee interacts with other employees due to knowledge of the person's work history and performance. Hence, because lateral mobility is an arrangement that is established after employment commences and occurs within a job, this mutes the informational relevance of social networks.

In terms of the latter, the spatial, temporal, and social proximity that is afforded by employment allows for greater opportunities for social influence between an employee and her social contacts. Employment acts as social foci, providing employees opportunities and incentives to interact and forge relationships (Feld, 1981). While sometimes remaining purely formal, it is not uncommon for relationships at work to become imbued with trust, familiarity, and mutual obligations (Ibarra and Andrews, 1993; Briscoe and von Nordenflycht, 2014; Bond, Labuzova, and Fernandez, 2018). Even ties that simply begin as formal work relationships often develop into social attachments, such as friends, confidants, allies, and mentors (Oh, Chung, and Labianca, 2004; Briscoe and Kellog, 2011). Connected individuals can succumb to social influence when they are exposed to the same environmental stimuli, as they are in an organization with shared goals (Cialdini and Trost, 1998). Hence, although employment reduces the overall need for secondary information from PMCs, it simultaneously increases the likelihood of social influence by PMCs.

Therefore, while there is no reason to suspect that information would no longer flow through relationships in the context of lateral moves, an array of factors suggest that social influence can overwhelm the lateral mobility process, due to the redundancies of social networks with information and the heightened level of social influence in organizations. Stated differently, we anticipate that the effects of social influence can overpower those of information in lateral job changes in ways that have persistent effects on the performance of employees *after they move.* The social influence modality is consistent with our prior prediction about mobility increasing with PMCs, but it also leads to the expectation that post-move performance may be lower for those with PMCs than for those without PMCs, for at least three reasons.

To start, social influence can restrict the extent to which employees seek out new opportunities within their organizations. As compared to searches within external labor markets, the employee's ability to find positions through their internal interactions and communication potentially improves internal job searches. However, employees may become overly reliant on PMCs and place greater weight on communications with them (Sorenson and Waguespack, 2006; Rogan and Sorenson, 2014). Relying on their social contacts, employees artificially limit the lateral opportunities they discover. In turn, this may hinder their ability to locate the most appropriate position within the firm. In such cases, social influence is simply a function of how employees seek out and attend to positions. Moreover, employees may be swayed more positively toward opportunities that are associated with PMCs, simply due to positive anticipated spillovers. Taking for granted that they have greater familiarity with opportunities associated with their PMCs, employees may be lax in assessing positions and assuming compatibility and will simply accept the offered position (Shewd and Kalev, 2014).

Next, from the employer's vantage point, social influence may affect the evaluation of internal employees. In addition to providing richer information on employees, social contacts may exert pressure on managers and lead to less rigorous vetting (Pinkston, 2012). Additionally, PMCs might influence managers to be unduly favorable toward the employee. In some cases, managers may simply conclude that the employee will be well-suited to the position because of the performance of the PMCs currently in the job (Yakubovich and Lup, 2006) rather than the employees themselves. This parallels with the notion of 'slotting' jobs, where those who apply to internal jobs are scrutinized less by evaluators due to the endorsements of their contacts, leading them to be more poorly matched than those who found and applied for jobs without contacts (Castilla and Rissing, 2019; Keller, 2018). In essence, PMCs may both directly and indirectly sway the staffing process in favor of the socially-tied employee.

The third reason, *social velleity*, suggests that when employees are connected to PMCs, they may feel compelled to accept a position, and employers might feel obliged to staff an employee for largely social reasons. The presence of liking, trust, social similarity, and shared membership in a social or organizational community can lead individuals to be susceptible to the behaviors and advice of others (Krackhardt and Porter, 1985; Portes, 1998). For instance, employees and employers may feel an obligation to reciprocate past favors, or employees and employers might acquiesce due to the anticipation of favors in the future (Gouldner, 1960). In addition, social velleity can lead employees and managers to favor social factors, such as friendship or collegiality over productivity (Podolny and Baron, 1997; Cascirao and Lobo, 2008), or favor those with social attachments based on the belief that they will be more committed to their jobs (Galperin et al., 2019). Along those lines, Fernandez, Castilla, and Moore (2000) found that in a call-center, it was a sense of loyalty to current employees, rather than any sense of higher performance expectations for candidates, that prompted managers to provide offers to candidates who were socially tied to the center. In other words, both sides may simply place greater weight on social aspects rather than performance in staffing a new position. Employees with social contacts and employers might also experience a sense of obligation to "make it work," even if they are aware that it might not be the best match (Moss and Tilly, 2001). Hence, social velleity may lead employees with PMCs to accept positions that are poorly suited to them, which subsequently hinders their ability to perform.

High numbers of PMCs, common to internal employees, may also act to exacerbate social influence in lateral moves. When employees have one or more PMCs who alert an individual of an opening, the saliency of the potential opportunity increases. By the same token, when higher numbers of individuals alert the prospective employee of the job opportunity, the credibility or merits of it may increase by simple social proofing (Uzzi, 1997; Krackhardt, 1999). In such cases, employees are prone to give PMCs' opinions greater weight and to move forward based on their recommendations without thoroughly evaluating the opportunity. Further, higher numbers of PMCs may also lead to higher levels of social velleity, either on the side of the prospective mover, the unit where the PMCs resides, or both. Overall, while an informational perspective would suggest that the number of relationships enhance mobility and subsequent performance outcomes, a social influence perspective implies otherwise in terms of the latter. Formally, we expect the following:

> *Hypothesis 2: There is a negative relationship between the number of PMCs and the objective performance of employees after they move.*

GEOGRAPHIC PROXIMITY AND FORMAL RANK OF PRE-MOVE CONTACTS

The aforementioned arguments detail the underlying logic of our social influence approach to mobility. Critically when turning to post-move performance, our attention has been on *objective* performance, rather than the career outcomes of employees or subjective assessments of performance. It is entirely possible that from the standpoint of the employee, lateral moves with PMCs have career benefits and/or lead to favorable subjective assessments. In a study of inter-organizational mobility, Shwed and Kalev (2014) found that there are reasons outside of performance that new hires with social ties to employees have accelerated promotion trajectories once they join organization. Indeed, social influence could be a reason for such career advancements (Shwed and Kalev, 2014: 289-292). While these downstream career consequences informed by subjective evaluations might affect internal mobility, they fall outside of our purview.

Our focus centers on mobility and the near-term consequences of these moves on the *actual* performance of employees, and faces a key challenge, which is that these modalities of networks—i.e. information and influence—cannot be easily separated. The two co-occur in natural settings and researchers have yet to find appropriate means to simulate such rich relationships within artificial settings. Moreover, scholars have noted the particular difficulties of studying networks in experiments to inform actual workplace outcomes and behaviors (Mouw, 2003; 2006, Obukhova and Lan, 2013). Thus, in order to extricate the role of social influence on mobility and performance, we develop theoretical predictions that would be consistent if social influence is the dominant modality in lateral mobility in organizations (see Lave and March, 1975 for a well-known discussion of this approach). That is, we proceed to discuss the potential conditions that amplify the divergent effects of social influence and information on post-move performance—i.e. the conditions that would be consistent with the former and inconsistent with the latter. The first condition is geographic proximity and the second is the formal organizational rank of the pre-move social contacts.

Geographic Proximity

We consider how the geographic proximity of the prospective mover's current job to the new job, as well as to the PMC(s), may help distinguish the modalities of information and social influence. To begin, there are redundancies in the information provided in networks and the knowledge employees have about lateral opportunities, when lateral moves under consideration are in close proximity. A reason for this is that employees who make nearby moves are apt to already have pertinent knowledge about the job, since propinquity often allows employees to know more about and directly observe those holding the jobs. For example, a lateral move to a nearby location may mean that the employee has already observed tasks, co-worker interactions, and supervisors' behaviors that are relevant to the move under consideration. Proximate lateral moves oftentimes coincide with a familiarity with the customers, clients, and local markets that an employee may be tasked to serve. Likewise, managers have often been able to acquire knowledge about proximate employees being considered for moves outside of their own employees' recommendations. In other words, when lateral moves are more physically proximate, social networks as a source of information may become less valuable (Argote, Beckman, and Epple 1990; Jaffe, Trajtenberg, and Henderson, 1993), as focal employees may have learned about opportunities through first-hand experience and observation, and managers have been able to ascertain the prospective mover's abilities and skills (Jovanovich, 1979).

Thus, the information modality of PMCs on performance could be muted for proximate lateral moves. This logic is consistent with findings in empirical studies. For example, studies of entrepreneurs suggest that social ties are more valuable with distance (Sorenson, 2005; Roberts and Sterling, 2012; Sorenson and Stuart, 2008). Our reasoning also parallels arguments whereby connections to individuals in socially-distinct contexts, rather than proximate ones, are channels for the most helpful information (Burt, 1992; Corredoira and Rosenkopf, 2009). A related but distinct point has to do with how the environment itself changes with distance. In a mobility context, individuals considering a move to another region, city, or country may have to contend with different local cultures and variation in work requirements, as well as unfamiliar clients and co-workers. For all these reasons, the informational value of social ties in a mobility context ought to decrease with propinquity, leading to a negligible effect of social ties on performance when moves are close.

On the contrary, propinquity heightens the effects of social influence, such that when units are geographically close, social influence via social contacts outpaces information. When individuals are close in proximity, they have greater opportunities for social interaction, which in turn can increase their capacity to influence one another (Blau, 1970; Sorenson and Stuart, 2001). Evidence in both the lab and the field indicates that higher levels of interaction help to promote feelings of attachment, heightening social influence within relationships (e.g. Zajonc, 1968; Casciaro and Lobo, 2008). Further, geographic proximity increases opportunities to monitor others directly and through shared third parties (Portes, 1998).

Given this, as we consider the aforementioned means by which social influence may impinge upon performance, we argue that propinquity has the capacity to amplify each of them.

To the degree that a more cursory lateral search is prompted by PMCs, each side may be remiss to thoroughly vet the other side given the sense of familiarity that propinquity brings. Likewise, pressure to staff employees tied to PMCs is likely amplified with propinquity due to the ways by which geographic proximity boosts social monitoring in networks, leading to increased levels of social influence. Lastly, in terms of social velleity, a sense of obligation to staff in socially-attuned ways is apt to increase with propinquity, because it heightens the visibility of staffing decisions, making it hard to avoid the consequences of not acquiescing to social influence. Thus, if our social influence effects are circumscribed as we previously discussed, we predict the following:

> Hypothesis 3: *The negative association between PMCs and an employee's subsequent performance is stronger when the employee moves between geographically-proximate business units than between distant ones.*

Organizational Rank of PMCs

Finally, the organizational rank of PMC(s) likely heightens social influence while decreasing information value. When a PMC outranks the employee, it alters two factors that are important to the employee's mobility and subsequent performance. First, higher-ranked PMCs wield a greater capacity to affect the staffing outcomes that they seek due to their elevated power. Second, when employees' PMC(s) are of higher rank, they no longer share a similar occupational vantage point and may not be able to apprise employees of some of the context that should inform their ability to perform after a move.

Considering the first, PMCs with a higher rank than the employee tend to have greater resources and visibility than those lower in the organization. For this reason, those of higher rank might have a greater ability to affect the hiring processes both directly and indirectly. Organizational structure, such as formal titles and position, are commonly comprised of hierarchical roles, where one employee has formal or informal authority over another employee. Such hierarchical arrangements become fonts of informal power and status among employees (French and Raven, 1968; Pfeffer, 1992), leading to deference for those of higher rank when they endorse their candidates (Keller, 2018). Indirectly, the esteem or positive reputation of high-ranking PMCs might spill over to perceptions of employees, irrespective of the candidate's ability to perform (Yakubovich and Lup, 2006; Liu, Lee, and Kilduff, 2017). Directly, high-ranking PMCs can pressure managers to favor their choice, potentially lowering the vetting of a high-ranking PMC's preferred connections.

Second, the value of information decreases for the focal employee with the rank of the PMCs. PMCs at the same level as the focal employee should be better than higher-ranking employees in providing first-hand accounts of a job and the explicit and implicit knowledge of the tasks required in the organizational subunit. When social contacts are higher in the organization, they may not have tacit knowledge about tasks or have the idiosyncratic information about everyday job requirements like as those PMCs at the same level with the prospective mover (Hansen, 1999). As individuals move up in organizations, they pay less attention to the skill-set requirements of those below them, in part because they are more attentive to the behaviors of those who are of higher status (Krackhardt, 1990; Casciaro, 1998). To be clear, we are not arguing that information in lateral moves is always necessary, as we have suggested that some circumstances should render it less so (e.g. local moves). Rather, again, we are circumscribing that if the dominant modality is information in relationships when lateral moves are being considered, the relationships that ought to be valuable for informing one's day-to-day skills and knowledge affecting performance are those with employees of the same rank, not those of higher rank in the organization. If we find that higher-ranking PMCs do indeed negatively affect performance, this is consistent with our arguments about the countervailing force of social influence as compared to information with increasing rank.

In summary, when the PMC's rank is higher than the employee's, the relational modality should tilt toward social influence. Again, we align organizational rank of the PMCs to an employee's post-lateral move performance. PMCs of higher rank, and more of these PMCs, should truncate search for the prospective mover and the employer. If a notification about an opportunity comes from high-ranking social contacts, it may be hard for employees to search broadly for opportunities at the expense of seeming to ignore the suggestions of high-ranking PMCs, and likewise it may be difficult for the employer to ignore such suggestions. Vetting for lateral moves may run thin with the rank of the PMCs, as endorsements from high-ranking individuals hold weight for those on both sides of the staffing process (Castilla and Rissing, 2019). Finally, in terms of social velleity, obligations from PMCs are apt to amplify with rank, even if pressure is not overt or explicit. For employees, if one were to not pursue an opportunity at the PMC's request, doing so could be perceived as coming at a "cost" that jeopardizes sponsorship. On the employer side, a manager might be apt to feel pressure to acquiesce to a request out of loyalty to high-ranking PMC(s). Formally, we predict the following:

> <u>*Hypothesis 4*</u>*: The negative association between the total number of PMCs and an employee's subsequent performance is stronger the higher the organizational rank of the PMCs.*

METHOD

Research Setting

To test our hypotheses, we examined employee mobility and performance within Big Bank, a large financial institution. Big Bank is a U.S. based-bank organized into four large departments: retail sales, asset management, corporate and institutional banking, and mortgages.

We obtained data from the retail sales department at Big Bank, which specializes in providing personal financial tools and products to consumers and small businesses. Within the retail sales department, there are 2,830 business units that are spread across 36 major markets in the United States. Each business unit occupies a unique location and primarily serves customers within the specific geographic region. We elected to focus on mobility among those in the role of 'platform sales' because these jobs are common to all of Big Bank's retail sales locations. These platform sellers are tasked with customer service and the sales of Big Bank's financial products and solutions.

As a research setting, Big Bank's retail sales department provides a number of advantages for examining the role of social networks on intra-organizational mobility and subsequent employee performance. First, to fulfill personnel vacancies, every business unit in the retail sales department makes hiring decisions autonomously. That is, each business unit's manager has control over their hiring decisions. This autonomy allows the business units to post their job openings and evaluate potential candidates independently, rather than it being managed via a centralized human resource allocation process. The hiring process typically begins with the business unit posting the open job along with its description and characteristics of ideal applicants online, where both internal and external candidates can view it. Managers then spend an average of two to three weeks identifying potential candidates from the pool of applicants. Following this, managers and staff interview the job candidates.

Second, employees in retail sales work independently to sell similar products to local customers, and each month, Big Bank calculates their monthly sales as a performance metric. Working individually to conduct sales as these employees do allows us to measure each employee's performance without interference from work group confounds, such as task or role interdependence (e.g., Argote, Aven, and Kush, 2018). Another key advantage of examining retail sales employees is availability of an objective measure of performance in the form of total monthly sales. This mitigates concerns from prior research that suggest that subjective performance—such as peer or supervisor evaluations—suffer from evaluation bias (i.e., Roberson, Galvin, and Charles, 2007; Castilla, 2011). In all, the fact work is independently completed along with the availability of monthly measures of each employee's sales value, which permits a detailed, objective measure of employee performance.

Third, interviews with HR executives at Big Bank indicate that the retail sales employees rely heavily on email communication to share job-related information, such as new product details and selling strategies. Thereupon, we collected the metadata of email exchanges among all employees at Big Bank, comprised of sender IDs, receiver IDs, email size, and email timestamps. This data allows us to capture the social networks at Big Bank, following similar approaches in prior research (Kleinbaum, Stuart, and Tushman, 2013; Srivastava, 2015). Email communication affords us a behavioral measure of social interaction that is less prone to biases that often affect self-reported data, such as network surveys. Existing evidence indicates that email provides a reliable proxy for other mediums of communciation (Quintane and Kleinbaum, 2011; Aven, 2015).[4]

Overall, we obtained three sources of data in order to investigate our key research questions regarding the role of social relationships for intra-organizational mobility and performance, which is rare given the different ways such data is typically stored in organizations. This affords us an unprecedented chance to better understand lateral mobility. For our observation period, this data includes: (1) employees' monthly sales records in dollars; (2)

[4] For confidentiality reasons, Big Bank did not supply email content.

metadata for all internal emails of Big Bank employees, and (3) employees' work and demographic information, such as gender, age, job role, organizational rank, tenure, and job location.

Given our aim of understanding the role of relationships for mobility outcomes, our sample focuses on full-time platform sales employees who moved laterally. Specifically our sample are employees who change jobs between business units within the retail sales department but retained the same job title and role at Big Bank. While our complete observation period was from November 2014 to April 2016, lateral moves that took place in the early or later months would not provide sufficient time by which to capture their monthly sales performance before and after moves. To account for such truncation issues, we adjusted our observation window by four months after the start date and by four months before the end date. Accordingly, we identify 672 retail sales employees that make a lateral move between March 2015 and December 2015.[5] Hence, for all retail sales employees who move business units laterally in our sample, we observe at least four months of sales information before and after the move to ascertain employee performance changes.

Dependent Variables

Testing our hypotheses requires the examination of two distinct but related outcome variables, lateral intra-organizational mobility and employees' subsequent performance. This necessitates two different sets of analyses. In the first analysis, we estimate the effect of number of PMCs on the individual's movement to a specific business unit, conditional on the employee making a lateral move within the organization. In the second analysis, we estimate the effect of network ties on the post-move performance of the employee. Both of these analytical approaches

[5] Ten employees who moved laterally twice were excluded from our analysis because their movements exacerbated truncation challenges for emails and sales performance.

are elaborated on in detail after describing the dependent, independent, and control variables that follow.

Lateral Mobility. *Lateral Mobility to a Unit*, our first dependent variable, is dichotomous. It equals 1 if the employee moved to a particular business unit and is otherwise 0 for the remaining business units to which an employee might have moved.

Individual Sales Performance. *Individual Sales Performance* of employees, our second dependent variable, is the dollar amount of products that the employee sells in each month. To account for the right-skewed distribution of *Individual Sales Performance,* we log-transform it. The main effects should be interpreted as a percentage change.

Independent Variables

Pre-Move Contacts (PMCs). *PMCs* is the total number of job candidate's social contacts in the receiving business unit prior to the move. For each job candidate, we extract the list of unique email contacts that they corresponded with before their moves every month. Next, we look for the period of time that could yield a reasonable number of unique contacts that exist over our entire observation window, and it was two months. For 95.2% of the employees, all of the unique contacts that an employee had prior to a move were captured by using a two-month window immediately prior to the move. PMCs are measured as the total number of unique contacts that an employee communicated with two months prior to the move and two months after the move, or four months total. These windows were robust to sensitivity checks in post-move window length specification. Results also hold for the post-move window set to the zeroth month (where there is no restriction that a PMC and individual need to communicate further), one month (a shorter restriction where the employee and PMCs continue communication for at least one month after the move), and three months (a longer time restriction where the employee and PMCs continue communication for at least three months after the move).[6]

We measure the geographic proximity between the positions that an employee moves in three ways: *Same-City Moves*, *Geographic Distance*, and *Proximate Moves*. We describe each variable construction below.

Same-City Move. *Same-City Move* is a dichotomous variable that takes the value of 1 when an employee moves to a new position that is in the same city as their current job and 0 when they move to a position in a different city. Focusing on mobility across municipalities follows extant research underscoring the importance of discrete geographic regions and boundaries for outcomes (e.g., Corredoira and Rosenkopf, 2007). These boundaries are particularly important in our setting as retail sales employees most often sell and service mortgages, small business loans, or other financial products tailored by local markets and sometimes governed by municipalities.[7]

Geographic Distance. We also examine geographic proximity as a continuous measure. Specifically, we measure the physical distance based on the zip codes of the employees' former job locations and their new positions. As such, *Distance* is the span in miles between the two jobs. When the two business units are located in the same zip code, *distance* equals 0. We log transform *distance* due to its skewed distribution.

Proximate Move. *Proximate Move* is a dichotomous variable that takes the value of 1 when the geographic distance between the employee's prior and receiving business units is below the median value, and 0 when it is above the median. In other words, this variable captures the extent to which employees' move above or below the common mobility patterns of distance within our sample.

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[6] These robustness checks are reported in Appendix C.

[7] In addition, we explored movements across state boundaries as well, but only 6% of the employees in our sample moved to positions in another state. By contrast, 25.3% of the employees in our sample move within the same city, permitting us enough observations to estimate the differential effects.

The Proportion of Higher-Rank PMCs. Rank here is the formal level in Big Bank's organizational hierarchy, indicating position in its authority structure. Each position at Big Bank is assigned to a numerical rank, ranging between 8 and 24. Responsibility, pay, and span of control increase with rank. The *Proportion of Higher-Rank PMCs* is the ratio of PMCs who hold a rank higher than the employee divided by the total number of the employee's PMCs.

Control Variables

There are other factors that could affect the likelihood that someone moves to a business unit. Thus, additional control variables that we incorporate into the analysis for lateral mobility include *Average Organizational Tenure* and *Average Job Tenure* of the hiring business units, which is the mean in years of all of the members of the business units. To control for aspects of other employees' mobility and its effect on the focal employee, we control for the *Total Number of Newcomers,* which measures how many other employees who also join the business unit. To ascertain the amount of churn the subunit is experiencing, we control for the *Total Number of Leavers,* which are a count of the number of exiting employees for the quarter prior to the focal employee joining the business unit. Finally, we control for the *Total Number of Supervisors* because the relative influence of any one PMC could be affected by the number of other supervisors in a unit.

Intra-Organizational Lateral Mobility to a Unit Analyses

Hypothesis 1 requires that we estimate the effect of the number of PMCs on the focal employee's decision to take a job at a specific business unit.[8] Estimating intra-organizational

[8] A related but distinct question is which employees elect to move positions. The comparison set thus is all of the candidates who were considering moving but did not move. The answer to this question is well-documented in the literature. Specifically, 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. In light of these studies, we expect that individuals with more extensive ties to other business units are more likely to

mobility requires the comparison of all of the business units that the focal employee considered to the one that the she ultimately joined. In other words, such an analysis requires knowledge of all of the positions in a focal employee's consideration set. Unfortunately, our data does not provide a measure of all of the positions that a focal employee considered joining, because employees do not convey to Big Bank all of the jobs in their consideration set for a move. Further, due to the latitude that the business units have to operate autonomously in hiring, there is no central database of all jobs that employees have applied. As a consequence, we only observe the job that the focal employee *eventually* moved to and not all of those considered.

Since we lack knowledge of potential alternative positions that the employee considered, we construct a subset of business units that are comparable to the one that was actually joined for each employee who moved. Ideally, this subset of business units would be identical except for variations in the availability of prior networks, as both observed and unobserved differences among the units could have biased our results. As a means to minimize such variations, we adopted a case-match design to identify the potential set of business units for each focal employee where they likely did consider applying. We made the assumption that employees who move consider business units with similar attributes. Specifically, the "case" is the business unit that an employee actually joined, and the "matches" are business units that are observationally equivalent to that case.

We use the coarsened exact matching (CEM) procedure to construct the case-match sample (Iacus, King, and Porro, 2012). This non-parametrical matching method segments the

make intra-organizational moves. We replicate the existing findings and report the results in Appendix A.

joint distribution of business units' characteristics into a finite number of strata using cut points for each characteristic, resulting in a subsample of similar business units belonging to the same strata. Specifically, we matched on the following characteristics: *month of moving*, *primary market of focus*, *the average performance of a business unit in the prior quarter* (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 levels of formal hierarchy*.[9] This matching allows us to achieve balance on the selected characteristics (Multivariable Imbalance Measure $L1$ = 0.000). For the 672 business unit "cases" in our sample, 3,292 business unit "matches" were identified; each "case" was matched to approximately 3 to 6 corresponding "matches."[10] With a logistic regression, we then estimate the likelihood of an employee moving to a particular business unit from this comparable set. Our analytical approach is consistent with a test of H1, wherein we predict the likelihood of an employee joining a particular unit increases with the total number of PMCs that the employee has to that specific unit when employees move within organizations (see Appendix A for an analysis of all employees and the effects of social relations on the likelihood of lateral movements).

Post-Move Performance Analyses

In the second analysis, we estimated the effect of PMCs on the objective post-move performance of the employees. Specifically, we estimate the effect of PMCs on employees'

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[9] We did not match on the availability of jobs because Big Bank did not document this information officially. Meeting notes and additional analyses suggest that business units hire mainly to 1) replace employees who left and 2) to expand and fit the market's needs. Expansion appeared to be more common than replacement, so if we matched based on leavers or newcomers only, we would end up dropping many cases. We thus control for the total number of newcomers and leavers in the analyses, with the hope to capture variation in the job opportunities available among the units.

[10] One branch could be picked as "possible controls" for several observed moves, thus this number is higher than the total number of business units at Big Bank. This is not concerning, because (1) our independent variable in this analysis, the PMCs between the employee and the business units, varies despite of the pick of duplicate matches. (2) more importantly, we control for matching group fixed effect, thus only comparing each observed move with its cohorts, not the others.

Individual Sales Performance by including a fixed effect, which adds more stringent specification as compared to random effect specification, for the employees. The employee fixed effect allows us to compare the monthly performance of the *same employees before and after their lateral moves*. We also include the *Business Unit* fixed effects to control for the unobserved differences across the various business units and *Month* fixed effects to account for temporal variations. Specifically, we use a thirteen-month window with six months prior to the move, six months after the move, and the month of the actual move.[11] We exclude individual-month observations outside of these specific windows.[12] This analytic strategy mitigates concerns of cross-sectional variation among individuals by including individual-specific fixed effects as well as time fixed effects to estimate performance. We use *Post Move*, a dummy variable that takes the value of 0 in months preceding the employee's move and 1 in months following the move to the new business unit. Thus, the interaction term of *Post Move x PMCs* reflects the differential effect of PMCs on performance following the lateral move. After we examine the effect of lateral moves on employees' *Individual Sales Performance*, we then estimate the effect the numbers of PMCs and moving on that employees' *Individual Sales Performance*.

Although there are several strengths to our approach of examining within employee variations in performance before and after a move, it is still possible that unobserved heterogeneity exists that affects who moves and their social networks. We address this possibility in several ways which we elaborate on later, two of which we foreshadow here. As a robustness check to the within-employee modelling approach, we construct a sample of employees who are

[11] Interviews with HR executives indicate that six months (precisely two financial quarters) is a reasonable window for newcomers to get fully adapted to their new working environments. In addition, in a different sample where employees moved multiple times during our observation period, the average time span between two moves was five months.
[12] Results remain robust, including these observations.

observationally similar in individual characteristics to our sample but did not change jobs during our observation period. We then performed a triple diff-in-diff analyses estimating the effect of the three-way interaction of *PMCs*, *Post Move*, and a variable indicating whether the employee moved or not on performance. One can think of this approach as first estimating diff-in-diff for employees with a specific number of PMCs. Then the triple differences estimator provides the differences between these differences, to arrive at an estimate of how the effects of lateral moves depend on PMCs. In this way, this model helps to mitigate concerns about selection regarding who moves and instead examines variations in the effects of lateral moves as a function of PMCs (see Appendix B).

Although this triple diff-in-diff analysis investigates endogeneity concerns regarding who moves, it does not address potential endogeneity of PMCs. Our main analyses are shown with the identifying assumption that PMCs, after an individual has chosen to make the move, are exogenous. It is reasonable, we believe, that once employees have decided they would like to move, that the availability of PMCs is affected by external factors such as prior job assignments (c.f. Kleinbaum, Stuart, and Tushman, 2013). If employees attempt to develop relationships for strategic intent or for the explicit purposes of moving, this runs orthogonal to the social influence modality as described in our theory.[13] Nonetheless, we return to this concern after presenting our main analyses.

RESULTS

Table 1 presents descriptive statistics for the sample of employees who moved laterally within Big Bank. These employees had a mean organizational tenure of 3.94 years, experience as

[13] If PMCs represent the outcome of a successful attempt to form relationships explicitly to move, this would also most reasonably counter the expectation that PMCs have a negative effect on performance, since social influence would not be espoused in these relationships.

a retail sales employee for 0.89 years, and were on average 33.65 years old when they made the lateral move. Slightly more than half of the employees in our sample are women (61.61%); the percentage is similar to that of the entire population (61.87%). Note that demographic variables are not included because our primary specifications of interest include individual fixed effects. Regarding our independent variable, 285 employees who move (45.45%) did not have any PMCs in the business units that they joined and those with PMCs (n = 387) had on average 3.28 PMCs. We also report the descriptive statistics separately for the employees who move with PMCs versus those without them. Employees who move with PMCs exhibit similar levels of gender composition and age distribution as those who move without any PMCs. These employees with PMCs had a mean organizational tenure of 4.16 years, which is about half-year higher than those moving without PMCs. And they had on average 0.94-year experience as a retail sales employee, which is about one-month higher than those moving without PMCs. These employees with PMCs are more likely to move proximately, and they on average perform better than those employees without PMCs. Considering the possibility that our results are being driven by regression to the mean, we match directly on prior performance and still find the same effects shown below (see Appendix B).

[TABLE 1 ABOUT HERE]

PMCs and Lateral Mobility to a Unit

Table 2 reports the logistic regression estimates of the employee moving to a specific business unit. Model (1) in Table 2 indicates that the total number of *PMCs* is positively associated with *Lateral Mobility* to a unit ($\beta = 1.22$, $p < 0.01$).[14] On average, one increase in the number of PMCs increases the candidate's likelihood of joining the business unit by 3.08 times.

[14] We additionally explore the categorical differences between each number of PMC and discuss the results in Appendix A.

Model (2) adds control variables to Model (1) and the result for *PMCs* remains consistent ($\beta = 1.00$, $p < 0.01$). The results in Table 2, taken together, support Hypothesis 1 that the likelihood of an employee joining a specific business unit increases with the total number of *PMCs* that the employee has in that unit.

[INSERT TABLE 2 HERE]

PMCs and Post-Mobility Performance

Figure 1 presents the relationship between *PMCs* and all employees' productivity after they move as a percentage of their four-month performance average before the move.[15] This figure shows that on average, the performance of employees decrease after they move, which is consistent with the existing literature investigating employees moving across organizational boundaries (Huckman and Pisano, 2006; Groysberg, Lee, and Nanda, 2008). Importantly, and as we expected, the performance decrease varies by the total number of *PMCs* that candidates have to the receiving business units.

[INSERT FIGURE 1 HERE]

Models (1) and (2) in Table 3 present the estimated effects from a linear regression on *Individual Sales Performance* following an employee's move. We include business units, fixed effects, and month fixed effects for all models in Table 3.[16] In Model (1) where we include employee random intercepts, we find *Post Move* is negative and significant ($\beta =$

[15] We use the average quarterly (three-month) performance here as a measure of the employee's pre-move performance. Because the average quarterly performance is a denominator that helps to depict individual post-move performance changes; it remains constant for each individual. Hence, changing the measure to include more data does not affect the results presented in Figure 1.
[16] In Appendix B, we further exploit the nonlinear nature of post-move performance by employing random-coefficient models and all of our results remain consistent. Analyses suggest that employees with more PMC exhibit both larger performance decrement right after the move and slower performance recovery.

$-0.63, p < 0.01$). Model (2) includes employee fixed effects as well as month and business unit fixed effects and *Post Move* remains largely unchanged ($\beta = -0.60, p < 0.01$). Hence, when employees move their performance decreases by 45.28%, as compared to their performance before the move, controlling for employee and business units.

Models (3) and (4) in Table 3 present estimates for *Post Move*, the number of *PMCs*, and the interaction term *Post Move x PMCs*. In Model (3) we use random effects for employees instead of fixed effects, and the coefficient for *PMC* is significantly positive ($\beta = 0.16; p < 0.01$), suggesting that employees with greater PMCs have higher performance than those with fewer PMCs at the aggregate, or at the cross-section. The significant main effect for *PMCs* suggests that individual differences might exist among the employees. Consequently, it is important to estimate the interaction effect of *Post Move* x *PMCs* while accounting for unobserved heterogeneity among individuals with a fixed effect specification as we do in Model (4). However, the main effect for *PMCs* cannot be estimated with an employee fixed effect, because it does not vary before and after the employee's move. Thus, we model the effect with an interaction. In Model (4), *Post Move* and the interaction term is negative and significant ($\beta = -0.53; p < 0.01$; $\beta = -0.05; p < 0.01$). The interaction term indicates that when employees move to business units where they have a greater number of contacts, their performance is 4.6% lower. For an average retail sales employee at Big Bank, the performance decrement is approximately $2,500 monthly. Overall, the results in Models (3) and (4) demonstrate that employees with a greater number of PMCs experience larger decreases in their performance than those with fewer or no PMCs. Hypothesis 2 is supported.

[INSERT TABLE 3 HERE]

Geographic Proximity

Next, we examine the role of geographic proximity between jobs on employee performance following their moves. We report models with individual, business unit, and month fixed effects in Table 4. Thus, the models do not estimate *PMCs*, *Same-City Move*, or the two-way interactions, *PMCs x Same-City Move,* as they do not vary by employee. Models with random effects for the employee are largely similar to those reported here.

In Model (1) in Table 4, we include *Same-City Move* and the interaction term *Post Move x PMCs x Same-City Move*. The results suggest our logic for how the distance of moves influence post-move performance is as expected. *Post Move x Same-City Move* has a positive (non-significant) coefficient, suggesting that employees moving within the same city do not significantly benefit from their past experience despite of the similar working policies and customers that they work with. As Hypothesis 3 predicts, the P*ost Move x PMCs x Same-City Move* interaction term is significant and negative ($\beta = -0.03; p < 0.01$), indicating that when employees move to jobs within the same city, *their performance suffers more as the number of PMCs increases*. In other words, the negative performance effect associated with PMCs is greater for moves within the same city.[17]

[INSERT TABLE 4 ABOUT HERE]

In Model (2) in Table 4, we replace *Same-City Move* with *Distance* and examine its interaction with *Post Move* and *PMCs*. As opposed to estimates for *Same-City Move,* which captures proximity, *Distance* reflects the opposite, by measuring how far away the two jobs are. Consistent with our logic about how the environment itself changes with distance, the *Post Move x Distance* interaction is negative and significant ($\beta = -0.009; p = 0.021$), indicating that

[17] In addition, we examined same-state moves, however, the majority of job changes are within the same state, and because of this lack of variation, we do not find the interaction *Post Move x PMCs x Same-State Move* significant.

moves which are farther in distance have a larger negative effect on performance. This negative interaction effect shows that the performance of distant movers suffers more than employees who move to business units that are close by. When moves are more distant, we expect the information value added from PMCs to be higher, the social influence effects to be muted, and in turn for the three-way interaction *Post Move x PMCs x Distance* to be positive. Results based on the continuous measure of geographic span remain congruent with our theoretical expectations. However, they are less statistically informative than estimates in Model (3) based on p-values ($\beta = 0.003; p = 0.067$). While the positive coefficient for the three-way interaction is suggestive that higher numbers of PMCs hinder job performance when *Distance* is low, this continuous measure of spatial proximity is less instructive than those that account for geographic boundaries.

Model (3) examines *Proximate Move.* Again, consistent with Model 1 in Table 4 and our logic about how the environment itself changes with distance in ways that may affect performance, the coefficient of *Post Move x Proximate Move* is positive yet not significant ($\beta = 0.063; p = 0.061$). Model 4 also includes the three-way interaction term for *Post Move x Proximate Move x PMC*, which is negative and statistically significant ($\beta = -0.03; p = 0.026$). Consistent with our expectations, the effect of one more PMC decreases performance by 2.66% when the business unit that an employee joins is below the median distance of employee moves or is closer to the employee's former job.

Taken together, models presented in Table 4 provide additional evidence in support of Hypothesis 2. Further, they also provide support for Hypothesis 3. PMCs are more detrimental for performance when they are geographically proximate to the employee. We also find modest evidence that when moves are more distant, there is a positive effect of PMCs on post-move performance (p = 0.067). Although we did not formally predict this result, it is consistent with our arguments that with greater distance, social ties become more important for their information value. In addition, the modalities of information and social influence switch depending on the context.

Higher-Ranked PMCs

We proceed to analyze the effects of PMCs with higher organizational rank relative to the focal employee's rank. Table 5 presents estimates from a linear regression model including variables for *Post Move*, *PMCs,* and *Proportion of Higher-Rank PMCs*. The first model presents estimates for the three-way interaction term, *Post Move x PMC x Proportion of Higher-Rank PMCs,* which is negative and statistically significant ($\beta = -4.27; p < 0.01$). This three-way interaction term demonstrates that *Proportion of Higher-Rank PMCs* moderates the negative effect of PMCs; performance decreases as *Proportion of Higher-Rank PMCs* increases.

In the subsequent two models in Table 5, we investigate whether the moderating effect of *Proportion of Higher-Rank PMCs* is driven either by the absolute number of high-ranking PMCs or PMCs of different ranks, in this case lower. Models (2) and (3) include the absolute number of *Higher (Lower)-Rank PMCs* respectively, instead of the *Proportion of Higher-Rank PMCs*. These variables provide the total count of PMCs who had higher (lower) ranks than the employee. Models (2) and (3) show that only the number of *Higher-Rank PMCs* ($\beta = -0.12; p < 0.01$) serves as a significant moderator as compared to the number of *Lower-Rank PMCs* ($\beta = 0.05; p = 0.11$). These estimates indicate that for each additional PMC with a higher rank, the employee's post-move performance is reduced by 11.58%, whereas moving to business units where the employee has one additional lower-rank PMC does not significantly affect the employee's subsequent performance.

In line with Hypothesis 4, models in Table 5 indicate that the negative association is much stronger between PMCs with higher organizational ranks and an employee's post-move performance. These findings demonstrate that pre-existing network ties to employees with higher formal ranks (i.e., possible future supervisors or mentors) are likely to be more influential than ties to those of lower rank.

[INSERT TABLE 5 ABOUT HERE]

Additional Analyses

Thus far, our results suggest that lateral moves are more likely to occur when focal employees have greater number of PMCs to specific business units. Such moves lead to a decrease in performance, which is greater for employees with more *PMCs* than for those with fewer or no *PMCs*. These effects are amplified when employees move to geographically proximate locations or when their PMCs are of a higher-rank in the organization. Overall, the results are consistent with a social influence modality that operates in social networks to affect lateral moves, and is amplified when moves are closer in proximity and occur with PMCs of higher ranks.

We conducted several additional analyses to understand the nature of our results further. First, we tested if the results were to hold using different means of measuring *PMCs*. In particular, we constructed three new measures of *PMCs*: 1) ties with a higher-than-average volume of email exchanges (PMCs in this instance are the contacts over the focal employee's mean communication volume based on all of her email exchanges); 2) symmetrical ties (PMC*s* are constituted here as contacts with whom the number of messages sent versus received are lower than median difference for the focal employee); and simmelian ties (contacts qualify as PMCs if they also share at least one third-party tie with the focal employee, as defined in

Krackhardt, 1999). Table 6 (Models (1)-(3)) report the estimations for these alternative measures of PMCs and shows consistent results to the findings reported in the main models. The hypothesized effect that having more PMCs increases the employee's performance disruption remains robust when we vary the means (including communication volume, symmetry, and embeddedness) by which we define pre-move contacts.

[INSERT TABLE 6 HERE]

Second, we previously outlined why it is unlikely that relationships with PMCs could be created with strategic intent and concomitantly generate social influence. Nonetheless, we return to our consideration about the exogeneous aspects of PMCs that affect social influence. We find a sample of employees for whom, if it were possible to form ties strategically, had a strong reason to do so. Specifically, we examined the effects *PMCs* and *Individual Sales Performance* on a sample of employees who moved due to business units that closed (*n*=126). The primary reason provided as to why these business units closed at Big Bank was the shift to mobile banking and associated changing consumer demand for in-person service. These external factors forced employees to move within Big Bank. Importantly, these closures help to mitigate the concerns of endogeneity not only about employee's motives for moving but allow us to examine a case wherein, if it were possible to develop ties to move this would be the time for employees to do so. Our prediction would be that if PMCs are being developed strategically, then employees who were able to acquire them should perform better, not worse, after moves. Model (4) in Table 6 investigates this sub-sample, and the negative effects of *Post Move x PMCs* remained robust despite the decreased sample size, which reduces power. Employees who change jobs due to business unit closure experience a 31.81% performance decrease ($\beta = -0.38; p = 0.043$), and an additional PMC decreases their subsequent performance by

11.93% ($\beta = -0.19; p = 0.019$).

Additionally, we also attempt to leverage exogenous variation in the total number of PMCs to control for the possibility that unobservable characteristics would influence both the number of *PMCs* an employee might have and the employee's *Individual Sales Performance*. As already conveyed, if unobserved aspects affect both our independent and dependent variables, it would likely bias our results in the opposite direction: if employees establish pre-existing social ties as a fallback option, employees with greater number of PMCs should outperform employees with fewer PMCs. We nevertheless address this potential source of endogeneity through the use of an instrumental variable: *the total number of employees moving from the receiving unit to the home units prior to employees' lateral moves*. Appendix C details the choice of instrumental variable and the results of the analysis. The IV model reveals a negative and significant interaction effect of *Post Move x PMCs* on employees' subsequent performance and the results remain robust.

Finally, we control for the alternative factors that can also affect individual performance. Specifically, individual network centralities have been widely documented to affect individual performance (Burt, 1992). Individual performance can also be affected by colleagues and the working context where tasks are performed (Groysberg, Lee, and Nanda, 2008). We thus assess the robustness of the results to a broader range of individual-level controls and business-unit-level controls, and report the results in Appendix C. All of the hypothesized effects remain robust with the inclusion of these control variables.

DISCUSSION

Social networks are known to play an important role in mobility and have been investigated when moves occur across jobs and organizations. In our paper, we turn attention inside organizations to posit that networks play a pertinent role, especially for moves with great similarity to former jobs, as is the case in lateral intra-organizational mobility. Consistent with mobility of other types, we argued and found that focal employees with relationships to contacts in other business units are more apt to move to those locations than other units. Nonetheless, we also argued that social influence is apt to be operant in lateral mobility, owing to the nature of employment in ways that affect performance negatively after mobility has occurred. The spatial, temporal, and social proximity that is afforded by employment shifts relationships from the modality of sources of information—which have been widely highlighted in prior accounts of inter-organization and inter-job mobility—to one of social influence. We argued that this leads to a negative effect of the number of PMCs on performance, due to the focal employee engaging in limited search and employers engaging in a lack of vetting, as well as social velleity or obligation. We also found empirically that PMCs indeed have a negative impact.

Further, we not only circumscribed the relationship between networks and lateral mobility, but two moderators of this relationship. Noting that information and influence in networks cannot be easily separated, our approach to extricating the role of social influence on mobility and performance was to develop theoretical predictions that would be consistent *if* social influence is the dominant modality operating. We were able to focus on the proximity of moves as a moderator. We argued that when individuals are close in proximity, that they have greater opportunities for social interaction and social monitoring such that social influence should be triggered in near-locale moves compared to moves that span farther distances. In line with these arguments, we found that proximate moves or moves within the same city exacerbated the detrimental effects for post-move performance brought about by increases in the number of contacts. The second moderator that helped us apprise how network modalities lead to performance was the organizational rank of the PMCs. We argued that higher-ranked PMCs wield a greater capacity for generating outcomes on the basis of social influence, in that they can affect staffing outcomes while they simultaneously lack day-to-day, first-hand recent experience with tasks that can improve the focal employees' performance after moves. We thereby expected them to amplify the negative relationship between PMCs and post-move performance and found results consistent with this expectation.

This study makes several contributions to literature on mobility, networks, and social influence. Our social influence approach offers to help inform the equivocal findings of prior studies on the nature of the effect of pre-entry relationships on performance. The findings presented in this paper and some other work (e.g., Keller, 2018) contrast with what we might have expected, especially in light of work that has found relation-based referral practices lead to positive outcomes (i.e., Castilla, 2005; Merluzzi and Sterling, 2017). If we had assumed that the underlying logics shaping social networks and post-move performance operated in the same way for moves both within and between organizations, we would have expected effects consistent with prior work. However, by positing how the uncertainty surrounding individuals in labor markets dissipates within organizations, we were led to believe that the positive effects may have been too naïve of a starting point for an investigation of lateral intra-organizational mobility. The inner-workings of organizations and the nature of lateral moves may heighten the more social aspects of networks, while lessening their information value. What our social influence approach produces is a way to understand the more nuanced nature of mobility as it exists in modern organizations and the varied ways that networks matter to mobility.

Incorporating a social influence lens for understanding mobility and the scope conditions we have delineated, such as reduced uncertainty, provide the theoretical canvas to make more nuanced predictions in studies that extend beyond internal moves to external labor markets. In our study, we found evidence that there are 'shifting modalities' in networks which promise theoretical insights for the effects of relationships and their contingencies. By this we mean, as previously stated, that the environment affects the degree to which one modality is muted whilst another is heightened. For instance, we found that when the moves were more distant, the results suggest the increased value of PMCs, owing to the information modality becoming more important and thereby activated. When distance renders information more valuable, the more social ties that exist, the greater positive effect such ties should have on performance. In the context of external labor markets, perhaps a 'tipping point' occurs wherein externally filled positions may be more subject to greater social influence as compared to information via social networks. This could occur, for example, when the jobs are very similar in nature to ones previously held by candidates, and the candidate is well informed about the firm. In such instances, our perspective would suggest that rather than simply providing information, social contacts are more apt to be exerting social influence on the candidate.

Additionally, our results not only complement extant understandings on how networks affect employees' career outcomes in organizations, but refines our understanding of the relationships and the complexities that they entail. Though it is impossible to fully achieve empirically, our study approximates a counterfactual which helps address the aforementioned methodological challenges in studies of mobility and social networks. Typically, scholars observe just the realization of employment relationships, with a corresponding indicator being who has been referred or not, and then look at the performance of those people with or without pre-existing social contacts after they are hired (e.g., Castilla, 2005; Yakubovich and Lup, 2006; Shwed and Kalev, 2014; Pallais and Sands, 2016). Moreover, examining changes within individuals and using objective performance data afforded a better opportunity for us directly ascertain the effects of social networks on performance.

By highlighting the modality of social influence and its implication for mobility, this paper also contributes to the social influence literature. Social influence is a widely existing phenomenon in organizations, as demonstrated by studies in social information processing (e.g., Salancik and Pfeffer, 1978; Ibarra and Andrews, 1993) and organizational change (e.g., Krackhardt, 1999). And yet despite its ubiquity and relevance for organizations, little research extends beyond its interpersonal dyanamics (Cialdini and Goldstein, 2004). We provide evidence that social influence is consequential for mobility choices and indivdiual's subsequent performance. This reseach underscores that relationships within organizations convey not only information but an array of social psychological process. By enriching our understanding of the particular contingencies under which social influence may become the dominante modality over information, this research extends the frameworks for theorizing how relationships alter individuals' choices and behaviors.

Our paper also contributes to the organizational mobility literature by advancing our understandings on intra-organizational lateral mobility, a type of mobility relatively understudied compared to mobility of other types. For organizations, internal hires may be substantially less expensive and much less likely to fail in their new roles than external hires, owing to the knowledge employers have about these employees and the training that they have received (Groysberg, Lee, and Nanda, 2008; Bidwell, 2011). While less studied in terms of employee effects, studies on internal labor markets have provided 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, and Rogan, 2015), and because of this focus, the consequences associated with how employees move between jobs within organizations have largely remained under investigated.

Our paper directly theorizes and explores performance variation among intra-organizational candidates on the basis of their relationships. To the degree that work exists, the current work on hiring (e.g., Bidwell et al., 2013; Breaugh, 2013), as well as work examining the differences between job changes within and between organizations (e.g., Bidwell, 2011; Benson and Rissing, 2017), has conceptualized that intra-organizational mobility has largely left social relationships as a "black box." It has also failed to study how they affect mobility and subsequently the way employees perform. Yet, from recent work, we know that contextual factors are at play. For example, consider the posting of open positions versus slotting an employee into an open position without posting it, which has proven to lead to substantial differences in the quality of hire and subsequent performance (Keller, 2018). Our paper extends this work and demonstrates that informal social processes matter even when formal postings occur. Intra-organizational mobility is not homogeneous, and in fact, intra-organizational social networks substantially change not only how individuals switch jobs within the organization, but also how they perform after they move.

Even with these contributions, there are limitations to our study. It is possible, for instance, that full performance recovery will occur given a long enough observation window. While six months may be too short to see full recovery, we would counter that six months in organizational life is not necessarily short, provided that these employees are evaluated on a regular basis. Regardless, within our given time frame, we were able to find the variation in performance decrements for the number of PMCs. Additionally, even if performance were to recover in ways that our window does not indicate, there is evidence to suggest that employees with the greatest number of PMCs and thus performance decrement would match or surpass those without connections after six months. That said, future work may consider extending the time period of observation beyond what we observe.

In addition, we focus on retail sales employees whose customer base is unlikely to be portable even within nearby vicinities. In our setting, customers's accounts were associated with a branch location, and customers generally prefered to frequent the same branch location despite changes in the sales employees. In other words, employees making local moves could not benefit from retaining loyal customers. It is possble, for instance, that employees in other industries could maintain their existing customer base or social relations in their new job so that job changes are less discruptive for their performance (e.g., Broschak and Block, 2013). Even though, the modality of social influence within intra-organzational networks might still affect their choices of jobs and susequent performance. Future work might investigate how the modality of social influence affects post-move performance of employees whose clients or resources are more like to be retained.

We also suggest that future work investigates other outcomes and career consequences for individuals who move laterally. Arguably, the actual career consequences of making these moves and the negative performance ensuing from doing so may be nominal for employees with many PMCs. While we have noted that a strength of our study is its objective performance data used to evaluate employees, the immediate performance deficit employees with many social connections may be offset in other ways. For example, the pre-existing social relations may lead to improved subject evaluations or promotion nominations. In organizations where such subject evaluations matter, employees might be able to advance in their careers more quickly despite their poor objective performance (c. f. Shwed and Kalev, 2014). This suggests future work should articulate how network relationships inform a variety of career consequences.

Additionally, although the use of email communication affords a behavioral measure of social interaction less prone to biases that affect self-reported data, our data does not contain subject titles or message content, limiting the application of qualitative methods and text analysis to the emails as conducted in other research (Aven 2015; Goldberg et al., 2016). Despite the absence of content, email networks such as this oftentimes are used to understand the "resource-based" aspect of social networks such as information or advice (e.g., Srivastava, 2015). Arguably, one might surmise that to the degree effects for social networks channeling influence are found, they would be more pronounced with other types of network ties, such as professional friendships (Roberts and Sterling, 2012), which we were not able differentiate based on the meta email data. While we cannot directly ascertain these relationships within our data, incorporating network differences found in previous work, such as advice and affective relations (Krackhardt and Porter, 1985; Podolny and Baron, 1997; Casciaro, Gino, and Kouchaki, 2014), suggests a fruitful direction for future research.

Following other case study approaches common in this type of research, we studied these network effects on mobility within a single organization. Nonetheless, focusing on a single firm currently limits the extent to which we can generalize our findings to organizations beyond those similar to the one we examine. Also, the role that the quantity of social ties plays in internal mobility might be phenomenologically driven, as multiple connections are commonplace within organizations, but in external labor markets, it is far more common to only know one or a few individuals (see research on co-mobility, such as Marx and Timmermans, 2017). For the more robust analytical approach we have taken here, it would be extremely difficult to look at multiple organizations and context simultaneously. Such a study would require detailed within-person information, rich details on jobs and their firms, and the number of PMCs across such firms. All told, such a research endeavor would continue to pose comparability challenges given heterogeneity in the nature and form of lateral mobility once multiple organizations are examined.

In conclusion, it is also worth exploring how social networks change after people move. Avid discussions on the link between networks and career attainment outcomes (e.g., Burt, 1992; Granovetter, 2005; Podolny and Baron, 1997; Ahuja, Soda, and Zaheer, 2011) have led numerous scholars to note networks are not "given and static," rather, social relations evolve as career processes dynamically unfold. This dynamic view is important, because a career in organizations—as a "sequence of jobs occupied by an individual over time"—is inherently dynamic (Kleinbaum, 2012; McEvily, Soda, and Tortoriello, 2014). In this vein, Sterling (2015) has shown that new hires with more pre-existing ties are more likely to develop more extensive post-hire networks. We might also expect a similar pattern of results for employees who move within Big Bank. Nevertheless, in an intra-organizational context, employees have had the opportunity to associate with many employees in a prospective receiving unit (Blau, 1970; Feld, 1981; Kleinbaum, Stuart, and Tushman, 2013; McEvily, Soda, and Tortoriello, 2014; Sterling, 2015). This may be the case because a prospective candidate is in a more proximate space within the organization to other employees (Blau, 1970; Feld, 1981). For this reason, it is not just the presence of a pre-existing relationship or that the quantity of these relationships would affect the employee's post-move social interactions, but also the connections among these relationships—the extent to which PMCs connect with one another. We suggest future work explore these network dynamics and the many complexities underlying them. In doing so, such work would benefit from continuing in the stead we herein—by carefully considering the modalities of social networks— and their effects on how networks develop and the ways they matter for organizations as well as individuals' careers.

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Table 1: Descriptive Statistics of the Employees who Make Lateral Intra-Organizational Moves (N=672)

	Mean.	Std.	Min.	Max.
% of Women	61.61%			
Moving Distance (in miles)	34.31	124.19	0	1120.39
Age (in years)	33.65	11.21	19	73
Organizational Experience (in years)	3.94	6.04	0.67	44.90
Retail Experience (in years)	0.89	1.04	0.25	11.70
PMCs	1.89	2.12	0	16
Individual Sales Performance (logged)[1]	9.97	2.36	0	13.46
Employees with no PMCs (n = 285)				
% of Women	61.40%			
Moving Distance (in miles)	44.42	142.56	0	1120.39
Age (in years)	33	11.10	19	73
Organizational Experience (in years)	3.64	6.01	0.67	44.90
Retail Experience (in years)	0.82	0.85	0.25	9.3
Individual Sales Performance (logged)[1]	9.67	2.58	0	13.27
Employees with at least one PMC (n = 387)				
% of Women	61.75%			
Moving Distance (in miles)	26.87	108.29	0	1060.09
Age (in years)	34.13	11.28	19	64
Organizational Experience (in years)	4.16	6.06	0.83	37.9
Retail Experience (in years)	0.94	1.16	0.33	11.70
PMCs	3.28	1.80	1	16
Individual Sales Performance (logged)[1]	10.19	2.71	0	13.46

[1] The average monthly performance across the observation window.

Table 2: Conditional Logistic Regression Estimate of the Effect of PMCs on Movement to a Unit

	Dependent Variable:	
	Lateral Mobility to a Unit	
	(1)	(2)
PMCs	1.216***	0.997***
	(0.086)	(0.088)
Distance (logged)		-0.550***
		(0.057)
Organization Tenure		-0.008
		(0.014)
Job Tenure		-0.154
		(0.096)
Total Number of Newcomers		0.353
		(0.262)
Total Number of Leavers		0.123
		(0.163)
Total Number of Supervisors		0.210
		(0.172)
Observations	3,956	3,956
Log Likelihood	-700.107	-576.376

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$ (two-tailed tests)

Note: Fixed Effects of Matching Strata ID that groups matching subsamples with the respective observed cases are included in all of the models

Table 3: Panel Linear Models for the Effect of Lateral Move and PMCs on Job Performance

	Dependent variable:			
	Individual Sales Performance (logged)			
	(1)	(2)	(3)	(4)
Post Move	-0.631***	-0.603***	-0.555***	-0.526***
	(0.053)	(0.060)	(0.063)	(0.066)
PMCs			0.157***	
			(0.017)	
Post Move x PMCs			-0.029*	-0.047**
			(0.014)	(0.014)
Constant	10.026***		9.772***	
	(0.317)		(0.316)	
Observations	8,224	8,224	8,224	8,224
Adjusted R^2	0.186	0.065	0.191	0.066
Business Unit Fixed Effects	Yes	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes	Yes
Employee Fixed Effects	No	Yes	No	Yes

**p* < 0.05; ***p* < 0.01; ****p* < 0.001 (two-tailed tests)
Standard errors clustered by employee are in parentheses.

Table 4: Panel Linear Models for the Effect of Lateral Move on Performance for Distant versus Proximate Moves, by PMCs

	Dependent variable:		
	Individual Sales Performance (logged)		
	(1)	(2)	(3)
Post Move	-0.205	-0.185	-0.228*
	(0.333)	(0.331)	(0.109)
Post Move x PMCs	-0.027*	-0.041***	-0.025*
	(0.011)	(0.007)	(0.012)
Post Move x Same-City Move	0.016		
	(0.027)		
Post Move x Same-City Move x PMCs	-0.026**		
	(0.009)		
Post Move x Distance (logged)		-0.009*	
		(0.003)	
Post Move x Distance (logged) x PMCs		0.003+	
		(0.001)	
Post Move x Proximate Move			0.063
			(0.032)
Post Move x Proximate Move x PMCs			-0.027*
			(0.013)
Observations	8,224	8,224	8,224
Adjusted R^2	0.066	0.056	0.056
Unit Fixed Effects	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes
Employee Fixed Effects	Yes	Yes	Yes

+$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$ (two-tailed tests)
Standard errors clustered by employee are in parentheses.

Table 5: Panel Linear Models for the Effects of Lateral Move on Performance by the Proportion of Higher-Rank (compared to the Candidate's Organizational Levels) PMCs

	Dependent variable:		
	Individual Sales Performance (logged)		
	(1)	(2)	(3)
Post Move	-0.546***	-0.576***	-0.280***
	(0.066)	(0.061)	(0.074)
Post Move x PMCs	-0.034*		
	(0.016)		
Post Move x Proportion of Higher-Rank PMCs	0.573+		
	(0.300)		
Post Move x PMCs x Proportion of Higher-Rank PMCs	-4.268**		
	(1.402)		
Post Move x Higher-Rank PMCs		-0.123***	
		(0.034)	
Post Move x Lower-Rank PMCs			0.045
			(0.041)
Observations	8,224	8,224	8,224
Adjusted R^2	0.067	0.066	0.056
Business Unit Fixed Effects	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes
Employee Fixed Effects	Yes	Yes	Yes

+$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$ (two-tailed tests)

Standard errors clustered by employee are in parentheses.

Table 6: Models for Robustness Checks

	Dependent variable:			
	Individual Sales Performance (logged)			
				Closed Business Units
	(1)	(2)	(3)	(4)
Post Move	-0.554***	-0.551***	-0.542***	-0.383*
	(0.065)	(0.063)	(0.065)	(0.189)
Post Move x High Volume Ties	-0.047**			
	(0.016)			
Post Move x Symmetric Ties		-0.050*		
		(0.025)		
Post Move x Simmelian Ties			-0.046*	
			(0.023)	
Post Move x PMCs				-0.127*
				(0.054)
Observations	8,224	8,224	8,224	1,153
Adjusted R^2	0.066	0.066	0.066	0.083
Business Unit Fixed Effects	Yes	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes	Yes
Employee Fixed Effects	Yes	Yes	Yes	Yes

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$ (two-tailed tests)

Standard errors clustered by employee are in parentheses.

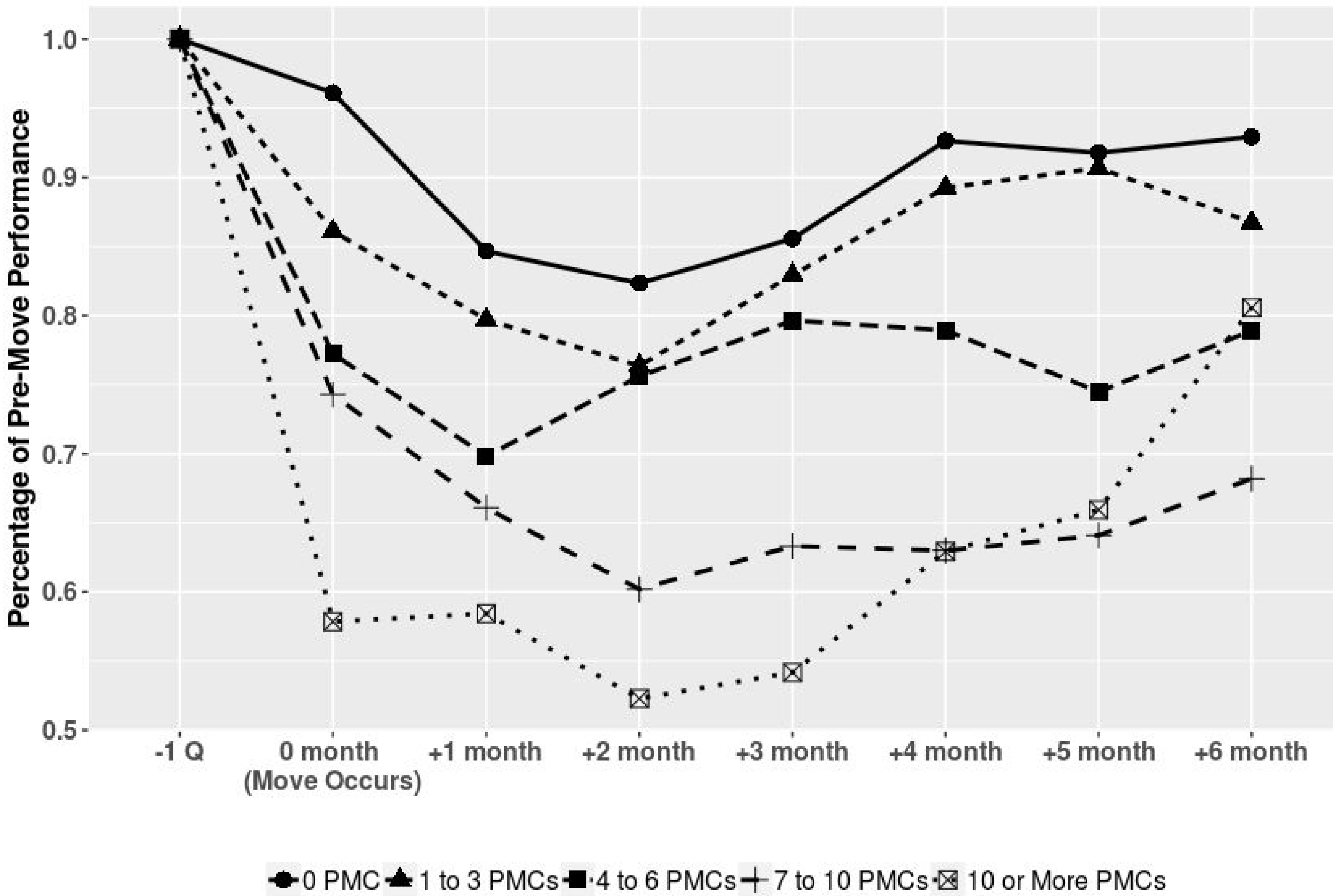

Figure 1: Post-Move Performance Percentage Changes as a Function of Pre-Move Performance Over Time

Appendix A:
Supplemental Analyses on Lateral Mobility

Estimating the Antecedents of Intra-Organizational Lateral Mobility

This section reports the analyses on the antecedents of intra-organizational mobility. Using longitudinal data that includes information on all retail sales employees' personnel records, monthly performance, and meta email exchanges, we estimate how an employee's communication networks affect the likelihood of the employee (1) moving laterally within Big Bank; (2) getting promoted within Big Bank; and (3) leaving Big Bank in the subsequent month.

In this set of analyses, we include all the employees in the retail sales department at Big Bank in our sample. We include all the observations on performance between February 2015 to April 2016. The first financial quarter in our observation period (between Nov. 2014 and Jan. 2015) is excluded from the analyses, because we need enough months before the first wave of performance observations to construct variables on social networks and control for past performance. Thus, the full sample consists of 110,208 individual-month observations on 12,914 individuals who were working in the retail-sales department. The total number of employees in the retail sales department ranges between 7,568 and 7,796 across the fifteen sampled months.

With this sample, we run multi-level logistic regressions to estimate the effect of individual network characteristics on the individual's probability of ***Lateral Move*** (which equals 1 if the employee left the current working business unit and moved to a new business unit within Big Bank, and is otherwise 0 for the employees who remained in current positions), ***Promotion*** (which equals 1 if the employee's formal rank at Big Bank increased and is otherwise 0 for the employees who remained in current positions), and ***Attrition*** (which equals 1 when the focal employee left Big Bank and is otherwise 0 for the employees who remained in current positions). The main independent variable in this analysis is the count of individual ***External Contacts*** (which is measured by the total number of communication contacts outside of the focal employee's current working unit). We log-transformed this variable to account for its skewed distribution.

In the models, we include individual ***Betweenness*** centrality (which measures the extent to which the focal employee communicates with other colleagues who do not otherwise communicate with one another) in the overall communication network and their ***Ego Network Density*** (measures by the ratio between observed communicating ties among the focal employee's communication contacts and the total number of all possible ties among them). Moreover, we control for individual demographical variables, including their ***Age***, ***Gender***, ***Organizational Tenure*** (in years), ***Job Role Tenure*** (in years), and a binary indicator ***Prior Job*** which is set to 1 if the prior job of the focal employee was related with retail sales job family and 0 otherwise. We additionally control for demographics of the business units to account for the contextual differences among the employees, including ***Size***, ***Average Organizational Tenure***, ***Average Role Tenure***, ***Average Performance*** in the prior financial quarter, the ***Proportion of Male*** employees, and the ***Total Numbers of Formal Hierarchy*** to capture the compositional variation among business units. Moreover, the fixed effects of *month*, *business units*, and *formal organizational ranks* are included in all of the models. All of the standard errors are clustered by employee. We include individual random effects and embed individual effects in the business units where they are working, to allow the probability of interest to vary across different employees. In this way, the analyses essentially estimate the effect of an employee's external communication ties on mobility by comparing the focal employee to other employees who work in the same business unit and have the same formal organizational rank.

[INSERT TABLES A1 ABOUT HERE]

The results are reported in Table A1. Models (1), (2), and (3) in Table A1 only include the fixed effects of *month, business units*, and *formal organizational ranks*. Model (1) in Table A1 reports the estimation of the ***External Contacts*** (logged) on the likelihood of intra-organizational ***Lateral Mobility*** in the subsequent month (β = 0.18, p < 0.01). A 10% increase in ***External Contacts*** will lead to an 1.80% increase in the likelihood of making a lateral move for the focal employee. Model (2) reports the estimation of the ***External Contacts*** (logged) on the likelihood of getting a **Promotion** in the subsequent month. The relationship is not significant, indicating having more ***External Contacts*** (logged) does not significantly affect a focal employee's likelihood of getting promoted. Model (3) in Table A1 reports the estimation of the ***External Contacts*** (logged) on the likelihood of ***Attrition*** in the subsequent month (β = -0.26, p < 0.01). A 10% increase in ***External Contacts*** will lead to a 2.21% decrease in the likelihood of leaving the organization in the subsequent month.

Models (4) – (6) include control variables in the analyses, together with the fixed effects of *month, business units*, and *formal organizational ranks*. Model (4) in Table A1 reports the estimation of the ***External Contacts*** (logged) on the likelihood of intra-organizational ***Lateral Mobility*** in the subsequent month (β = 0.56, p < 0.01). A 10% increase in ***External Contacts*** will lead to a 7.09% increase in the likelihood of making a lateral move for the focal employee. The effect size increases with the inclusion of control variables. Model (5) reports the estimation of the ***External Contacts*** (logged) on the likelihood of getting a ***Promotion*** in the subsequent month. With the inclusion of the control variables, compared to Model (2), Model (5) suggests that having more ***External Contacts*** positively relates with the likelihood of getting a ***Promotion*** (β = 0.20, p < 0.01). The effect size is small: a 10% increase in ***External Contacts*** will lead to a 2.04% increase in the likelihood of getting a promotion in the subsequent month for the focal employee. Model (3) in Table A1 reports the estimation of the ***External Contacts*** (logged) on the likelihood of ***Attrition*** in the subsequent month (β = -0.27, p < 0.01). Similarly to what we have shown in Model (3), a 10% increase in ***External Contacts*** will lead to a 2.21% decrease in the likelihood of leaving the organization in the subsequent month.

Exploring the Categorical (Nonlinear) Effect of PMCs on Lateral Mobility

This section aims to supplement the main results reported in Table 2 by modelling ***PMCs*** as a categorical variable rather than a continuous variable. In this way, we are able to look into the trend of changes for employees with various numbers of PMCs and explore if there is any nonlinear change as the number of PMCs increases. This set of analyses use the same sample as was used to test Hypothesis 1 in the main manuscript. The only difference here is that we change the main independent variable ***PMCs*** from continuous to categorical when we run the logistic regressions estimating the likelihood of lateral mobility.

Table A2 reports our logit regression estimates on ***Lateral Mobility*** (defined in the same way as in the main manuscript, it equals 1 if the employee moved to a particular business unit and is otherwise 0 for the remaining business units). In Models (1)-(5) in Table A2, we estimate the effect of ***PMCs*** on ***Lateral Mobility***. In these models, we chose not to assume a linear relationship between *PMCs* and the likelihood of focal employees moving to a particular business unit, thus we instead explored the categorical differences between each number of PMCs that the mover could possibly have to the possible receiving units. Each model chooses employees with one specific number of PMCs as the reference category, and the coefficients show the difference between other categories—employees with other numbers of PMCs—and the reference category.

[INSERT TABLE A2 HERE]

In Model (1), the reference category is the cases when the movers do not have any PMCs. In Models (2)-(5), the same model as in Model (1) is reported, yet the reference categories are the cases when the movers have one, two, three, and four PMCs, respectively. Taking together Models (1)-(5), we can see that the first PMC significantly increases the odds of the mover joining a business unit. When movers have one PMC in a business unit, the odds of joining the unit were almost 15 times higher ($\beta = 2.710$, $p < 0.001$) as compared to movers with zero PMCs. Subsequent increases in the total number of PMCs exhibit an increasing marginal return on the odds. When movers have three PMCs in a unit, the odds of joining the unit were 2.93 times higher ($\beta = 1.077$, $p < 0.05$) when compared to movers with one PMCs. And when movers have four or more PMCs, the odds of joining the unit were about 15 times higher ($\beta = 2.743$, $p < 0.01$) when compared to movers with three PMCs.

Models (6) and (7) further add more control variables to Model 1. The control variables here are the same ones as described in the main manuscript for Table 2. Specifically, we control for the total number of email recipients of the mover in the two months prior to moving, the distance between the mover’s original business units and the target business units, the average organizational and role experience of the target business units, the total number of newcomers and leavers of the target business units in the two months prior to moving, and the total number of unique supervisors (reporting lines) in the target business units. While the effect of PMCs remains, we also find that movers are more likely to choose business units that are expanding and locate closer to them. These results in Table A2, taken together, support Hypothesis 1 that the likelihood of an employee joining a new business unit increases with the total number of PMCs that the employee has to that specific unit.

The nature of the nonlinear effect shown in Table A2 provides some interesting hints on *why* networks may be affecting moves. Before the probability reaches the plateau, if PMCs are mainly being used for their informational modalities (note: remember the jobs before and after the move remain the same), from both perspectives of social information exchange (McFadyen and Cannella, 2004) and limited information-processing capacity of each individual (Arrow, 1974), we should be able to observe a *diminishing-return effect* that the marginal increase of one or more PMCs decreases in "value" of information from the same unit. That is, the third person conveying information about a business unit is less valuable than the second person. By contrast, if social influence is a primary logic underlying which networks affect intra-organizational mobility, we ought to see an increasing-return effect of PMCs as the number of PMCs grows, because the marginal increase of one more PMC increases for social influence before the probability reaches the plateau. In the case of Big Bank, the relationship that we observe is more consistent with mobility being driven by social influence modality.

Table A1: The Effect of External Contacts on Intra-organizational Mobility

	Lateral Mobility (t+1)	Promotion (t+1)	Attrition (t+1)	Lateral Mobility (t+1)	Promotion (t+1)	Attrition (t+1)
	(1)	(2)	(3)	(4)	(5)	(6)
External Contacts (logged)	0.175*** (0.032)	-0.021 (0.011)	-0.264*** (0.012)	0.558*** (0.076)	0.195*** (0.037)	-0.268*** (0.054)
Betweenness				-0.050 (0.039)	-0.027 (0.018)	-0.063 (0.041)
Ego Network Density				-0.194 (0.512)	-2.306 (0.232)	-0.235 (0.269)
Age				-0.010** (0.003)	-0.007*** (0.01)	-0.016** (0.002)
Gender: Male				0.206** (0.066)	-0.020 (0.031)	0.163*** (0.042)
Org Tenure				-0.020** (0.007)	-0.023*** (0.003)	-0.047*** (0.06)
Job Tenure				0.065* (0.026)	0.211*** (0.012)	0.124*** (0.021)
Prior Job				-0.109 (0.068)	1.266*** (0.030)	0.055 (0.045)
Unit Size (logged)				-0.097 (0.066)	-0.063*** (0.015)	-0.014 (0.024)
Average Org Tenure				0.016 (0.013)	0.041*** (0.006)	-0.010 (0.009)
Average Job Tenure				0.046 (0.037)	0.081*** (0.016)	-0.062* (0.026)
Prior Quarterly Performance				00.043* (0.021)	-0.475*** (0.009)	-0.014 (0.013)
Proportion of Males				0.153 (0.165)	0.306*** (0.078)	-0.024 (0.105)
Total Number of Formal Hierarchy				-0.027* (0.012)	-0.054*** (0.005)	-0.003 (0.007)
Constant	1.145 (0.828)	-2.722** (0.861)	-6.737*** (1.013)	0.783 (1.153)	0.784 (1.022)	-5.163*** (1.040)
Observations	110,208	110,208	110,208	110,208	110,208	110,208
Log Likelihood	-7,610.986	-29,396.700	-1,7122.130	-6,853.712	-21,731.370	-14,340.690
Month	Yes	Yes	Yes	Yes	Yes	Yes
Formal Rank	Yes	Yes	Yes	Yes	Yes	Yes
Business Units	Yes	Yes	Yes	Yes	Yes	Yes

*$p<0.05$; **$p<0.01$; ***$p<0.001$ (two-tailed tests)

Table A2: Conditional Logistic Regression Estimate of the Effect of PMCs on Lateral Mobility to a Specific Business Unit

	Dependent variable: Lateral Mobility to a particular business unit						
	Ref: Zero	Ref: One	Ref: Two	Ref: Three	Ref: Four	Control	Control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PMC: zero		-2.710***	-3.029***	-3.787***	-6.239***	-5.563***	-5.541***
		(0.233)	(0.042)	(0.433)	(0.433)	(0.710)	(0.708)
PMC: one	2.710***		-0.319	-1.077*	-3.528***	-3.333***	-3.308***
	(0.233)		(0.421)	(0.437)	(0.699)	(0.711)	(0.709)
PMC: two	3.029***	0.319		-0.758	-3.209***	-3.044***	-3.005***
	(0.420)	(0.421)		(0.557)	(0.767)	(0.794)	(0.791)
PMC: three	3.787***	1.077*	0.758		-2.451**	-2.070**	-2.019**
	(0.433)	(0.437)	(0.773)		(0.781)	(0.781)	(0.778)
PMC: four	6.239***	3.528***	3.209***	2.451**			
	(0.701)	(0.699)	(0.767)	(0.773)			
PMC: >=4	6.531***	3.820***	3.501***	2.743***	0.292	0.405	0.437
	(0.550)	(0.545)	(0.632)	(0.643)	(0.585)	(0.598)	(0.00)
Distance (logged)						-0.513***	-0.505***
						(0.053)	(0.052)
Organization Tenure							-0.008
							(0.014)
Job Tenure							-0.165
							(0.098)
Total Number of Newcomers							0.396
							(0.265)
Total Number of Leavers							0.062
							(0.168)
Total Number of Supervisors							0.248
							(0.171)
Observations	3,956	3,956	3,956	3,956	3,956	3,956	3,956
Log Likelihood	-665.739	-665.739	-665.739	-665.739	-665.739	-563.419	-557.528

*p<0.05; **p<0.01; ***p<0.001 (two-tailed tests)

Fixed Effects of Matching Strata ID that groups matching subsamples with the respective observed cases are included in all of the models

Appendix B: Robustness Checks on Performance Analyses with Different Modeling Strategies

Triple Diff-in-Diff Analyses on Individual Sales Performance

An alternative empirical strategy to the within-employee analysis on individual performance is to compare intra-organizational focal employees who have made lateral moves to a different set of employees who stay in their jobs. This approach helps to mitigate the concern that unobserved variables exist and affect both who move and their social networks. We run this complimentary analysis that accounts for the variations between employees who move and those employees who are observationally similar but do not change jobs. To estimate the effects of PMCs on post-move individual sales performance, herein we adopt a differences-in-differences-in-differences (triple differences) approach.

One can think of this approach as first estimating diff-in-diff for employees with a specific and fixed number of PMCs. The triple differences estimator then provides the differences between these differences, to arrive at an estimate of how the effects of lateral moves depend on PMCs. In detail, a basic differences-in-differences (diff-in-diff) setup compares the changes in a set of actors exposed to treatment with those not exposed to it. In our case, treatment means moving within an organization. We seek to compare the trajectories of employees who make lateral moves with matched control set of employees who are the observationally equivalent employees that do not move. The diff-in-diff estimator essentially subtracts the average change in the control group (employees who did not move) from the average change in the treatment group (the employees who moved laterally), thereby removing confounds that could result either from trends or from stable differences across groups (Ashenfelter and Card, 1985). When the treatment has been randomly assigned, one can interpret the estimated effects as causal (as opposed to simply correlational). But it seems impossible that voluntary lateral moves would occur at random, especially from our analyses we know lateral mobility associated with social networks, as required by the diff-in-diff estimator. We, therefore, introduce an additional differencing into the estimator to purge our results of factors correlated with moving, a triple differences approach (see Rogan and Sorensen, 2014 for an example on the usage of a similar approach).

The first step of the triple differencing approach is to estimate the diff-in-diff effect with PMCs set as fixed. In other words, how do employees with no pre-existing ties before the moving change after the moving relative to employees without pre-existing communication ties that remain not moved? How do employees with one PMC before the move perform relative to similar employees with one communication contact to the receiving business units but remain not moved? And how do employees with two (or other numbers of) PMCs before the move perform relative to similar employees with the same number of communication contact to the receiving business units but remain not moved? Each of these differences provides an estimate of the effect of intra-organizational lateral mobility on individual sales performance, conditional on the number of PMCs. The triple differences estimator then represents differences between these differences, to arrive at an estimate of how the effect of intra-organizational lateral mobility depends on the number of PMCs. The analyses, therefore, help mitigate the concerns associated with the selection in who move and focus on variations in the effects of intra-organizational mobility as a function of PMCs.

To conduct the aforementioned triple diff-in-diff analyses, we construct a sample that matches the observed lateral moves (cases) with a set of synthetic counterfactual lateral moves (control)—combinations of moves that could have occurred but that did not. We begin by creating two separate sets of matched samples, one for the employees and the other for the receiving business units. For the employees, our "case" employees (the "treatment" group of employees) are the employees who move laterally within Big Bank. We followed the CEM procedure and identified a control set of employees that matched the employees who make lateral moves on *Gender, Market of Focus*, *Formal Organizational Rank, Organizational Tenure* (years), *Job Tenure* (years) and *the Average Individual Performance in the prior quarter* (categorized according to aggregated unit sales into four categories: < 25%, 25-50%, 50-75%, > 75%) in the months when the lateral moves were made. For the business units, we followed the same CEM procedure as described in the main manuscript for the analyses on lateral mobility to a specific unit. We then randomly combined these matched employees who might move with the matched potential business units that may receive the movers to create synthetic lateral moves. With this procedure, we matched 549 observed lateral moves (in total 672) to 3,420 synthetic lateral moves. With this sample of matched cases and controls, we construct a panel dataset with individual-month observations on performance. For each individual, we use a thirteen-month window with six months prior to the move, six months after the move, and the month of the actual move. We exclude individual-month observations outside of these specific windows. The triple diff-in-diff analysis includes 51,391 employee-months.

Here is an example that illustrates the sampling process. Suppose Person A moved from Business Unit 1 to Business Unit 2 in month t, ***Mover*** for Person A is set to 1. We then calculate Person A's demographic variables and performance by month t, including Person A's gender, the market of focus, organizational tenure, job tenure, formal rank, and average performance between month t-4 and month t-1. With these variables, we proceed to identify a list of employees who have the same gender, the market of focus, organizational and job tenure, formal rank, and average performance (in the form of performance quantile) as Person A but did not move in month t. These employees are the control set of employees “matched” to Person A. Their **Mover** variable is set to 0. Similarly based on the observed characteristics of Business Unit 2, we identify a list of business units that look “identical” to Business Unit 2. Then with all these employees who are “matched” to Person A and all the business units that are “matched” to Business Unit 2, we randomly generate individual-unit pairs for each employee who are matched to Person A, these pairs are thus our synthetic lateral moves. The ***PMCs*** then are the number of social ties between the employees and their social contacts within their particular units prior to the month of lateral move. As a final step, we expand the data and include monthly observations on ***Individual Sales Performance*** of Person A and all the “matched” employees between month *t-6* and month *t+6*. ***Post Move*** takes 0 in months prior to month t and 1 in months after month t.

Our identification approach again relied on triple differencing. Hence, we essentially examined whether the employees who moved perform better or worse than those that did not and the extent to which that differential depends on PMCs. The dependent variable in this triple-differences analysis is ***Individual Sales Performance*** (logged), measured in the same way as we presented in the main manuscript. ***Mover*** is a dummy variable that takes the value of 1 for employees who made lateral moves and 0 for those in the control set. Similar as in the main models, we use ***Post Move***, a dummy variable that takes the value of 0 in months preceding the employee’s move and 1 in months following the move to the new business unit. ***PMCs*** is the total number of intra-organizational communication ties between the employee who moves (or the control set of employees who remain not moved) and their colleagues in the receiving business units (or the control set of potential receiving business units) prior to the move.

Table B1 provides the descriptive statistics for the models, describing the sample employees included in the analyses. Table B1 suggests that the matching procedure has effectively constructed a similar control set to the employees who move. The two groups of employees only differ significantly on their performance and PMCs, but not the other dimensions.

[INSERT TABLE B1 ABOUT HERE]

Table B2 report the results from these additional analyses. All the models in Table B2 include the fixed effects of matching strata ID that groups matching subsamples with the respective employees who made the lateral moves. As the comparison is between individuals, we also include individual random effects and embed them within business units. Finally, we include monthly fixed effects in all the models. We begin by following the usual diff-in-diff strategy. In Model (1) we only include the independent variables *Mover*, *Post Move* and the interaction of the two. Model (1) suggests that, on average, Mover x *Post Move* has a significant and negative effect on performance $(\boldsymbol{\beta = -0.37; p < 0.01})$. That is, lateral moves are challenging for the employees and could lead to a performance disruption. Specifically, compared with those who do not move, the performance of employees who move declined by 30.86%. To account for the potential effects of *PMCs*, Model (2) and Model (3) include the variable PMCs, as well as the interactions of this variable and the other diff-in-diff terms. In Model (2), we proceed by including more two-way interactions: *Mover x PMCs* and *Post Move x PMCs*. The effect of Mover x Post Move remains negative and significant. In Model (3), we add our primary variable of interest: the three-way interaction *Mover x Post Move x PMCs*. Consistent with hypothesis 2, this variable has significant and negative effect on performance $(\boldsymbol{\beta = -0.178; p < 0.01})$, indicating that the performance of employees who have PMCs to the receiving business units prior to the lateral move suffer more following the move than those who do not have many PMCs prior to making the lateral move, relative to employees who could have moved but did not.

[INSERT TABLE B2 ABOUT HERE]

Multi-level Analyses with Random Coefficient Models

As is shown in Figure 1 in the main manuscript, the relationship between lateral mobility and individual sales performance is not linear, and instead, quite complex. Employees first experience a performance decrease right after the move, then their performance could slowly recover. Although it is possible, for instance, that full performance recovery will occur given a long enough observation window, from the data we have, we could estimate the trend of recovery by modelling the effect of "time since move" on individual performance in subsequent months.

We estimate individual performance decrease and the subsequent recovery by building on a model used in the strategy research literature: a linear random-coefficients model (RCM) – also known as a mixed-effects model with varying slopes or a mixed-effects model with random slopes (Knott, 2008; Alcacer, Chung, Hawk, and Pacheco-de-Almeida, 2013). Such models include at least one coefficient that is not fixed (across members of a cross section or over time) and is instead comprised of two components: a mean effect on the outcome, and a randomly distributed component that varies for each sampling unit (here, business units). In this way, the model allows for unit-specific heterogeneity in slopes, i.e., heterogeneity in performance recovery rate. Thus, RCM allows for examination of heterogeneity in the estimations.

Further, we can take advantage of another feature of RCMs: a prediction of the random coefficients can be modeled as a second level in the multi-level regression. Specifically, we propose a model in which the random coefficients – in this case, the random slopes for two lateral mobility-related variables: ***Location Change*** (it equals 1 in the specific month when the focal employee makes a lateral move and 0 otherwise) and ***Time Since Move*** (starting from the specific month when the focal employee makes the lateral move, it increases by 1 in every subsequent month) – are predicted by ***PMCs***. This is, we expect the effects of ***Location Change*** and ***Time Since Move*** on ***Individual Sales Performance*** to depend on PMCs.

Note that one benefit of the RCM is that this second level of analysis (in which we estimate the random slopes for each employee who moved) can be done simultaneously with the prior level (estimating the ***Individual Sales Performance*** in the subsequent month). This can be done by including interaction terms between variables. In our case, we include interactions *PMCs x Location Change* and *PMCs x Time Since Move*, such that we can obtain estimates of how *PMCs* affect focal employees' responses to *Location Change* and their performance trends as *Time Since Move* increases. For example, the estimate of the interaction between *PMC*s and *Time Since Move* would indicate the effect of the PMCs on the random slope for Time Since Move whereas a positive number would indicate that a high number of PMCs increases the return on performance as time increases and a negative number would indicate that a high number PMCs decreases the return on performance as time goes by. The individual random intercepts are included to account for unobservable individual heterogeneity that vary consistently and account for the performance variations across employees. The individual random slopes are included to account for individual variation in their performance response to job changes. In essence, the mixed-effects RCM estimations allow the effect size of *PMCs* to vary for each employee. The estimated model is shown as follow:

Level 1:

$$\begin{aligned} Individual\ Sales\ Performance_{i,g,t} &= \beta_0 + \beta_1 X1_{i,g,t-1} + \beta_{2,i} Location\ Change_{i,t-1} + \beta_{3,i} Time\ Since\ Move_{i,t-1} \\ &+ v_{1i/g} + \varepsilon_{i,g,t} \end{aligned}$$

Level 2:

$$\beta_{2,i} = \gamma 1_i PMC + \gamma 1_0 + \varepsilon_{i,2}$$

$$\beta_{3,i} = \gamma 2_i PMC + \gamma 2_0 + \varepsilon_{i,3}$$

The coefficients of the interactions $\gamma 1_i$ and $\gamma 2_i$ represent the variation in the effect sizes of *location change* and *time since the move* that are associated with *the number of PMCs*. In other words, the interaction terms estimate how *the number of PMCs* affect the performance disruption associated with the two 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.

The results from the RCM estimations are reported in Table B3. Note that as we are interested in the trend of performance recovery, we include all available observations on post-move individual performance. Model (1) shows the main effect of *Location Change* and *Time Since Move* on *Individual Performance*. Not surprisingly, *Location Change* leads to a performance decrease in the subsequent month, and performance gradually recovers as *Time Since Move* increases. In Model (2) we include the interaction between *PMCs* and *Location Change*. Model (2) indicates that individuals suffer more disruption from *Location Change* when they have a greater number of *PMCs* ($\beta =$ -0.101, $p < 0.05$), that movers with one more PMC tend to experience more performance disruption than an average mover would do by approximately 9.60%. Moreover, in Model (3), we include the interaction between *PMCs* and *Time Since Move*; this negative and significant interaction effect suggests that *Individual Sales Performance* recovers more slowly when they have more *PMCs* ($\beta =$ -0.007, $p < 0.05$). Model (4) includes both interactions, and the results hold. Taken together, the results presented here complement our understandings on the performance changes associated with lateral mobility. Further, we show that employees with more PMCs not only suffer a greater performance disruption, but also experience a slower recovery compared with their peers who have fewer or no PMCs.

[INSERT TABLE B3 ABOUT HERE]

Table B1: Summary Statistics Between "Case" and "Control" Employees

	Employees who moved (n = 549)		Employees who stayed (n = 3457)	
	Mean	Std.	Mean	Std.
Age	33.62	11.43	33.51	12.07
Organizational Tenure	3.96	5.87	3.99	5.60
Job Tenure	0.84	0.89	0.95	0.81
Prior Quarterly Performance (four categories)	2.10	1.09	2.16	1.13
Mover	1	0	0	0
PMCs	1.98	2.21	1.21	3.37
Individual Sales Performance (logged)[1]	10.01	2.43	12.79	3.12

[1] The average monthly performance across the observation window.

Table B2: Triple Diff-in-Diff Analysis on Individual Sales Performance

	Dependent variable: Individual Sales Performance (logged)		
	(1)	(2)	(3)
Mover	0.303***	0.049	0.029
	(0.109)	(0.134)	(0.134)
Post Move	-0.388	-0.386	-0.407
	(0.206)	(0.207)	(0.207)
Mover x Post Move	-0.369***	-0.411***	-0.403***
	(0.072)	(0.083)	(0.090)
PMCs		0.010	0.004
		(0.011)	(0.011)
PMCs x Mover		0.084***	0.097***
		(0.031)	(0.031)
PMCs x Post Move		-0.016	0.099***
		(0.016)	(0.027)
PMCs x Mover x Post Move			-0.178***
			(0.033)
Constant	6.952***	6.869***	6.872***
	(1.005)	(1.005)	(1.005)
Observations	51,391	51,391	51,391
Log Likelihood	-93021.91	-93125.33	-93122.68
Business Unit Fixed Effects	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes

*p < 0.05; **p < 0.01; ***p < 0.001 (two-tailed tests)

Table B3: RCM Estimations on The Effects of Lateral Mobility and PMCs on Performance

	Dependent variable:			
	Individual Sales Performance (logged) (t+1)			
	(1)	(2)	(3)	(4)
Location Change (t)	-1.099***	-1.254***	-1.082***	-1.202***
	(0.068)	(0.079)	(0.077)	(0.077)
Time Since Move (t)	0.011*	0.015**	0.014***	0.014***
	(0.006)	(0.006)	(0.003)	(0.003)
Location Change (t) x PMCs		-0.101*		-0.099***
		(0.027)		(0.027)
Time Since Move (t) x PMCs			-0.007**	-0.006*
			(0.003)	(0.003)
PMCs	0.083***	0.091***	0.097***	0.095***
	(0.017)	(0.017)	(0.021)	(0.021)
Distance (logged)	0.062***	0.061***	0.063***	0.061***
	(0.028)	(0.028)	(0.028)	(0.029)
Organizational Tenure (t)	0.040***	0.030***	0.040***	0.042***
	(0.008)	(0.008)	(0.008)	(0.008)
Job Tenure (t)	0.273***	0.271***	0.269***	0.270***
	(0.032)	(0.032)	(0.033)	(0.033)
Constant	9.709***	9.695***	9.644***	9.721***
	(1.287)	(1.286)	(1.289)	(1.300)
Observations	10,855	10,855	10,855	10,855
Log Likelihood	-23,095.16	-23,058.32	-23,061.19	-23,032.05
Business Unit Fixed Effects	Yes	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes	Yes
Employee Random Slopes	Yes	Yes	Yes	Yes

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$ (two-tailed tests)
Standard errors clustered by employee are in parentheses.

Appendix C:
Robustness Checks on Time Window, Instrument Variable, and Alternative Explanations

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 PMC (pre-move communication contact) is an email recipient that the mover has communicated with prior to the move and continued communication with for *n* months after the move. In the main analyses reported in the manuscript, *n* is set to 2. We vary *n* and test the effects using the same models, with all of the controls included. The comparisons of key coefficients are reported in Table C1, where in Model (1), *n* = 0, in Model (2), *n* = 1, and in Model (3), *n* = 3. All interpretations on the findings remain the same.

[INSERT TABLE C1 ABOUT HERE]

Instrumental Variable Analysis

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. 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., Hasan and Bagde, 2015; Sterling, 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 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 (4) in Table C1. The count of employees coming from the receiving units to movers' home units must be correlated with the independent variable (specifically, *PMCs* here). The instrument variable and PMC variable are significantly correlated ($r = 0.25$, $p < 0.01$). The first-stage estimation revealed no concerns about instrumental weakness ($\beta = 0.43$, $p = 0.03$). The results are largely consistent with the findings reported above; aside from the magnitude of the coefficients, the main differences are that the IV models reveal no significant relationship between PMCs and movers' performance recovery rate. The overall interpretation of the results remains unchanged.

Additional Analyses on Alternative Explanations

We considered and controlled for the alternative mechanisms that can affect individual performance. Specifically, individual network centralities have been widely documented to affect individual performance (Burt, 1992). Individual performance can also be affected by both colleagues and the working context where tasks are performed (Groysberg, Lee, and Nanda, 2008). We thus assess the robustness of the results to a broader range of individual-level and business-unit-level controls. We report the correlation matrix in Table C2. Although some variables are correlated with each other, the VIF for all the variables are less than 5, thus multicollinearity is unlikely to be a concern. The results in Table C3.

[INSERT TABLES C2 AND C3 ABOUT HERE]

Model (1) in Table C3 reports the analysis with individual demographic controls. Here, we control for individual demographic characteristics including *age (in years), organizational experience (in years)*, and *role experience as retail sales (in years)*. Model (2) in Table C3 reports the analysis controlling for employee ego-network characteristics. The employee ego-network represents the email recipients with whom the focal employee communicates and how they communicate with each other. This is an efficient way to capture individual network variation when the whole network is large (Carley, 2002). Specifically, in Model (2), we include *network size (*the total number of email recipients)*, density* (the total number of observed communications divided by the total number of all possible communication channels) and *degree centralization* (the extent to which communication is distributed equally). In particular, the variable *network size* is separated into two parts: *the total number of external ties*, which measures the total number of email recipients that work in different business units other than the individual's current one, and *the total number of internal ties*, which measures the total number of email recipients that work in the same business unit as the focal individual.

Although fixed effects of business units are included in the main models, we additionally check the robustness of our results with controls of observable characteristics of the business units. Model (3) in Table C3 reports the analysis controlling for business-unit-level characteristics such as average organizational experience, average retail sales experience, the height of formal hierarchy in the business units, and the communication cohesion within the business unit (measured by *clustering coefficient*, representing the extent to which communication exhibits high transitivity). Model (4) presents the analysis controlling for all individual-level and business-level predictors, together with individual, time, and business unit fixed effects. Models (5) and (6) present the analyses for *Proximate Move* and *Proportion of Higher-level PMCs*, respectively. All of the hypothesized effects remained robust with the inclusion of these control variables.

Table C1: Robustness Checks on the Time Window in Calculating PMC

	Dependent variable:			
	Individual Sales Performance (logged)			
	(1)	(2)	(3)	*Instrument Variable* (4)
Post Move	-0.527** (0.066)	-0.562*** (0.065)	-0.537*** (0.065)	-0.282* (0.099)
Post Move x PMCs (n = 0)	-0.002** (0.0008)			
Post Move x PMCs (n = 1)		-0.036* (0.015)		
Post Move x PMCs (n = 3)			-0.066*** (0.011)	
Post Move x PMCs (2SLS)				-0.132* (0.061)
Observations	8,224	8,224	8,224	8,224
Adjusted R^2	0.063	0.066	0.066	0.070
Business Unit Fixed Effects	Yes	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes	Yes
Employee Fixed Effects	Yes	Yes	Yes	Yes

**p*<0.05; ***p*<0.01; ****p*<0.001 (two-tailed tests)
Standard errors clustered by employee are in parentheses.

Table C2: Correlation Statistics Among Variables

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13
Individual Performance (logged)													
PMCs	0.14												
Proportion of Higher-Ranked PMCs	-0.01	-0.09											
Proximate Move	-0.03	0.08	0.05										
Age	0.12	0.06	-0.01	0.02									
Organizational Tenure	0.21	0.08	-0.04	0.03	0.53								
Job Tenure	0.22	0.17	-0.03	-0.03	0.31	0.35							
Extensive Ties	0.23	0.23	0.01	-0.03	0.14	0.18	0.23						
Internal Ties	0.00	0.14	-0.02	0.03	0.02	0.02	0.05	0.06					
Ego Net Density	-0.35	-0.09	0.01	0.03	-0.12	-0.16	-0.17	-0.31	-0.06				
Unit Average Organizational Tenure	0.08	0.11	-0.04	0.01	0.21	0.41	0.18	0.06	0.17	-0.04			
Unit Average Job Tenure	0.08	0.12	-0.05	0.03	0.16	0.23	0.26	0.07	0.14	-0.06	0.72		
Total Number of Formal Hierarchy	0.06	0.23	-0.06	0.04	0.05	0.09	0.10	0.14	0.52	-0.09	0.34	0.39	
Unit Network Cohesion	0.01	0.09	0.01	0.00	-0.05	-0.04	-0.05	-0.11	-0.03	0.66	0.03	0.02	0.04

Table C3: The Effect of PMCs on Post-Move Performance, Accounting for Alternative Explanations

	Dependent Variable: Individual Sales Performance (logged)					
	(1)	(2)	(3)	(4)	(5)	(6)
Post Move	-0.487***	-0.250***	-0.467***	-0.251***	-0.230***	-0.257***
	(0.052)	(0.047)	(0.051)	(0.045)	(0.063)	(0.046)
Post Move x PMCs	-0.050***	-0.035**	-0.044***	-0.034**	0.016	-0.021
	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)
Post Move x Proximate Move					0.052	
					(0.063)	
Post Move x Proximate Move x PMCs					-0.060***	
					(0.023)	
Post Move x Proportion of Higher-rank PMCs						0.027
						(0.204)
Post Move x PMCs Proportion of Higher-rank PMCs						-4.970**
						(1.710)
Age	-0.047			-0.014	-0.015	-0.013
	(0.056)			(0.047)	(0.047)	(0.047)
Organizational Tenure	0.234			0.290	0.292	0.285
	(0.366)			(0.187)	(0.187)	(0.188)
Job Tenure	0.064			0.041	0.044	0.041
	(0.035)			(0.031)	(0.031)	(0.035)
Extensive Ties		0.001*		0.001*	0.003***	0.001*
		(0.0004)		(0.004)	(0.0004)	(0.0004)
Internal Ties		-0.064*		-0.024	-0.032	-0.024
		(0.029)		(0.031)	(0.031)	(0.031)

Ego Net Density		-6.023***		-5.335***	-4.897***	-5.342***
		(0.331)		(0.317)	(0.317)	(0.317)
Unit Average Organizational Tenure			-0.008	-0.017*	-0.016	-0.018*
			(0.010)	(0.008)	(0.009)	(0.008)
Unit Average Job Tenure			-0.064*	-0.028	-0.059*	-0.029
			(0.028)	(0.025)	(0.028)	(0.025)
Total Number of Formal Hierarchy			-0.004	-0.005	-0.006	-0.006
			(0.009)	(0.009)	(0.009)	(0.009)
Unit Network Cohesion			3.684***	3.137***	0.784	-5.163***
			(0.218)	(0.209)	(1.022)	(1.040)
Observations	8,224	8,224	8,224	8,224	8,224	8,224
Adjusted R^2	0.314	0.248	0.267	0.314	0.253	0.315
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Employee Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Business Units Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

*p<0.05; **p<0.01; ***p<0.001 (two-tailed tests)
Standard errors clustered by employee are in parentheses.