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Left but Not Forgotten: Gender Differences in Networks and Performance Following Mobility

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Abstract:	This paper investigates how shifts in an individual's communication network when the individual experiences a job change affect performance and how those effects differ between men and women. Using a rich proprietary dataset including the personnel records, monthly performance, and email communications of thousands of employees, we examine job changes occurring within a large financial institution. Comparing objective performance prior to and following each job change, we show that mobility is disruptive to individual performance, but that women's performance is less hampered than that of men. We argue and find evidence that this variation in performance can be explained by women's and men's differential likelihood of retaining ties to former colleagues at their previous jobs. While women tend to be embedded in dense networks that may limit their advancement in times of stability, these same network patterns may also foster the retention of relationships to colleagues when women employees move to new jobs. Such "network resilience" offers multiple benefits that bolster their post-move performance. Our results contribute to research on mobility, social network dynamics, and gender by showing that network characteristics that are conventionally considered disadvantageous in the cross-section may help mitigate performance challenges when individuals experience job mobility.

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ABSTRACT (199 words)

This paper investigates how shifts in an individual's communication network when the individual experiences a job change affect performance and how those effects differ between men and women. Using a rich proprietary dataset including the personnel records, monthly performance, and email communications of thousands of employees, we examine job changes occurring within a large financial institution. Comparing objective performance prior to and following each job change, we show that mobility is disruptive to individual performance, but that women's performance is less hampered than that of men. We argue and find evidence that this variation in performance can be explained by women's and men's differential likelihood of retaining ties to former colleagues at their previous jobs. While women tend to be embedded in dense networks that may limit their advancement in times of stability, these same network patterns may also foster the retention of relationships to colleagues when women employees move to new jobs. Such "network resilience" offers multiple benefits that bolster their post-move performance. Our results contribute to research on mobility, social network dynamics, and gender by showing that network characteristics that are conventionally considered disadvantageous in the cross-section may help mitigate performance challenges when individuals experience job mobility.

Keywords: Communication Networks; Intra-organizational Mobility; Gender.

INTRODUCTION

Organizational research has long recognized the importance of social networks—the patterns of interpersonal relationships among employees—within organizations. Fundamental to the organizational literature on social networks is the idea that connections bridging people, groups, and job roles and the information flows through them are consequential for important outcomes, such as performance and career advancement (Ahuja et al., 2012; Borgatti and Halgin, 2011; Burt, 1992; Kilduff and Brass 2010; Podolny and Baron, 1997; Tortoriello et al., 2012). This body of research substantiates not only the range of outcomes for individuals deriving from bridging ties, but also the challenges to establishing and retaining such interactions (Biancani et al., 2014; Burt, 2001; Jonczyk et al., 2016). Moreover, both individual preferences and organizational design often conspire for network closure (i.e., densely connected structures that create coordination and integration advantages); employees tend to confine their intra-organizational social relationships to formal structures corresponding to their roles, departments, and business units (Kleinbaum et al., 2013; Lee, 2019; Mehra et al., 1998; Sasovova et al., 2010).

Given the influence of formal structures on employees' social networks, mobility that changes employees' formal positions within the same organization can simultaneously serve as a catalyst in reshaping their social networks. Specifically, job mobility engenders two possibilities: employees could either relinquish prior relationships and quickly embed themselves into new social groups corresponding to their new roles, or they could maintain prior relationships and hence bridge between former and new colleagues. These two possibilities beg the question as to which relational response will most likely benefit employees' subsequent performance, particularly given that performance disruptions often follow such job changes (Groysberg et al., 2008; Groysberg and Lee, 2009). While prior work on social networks and careers suggests that certain sequences of jobs can give rise to increased brokerage within intra-organizational networks (Kleinbaum, 2012), this line of work has not considered the subsequent performance implications of such network changes. A different line of work focusing on mobility and performance explores the portability of employees' experience and relationships (Dokko et al., 2009; Groysberg and Lee, 2009; Groysberg et al., 2008). This research has found that the performance disruptions arising from job mobility can be attenuated when connections are "portable," for example, when employees change jobs together with their colleagues (Campbell et al., 2014; Groysberg and Lee, 2009).

While both literatures have underscored the importance of employee' relationships with prior colleagues, conspicuously missing is an exploration of how the effect of job mobility on performance flows through changes in social networks. This gap is puzzling given that job mobility inevitably restructures social networks (Jonczyk et al., 2016; Kleinbaum, 2012; Podolny and Baron, 1997), which in turn influence performance (Ahuja et al., 2012; Borgatti and Halgin, 2011; Burt, 1992; Kilduff and Brass 2010; Podolny and Baron, 1997; Tortoriello et al., 2012). Nevertheless, we also anticipate that movers will vary in their retention of social relations to prior colleagues, given prior findings that demonstrate individual characteristics are important determinants of social networks (Kleinbaum et al., 2015; Mehra et al., 1998; Sasovova et al., 2010; Walsh et al., 2018; Yang et al., 2019). In particular, we contend that the likelihood of retaining relations to prior colleagues following a move differs due to the employee's extant social network and normative expectations, both of which correspond with gender (Brass, 1985; Brands and Kilduff, 2014; Brands and Mehra, 2019; Ibarra, 1992; Jonczyk et al. 2016; Kilduff and Brass, 2010).

In the present study, we explore how changes in movers' social networks affect their performance following mobility and how these effects differ by gender. Building on research that demonstrates the importance of relationships to prior colleagues as valuable sources of knowledge and social capital (Dahlander and McFarland, 2013; Jonczyk et al. 2016; Walsh et al., 2018), we contend that maintaining relationships to prior colleagues following mobility—which we term *network resilience*—is an important factor for performance during job transitions. We find that high network resilience in the face of a job change corresponds with increased opportunities for bridging structural holes within the organization and for needed social support, both of which help to mitigate the performance disruptions associated with job mobility. We also find that not all individuals equally maintain network relations to prior colleagues. In particular, men's and women's differential pattern of relationship retention has implications for their bridging opportunities. Integrating literature on gender and social networks (e.g., Brass, 1985; Brands and Kilduff, 2014; Ibarra, 1992; Singh et al., 2010), we propose that women movers tend to exhibit higher network resilience than their male counterparts. Given that the effect of mobility on performance flows, at least partly, through its effect on networks, we argue and find that because of their greater network resilience, women experience fewer performance challenges upon mobility compared with men. We further explore the structural differences between networks of women and men who move to understand the possible mechanisms underlying these network differences.

For the purpose of this study, we focus on intra-organizational mobility events—moves where an employee changes jobs internally across working groups within an organization rather than across organizations (Bidwell and Keller, 2014; Keller, 2018). Focusing on internal mobility allows us to take advantage of longitudinal observations on a whole network and examine network dynamics before and after mobility. These internal moves also permit us to hold organizational characteristics, such as firm culture, performance calculation metrics, and incentive systems, constant. We obtained data from a large US-based financial institution that we call Big Bank, consisting of all employees' demographic information, human resource records, and metadata of email communications. We focus on email communications to construct intra-organizational social networks, as prior work has shown that email data is an effective representation of communication networks between employees (e.g., Aven, 2015; Kleinbaum et al., 2013; Quintane and Kleinbaum, 2011). We also collected objective monthly sales performance data for all retail sales employees. Using the email data coupled with objective monthly performance data, we employed a pre-post design to test our theoretical propositions on the differential effects of intra-organizational job changes on employees' social networks and performance for men and women. Consistent with our expectations, analyses suggest that job changes are disruptive to short-term performance, but that they are less disruptive to the performance of women, whose networks tend to be more resilient, than of men, who tend to more quickly realign their informal networks to the formal structure of their new work groups.

MOBILITY, NETWORK RESILIENCE, AND PERFORMANCE

Studies in organization theory and sociology have long recognized the importance of social networks and the information that flows through them in shaping individual outcomes (Ahuja et al., 2012; Borgatti and Halgin, 2011; Burt, 1992; Granovetter, 1973; Kilduff and Brass 2010; Podolny and Baron, 1997). By interacting with their network contacts, employees gain access to strategic information like gossip or the "goings on" of an organization; social support; and friendship (Burt, 1992; Podolny and Baron, 1997; Walsh et al., 2018). Within organizations, differences in social network positions contribute to differences in access to information, which is key to the execution of work, task performance, and opportunities to advance.

Although social networks constantly evolve as connections emerge and decay, an intriguing question is whether and how job mobility allows movers to benefit from ties to prior colleagues while adjusting to a new working environment. On the one hand, when an employee changes from one job position to another, she is required to form new position-relevant social relations, which in turn serve to expand the employee's intra-organizational network (Jonczyk et al. 2016; Kleinbaum 2012). The network literature has established the benefits of connecting with new colleagues as a means of adapting to new working contexts (Groysberg and Lee, 2009; Morrison, 2002; Sterling, 2015; Walsh et al., 2018) and whom individuals choose to add to their networks in the adjustment process varies (Jonczyk et al. 2016; Kleinbaum et al., 2013; Lee, 2019). On the other hand, even in the realm of instrumental relationships, workplace social networks rely heavily on stability and embedded ties to facilitate trust, reciprocity, and in-depth communication (Dahlander and McFarland, 2013). Individuals not only vary in choosing which new colleagues with whom to form new connections, but also which prior contacts with whom to retain past ties. Recent work has offered a more dynamic view by examining the ways in which network structures shift overtime, suggesting that both formal workplace changes (e.g. team re-assignments) (Burt and Merluzzi, 2016), individual characteristics (Sasovova et al., 2010), and social identity (Mehar et al., 2017) inform network arrangements. Yet, among these existing studies, attention has focused narrowly on changes to the network structure; equally important is the question of how these network dynamics can affect performance outcomes (cf. Burt and Merluzzi, 2016). As such, we focus on ties that persist to former co-workers following an employee's job change and their subsequent effects on performance.

We propose that individuals differ in their propensity to maintain ties in their social networks following formal positional changes in organizations. And we propose that the extent to which mobility alters the composition of individuals' networks will vary, particularly in terms of retaining ties. We conceptualize the degree to which individuals preserve prior network ties as *network resilience*. Furthermore, we expect that such network resilience —the maintenance of network ties across episodes of mobility—can help an individual navigate the performance challenges that occur during mobility.

Two possible mechanisms might enable network resilience to mitigate the performance disruption of mobility. First, persistent ties to former colleagues allow movers to bridge structural holes in the fabric of the organization (Burt, 1992; Kilduff and Brass 2010; Burt and Merluzzi, 2016; Kleinbaum, 2012; Tortoriello et al., 2012). Network resilience—and the brokerage that it gives rise to—enables movers to reap information, control, and vision benefits, permitting them to outperform those whose networks lack structural holes (Borgatti and Halgin, 2011; Burt, 1992; Tortoriello et al., 2012). For example, in the context of retail banking, a salesperson's communication network is typically comprised of coworkers, supervisors, and administrative staff or colleagues in other departments within the same organization. A salesperson benefits from timely access to strategic information or new sales tactics that are developed in her prior branch and could be usefully applied in her current tasks.

A second mechanism by which network resilience might mitigate the performance disruption of mobility lies in the fact that persistent ties to former colleagues could channel social support (both task-related and emotional) for movers during their transition period (Ibarra, 1992; Podolny and Baron, 1997). Surprisingly, rather than impeding an employee's integration into their new work settings, Walsh and colleagues (2018) found that ties to former colleagues even help to improve it. Even if they lack knowledge about the mover's new task environment, the contacts associated with the past position may still possess knowledge that is relevant for the mover's performance, especially when the content of the work is similar. Prior work has documented that ties that survive mobility events link current and prior groups, in turn benefiting both (Corredoira and Rosenkopf, 2010; Rosenkopf and Almeida, 2003; Singh and Agrawal, 2011). Accordingly, knowledge that circulates readily from their prior colleagues could help movers identify better solutions to their current challenges, improving their performance. In addition, movers with high network resilience can continue to receive the social support common to strong, established ties with former co-workers during the transition to a new role, while also beginning to foster ties to their new colleagues. In other words, as connections to new colleagues are emerging, these new colleagues may be less motivated to provide support, especially for complex problems, and in such cases, movers may rely on strong, long-standing connections to their former colleagues (Granovetter, 1973; Hansen, 1999). Similarly, strong, long-standing relationships may also continue to furnish the mover with mentorship, sponsorship, and advocacy that could still be beneficial in their new position (Kram, 1985). Taken together, we expect that high network resilience gives rise to greater brokerage opportunities, continuous access to knowledge of prior colleagues, and better social support for movers, all of which facilitate post-move performance.

While the performance and career benefits to network resilience at times of mobility are considerable, network resilience can be costly: it occupies movers' time and energy, and maintaining relationships to former coworkers may come at the expense of finding and forming new network connections (Jonczyk et al. 2016; Roberts and Dunbar, 2015; Walsh et al., 2018). In fact, the experience of former colleagues might hinder rather than help post-move performance when the shared experience or knowledge is irrelevant or inappropriate to the mover's new position (Dokko et al., 2009; Groysberg et al., 2008; Groysberg and Lee, 2009). Hence, we expect the performance benefits of network resilience to be most salient for individuals moving within similar work contexts and environments. We thus bound our hypothesis to situations when the benefits associated with network resilience are likely to outweigh the potential costs: namely, internal moves. Taken together, we expect:

Hypothesis 1: High network resilience facilitates post-move performance for internal movers.

GENDER AND NETWORK RESILIENCE

Despite the substantial benefits of network resilience for movers, the ultimate need to form new ties with current colleagues and the complexity of cooperation with multiple social groups can present challenges to maintaining social ties with prior colleagues. We propose that in the face of such challenges, movers vary in their likelihood of retaining connections to their former co-workers. Further, we posit that these network changes will differ between men and women. To develop this argument, we start by discussing the antecedents of network resilience. We then explicate how the different network patterns exhibited by men and women correspond with the forces that give rise to network resilience. Finally, we weave these threads together to discuss the performance implications of network resilience for men and women movers.

The Antecedents of Network Resilience

A core premise of network resilience is that it leads to brokerage, which enables individuals to leverage opportunities that exist among disconnected groups (Burt, 1992; Kilduff and Brass 2010; Burt and Merluzzi, 2016; Kleinbaum, 2012; Tortoriello et al., 2012). To the extent that these individuals are able to make sense of and mediate inconsistent, incompatible, and diverging perspectives, brokers—in this case, those who have experienced job mobility—have the potential to generate value for themselves and for the organization. Nevertheless, maintaining connections with coworkers in different groups and reconciling the divergent vantage points poses an array of challenges for the bridging employee. Research has highlighted substantial psychological and structural constraints on an individual's capacity to act as broker (Burt, 2001; Kleinbaum et al., 2013; Krackhardt, 1999; Lee, 2019). Following a job change, new ties may form between the mover and their new co-workers via increased interactions imposed by the mover's new role (Jonczyk et al. 2016; Walsh et al., 2018). And ties to former colleagues with whom the mover is no longer required to interact may decay as a function of reduced opportunities and frequency of interactions (Roberts and Dunbar, 2015; Walsh et al., 2018) as well as increased physical distance (Burt, 2001; Lee, 2019). To wit, Burt (2001) argued that: "As much as change is about adapting to the new, it is about detaching from the old," (p. 1).

Extant research on tie persistence and decay identifies several factors that help to reduce the rate of tie decay and should, therefore, promote network resilience in the face of mobility: *tie strength* and *common contacts*. Tie strength concerns the interaction frequency and emotional closeness in a relationship (Granovetter, 1973). Since frequent communication increases familiarity and mutual understanding, strong ties may require less effort to maintain once they are established. Consistent with this argument, strong ties have been found to decay more slowly than weak ties (Burt, 2001; Dahlander and McFarland, 2013; Jonczyk et al. 2016). In addition, research has also shown that when two connected individuals share contacts in common, they are significantly more stable and resistant to decay than those lacking such third-party connections (Dahlander and McFarland, 2013; Kleinbaum, 2018; Krackhardt, 1999). Underlying the effect of common contacts is that shared third parties create not only normative pressure to maintain connection, but also ongoing opportunities for two people to interact (Krackhardt, 1999). Hence, strong ties and common contacts can help movers maintain connections with prior colleagues.

Gender and Network Resilience

Social networks within organizations, to a significant degree, align with functional roles and task requirements; however, gender has also been shown as an important determinant of network structures (Brass, 1985; Ibarra, 1992; Kilduff and Brass, 2010; Mehra et al., 1998; Singh et al., 2010).

Organizational scholars have found women to be embedded within more homogenous and structurally cohesive networks (Brass, 1985; Ibarra, 1992; Mehra et al., 1998). These network patterns often translate into unequal access to the knowledge and resources critical to an employee's performance (Singh et al., 2010) and the fulfillment of career goals – unless, as some scholars have argued, women could "borrow" social capital from their male bosses (Burt, 1998). To the extent that women believe they need borrowed social capital – and the sponsorship or advocacy that comes with it – more than men do (Kram, 1985), they may be particularly motivated to retain ties to their prior work group. It is important to note that these network patterns may not be a choice for women. Networks are co-constructed, and therefore, network differences are not indicative only of individual preferences. Instead, several emergent processes, such as exclusion or avoidance, may conspire in ways that lead to network differences along gender lines.

In addition to network differences, women and men differ in how they sustain their relationships. When an employee leaves to join another group and ties can only be retained with communication tools such as email instead of in-person interactions, women may be better able to manage such remote connections than men (Dunbar and Spoors, 1995; Roberts and Dunbar, 2015). As a result, reduced propinquity arising from job mobility could lead men's relationships to prior colleagues to decay, whereas women's greater tolerance for maintaining non-propinquitous relations makes it less likely that their connections to former co-workers will decay. Because of their strong ties embedded in cohesive social groups coupled with their greater likelihood of maintaining distant relationships, women are more likely to maintain communication with their former co-workers when they move. Accordingly, we contend when changing jobs, women will exhibit greater network resilience than their male counterparts. Formally,

Hypothesis 2: When experiencing mobility, women will exhibit greater network resilience than men.

Gender, Network Resilience, and Performance

So far, we have argued that network resilience benefits post-move performance and that women movers are likely to exhibit greater network resilience compared with men. All else equal, it should follow that women movers experience fewer post-mobility performance challenges than men. Yet, research on gender biases suggest that network patterns might benefit men and women inequitably (Brands and Kilduff, 2014; Brands et al., 2015). Maintaining a brokerage position is often viewed as inconsistent with feminine stereotypes (Eagly, 2005; Eagly and Karau, 2002), leading women professionals who act as social network brokers and bridge various groups to experience backlash from peers or supervisors (Barbulescu and Bidwell, 2013; Brands and Kilduff, 2014; Brands et al., 2015). Relatedly, Brands and Mehra (2019) recently found that women themselves tend to feel anxious when they perceive their own friendship networks to be structurally diverse (i.e., they occupy brokerage positions), in turn undermining their ability to perform. Thus, although brokerage has generally been found to benefit performance, maintaining such networks may hinder women's performance.

Recent scholarship, however, has begun to reveal women's particular network configurations and contingencies that benefit their performance. For example, evidence from the Champagne industry suggests that women's network patterns translate into stable access to in-depth knowledge and social support (Ody-Brasier and Fernandez-Mateo, 2017). In a study of student placement into post-MBA leadership positions, researchers found women with gender homophily or an "inner circle" of other female contacts allowed women to place in higher leadership positions as compared to women with networks similar to high placing men or women with male-dominated inner circle (Yang et al., 2019). That is, while women may be excluded from joining certain networks (Mehra et al., 1998; Singh et al., 2010) or penalized for forming social networks similar to their male colleagues (Brands et al., 2015; Brands and Kilduff, 2014; Yang et al., 2019), alternative network configurations and contingencies may aid in women's performance.

Against this backdrop, we propose that job mobility may be an important contingent factor and the retention of ties to prior colleagues may provide a "legitimate" form of brokerage for women. In general, women are penalized when they are perceived to be too "agentic" or "instrumental" (Barbulescu and Bidwell, 2013; Brands and Kilduff, 2014; Brands et al., 2015; Eagly, 2005; Eagly and Karau, 2002). In the case of a job change, woman's brokerage is a consequence of the move rather than her actively cultivating a diverse portfolio of ties in order to occupy brokerage position. In such cases, brokerage might even be perceived as having been foisted upon women movers rather than something they cultivated or prefer. Under conditions of a move, rapidly dropping ties to former colleagues in order to establish relations to new co-workers may even be construed as overly instrumental. Furthermore, retaining workplace ties even when they may not present immediate utility is consistent with the stereotype that women are "social specialists" and person-oriented (Brands and Kilduff, 2014; Brands et al., 2015; Eagly, 2005; Eagly and Karau, 2002; Ibarra, 1992). In other words, retaining ties following mobility is role-congruent and "expected" of women and, therefore, they are less likely to feel anxious or be penalized when brokerage is predicated on a job change. Thus, we expect that the greater network resilience that women movers exhibit compared with men provides a unique, dynamic form of brokerage, and that women can benefit from the brokerage positions arising from network resilience without concerns about the backlash or stress that they might otherwise suffer. Taken together, these arguments suggest:

> *Hypothesis 3: Women movers will suffer less performance disruption from job mobility than men movers due to (i.e., mediated by) their greater network resilience.*

METHODS

Empirical Setting

In choosing an industry in which to pursue our research question, we sought to meet two criteria. First, testing performance implications of professional network changes requires multiple observations of intra-organizational networks and measurable individual performance. Second, as understanding differences between men and women is central to our question, the setting needs to contain a sufficient number of women and men in the same positions to enable comparison. Additionally, we sought to minimize the impact of other factors that are known to affect movers' performance, such as the portability of teammates or clients (Groysberg et al., 2008; Groysberg and Lee, 2009). The retail banking industry fulfills these criteria and offers a setting well-suited to the research purposes of this paper.

We investigate the effects of intra-organizational mobility for women and men in the retail sales department in a large US-based financial institution that we call Big Bank. Big Bank is organized into four large departments: retail sales, asset management, corporate and institutional banking, and mortgages. We focused on data from the retail sales department because the documentation includes objective performance for its employees. The data we collected consists of 102,841 monthly observations for 12,916 retails sales employees between November 2014 and April 2016, including both individuals who were at Big Bank prior to the beginning of the observation period and those who joined during the window. In November 2014, there were 7,486 retail salespeople; over the study period this number ranged from 7,568 to 7,760 per month.

To minimize confounds we focus on those retail salespeople who move within Big Bank and retain the same role and title, specifically platform retail sales associates. Big Bank's retail sales department is comprised of 2,850 unique business units across 36 regions, and while the majority of business units (N = 2,039) consist of one work group, some have more than one working groups (Max = 5, Mean = 1.30). Hence, movers could change jobs in one of two ways – change to a new work group but stay in the same business unit or change business units which also implies that they joined a new work group. In these cases, the mover's job requirements and work tasks remain the same, but their co-workers and job setting change. The change of business units oftentimes involved a simultaneous change of working groups (93%). Employees in our sample share the same job title of platform retail sales associate but varied by job level, which corresponds with seniority at Big Bank and the business unit. The results presented in Appendix A show that job level differences are not statistically informative for understanding gender differences at Big Bank. In addition, while our modeling strategy focuses on comparing movers' pre- and post-move outcomes to help account for unobserved differences, in supplemental analyses the inclusion of additional controls, such as level changes do not alter our findings (see Appendix A and Table B5 and Table B6 in Appendix B).

The retail sales department at Big Bank provides a number of advantages for examining the effects of gender and network dynamics on post-move performance. First, key to the choice of this setting, a high level of intra-organizational mobility at Big Bank allows us to get traction on the effect of mobility on networks and performance. As movers change jobs within the same organization, their past networking behaviors and objective performance information are both readily available in our dataset. Moreover, while these internal job changes are not random, Big Bank does not prioritize internal candidates over external candidates. Hiring managers post open positions along with job descriptions and characteristics of ideal applicants online, then interview all job candidates to evaluate their suitability and select the one most appropriate and qualified for the position. This feature of the hiring process is important because a job candidate is unlikely to know exactly when a vacancy will be posted to "prepare" their social networks accordingly. While this feature of the data set helps to address concerns about the endogeneity of mobility with networks, we take other, more direct measures to address this issue as well.

Second, this setting provides an objective and comparable measure of individual performance. Retail sales employees specialize in providing personal financial tools and products to consumers and small businesses. They work independently to sell similar products to local customers, and at the end of each month Big Bank calculates their individual monthly sales as a performance metric. This monthly calculation of total sales value provides a regular and objective measure of each employee's performance without interference from work group confounds, such as task interdependence (e.g., Argote et al., 2018). This objective measure also mitigates concerns from prior research that suggests subjective measures of performance—such as self, peer, or supervisor evaluations—suffer from evaluation bias (e.g., Brands and Mehra, 2019; Walsh et al., 2018).

Finally, interviews with human resource executives at Big Bank indicate that retail sales employees rely heavily on email communication throughout their work activities to share job-related information including product details and sales strategies. Big Bank allowed us to collect anonymized metadata—sender IDs, receiver IDs, email size, and timestamp—of email exchanges among all employees. The use of email communication affords a behavioral measure of social interactions in organizations that is less prone to the biases that often affect self-reported data, and existing evidence indicates email communication provides a reliable proxy for other communciation media (Aven, 2015; Kleinbaum et al., 2013; Quintane and Kleinbaum, 2011).

Data and Sample

We obtained access to three sources of data from Big Bank. These data, dated from October 2014 to April 2016, include: (1) individuals' monthly retail sales records, which are comprised of monthly observations of total sales value in dollars for each employee; (2) anonymized email metadata (including sender ID, receiver ID, message size, and timestamp) for all internal emails of Big Bank employees during the observation period; and (3) monthly updated data on employees' demographic characteristics, which includes gender, race, age, job, organizational tenure, tenure in the retail sales role, work group assignments, and business unit location.

Our sample consists of 1,137 retail sales employees with the title of platform retail sales associate who moved within the retail sales department between February 2015 (the third month following November 2014, the start of the observation period) and January 2016 (three months from the end of the observation period in April 2016) are included in the sample. Again, these internal movers do not experience changes in their primary tasks (e.g., selling financial products to customers), but instead, their work setting and colleagues are new.

To compare the performance of movers before and after job mobility, we examine monthly changes in movers' networks and performance. This final sample has in total 12,161 mover-month observations. For 82% of our sample, we can observe a six-month window pre- and post-move (i.e., ranging from month *t-5* to *t-1*, month *t*, and month *t+1* to *t+5*, respectively). Notably, for 140 employees, we have less than six-month observations before they moved, and for 67 employees, we have less than six-month observations after they moved. The inclusion of these employees does not change our analyses or the interpretation of results. This final sample has in total 12,161 mover-month observations.

Networks, Gender, and Performance at Big Bank. As a conservative representation of the intra-organizational communication network, we limit our analyses to one-to-one emails within the organization, excluding all one-to-many emails or emails sent to and received from external sources. Given our performance metrics are captured monthly, we count the number of emails received and sent per pair every month. As such, we construct *directed* and *weighted* intra-organizational networks for each month. This approach has been shown to reliably quantify longitudinal intra-organizational networks (Aven, 2015; Kleinbaum et al., 2013).

We report the relationship between all retail sales employees' communication network characteristics, gender, and their performance in the subsequent month in Appendix A. Consistent with prior research on social networks in organizations (Burt, 1992), we find that employees with higher *Brokerage* (measured by the inverse of the square root of Burt's *Network Constraint* measure following approach in Kleinbaum (2018)) exhibit significantly higher *Individual Sales Performance* (measured by objective monthly revenue, log-transformed) than their peers with lower *Brokerage* ($\beta = 0.23$, $p < 0.01$), that is, we expect about 26.11% increase in monthly sales revenue when *Brokerage* increases by one standard deviation from the mean. The positive association between *Brokerage* and *Individual Sales Performance* is stronger for men employees ($\beta = 0.28$, $p < 0.01$) than women employees ($\beta_{Women\ x\ Brokerage} = -0.13$, $p < 0.01$). That is, an increase by one standard deviation in *Brokerage* from the mean associates with 32.31% increase in *Individual Sales Performance* for men whereas an increase by one standard deviation in *Brokerage* from the mean associated with 16.18% increase in *Individual Sales Performance* for women. Consistent with prior literature (Burt, 1992; Brands and Mehra, 2019), these analyses provide two baseline understandings of our setting: (1) communication networks, particularly the network positions associated with brokerage, positively correspond with performance for retail sales employees; (2) The benefits that women employees can reap from brokerage positions are significantly less that the benefits that men could obtain from similar positions.

Variables

Individual Sales Performance. The dependent variable for Hypotheses 1 and 3, *Individual Sales Performance,* is a continuous variable that measures the dollar amount of products that an employee sold during each calendar month. To account for the right-skewed distribution of *Individual Sales Performance,* we log-transform it. The effects should then be interpreted as a percentage change because the models estimate the odds ratio of geometric mean of *Individual Sales Performance* in the log scale.

Network Resilience. Our main independent variable and the dependent variable for Hypothesis 2, *Network Resilience,* is a dynamic construct that captures the tendency to retain the contacts in one's network over the span of a quarter. We report results monthly over three-month moving windows, as a financial quarter is a very salient timeframe in the world of finance and, consequently, at Big Bank. Results hold when we vary the moving windows to two, four, or five months. For each month, we measure the extent to which a mover's network has changed by calculating the ratio of persistent ties to total initial ties. Notably, the measure of *Network Resilience* is based on changes in outgoing ties. Focusing on outgoing ties (i.e., emails sent by the focal employee) permits us to capture the extent to which the focal actor chooses to maintain the relationship (versus incoming emails, over which the employee has no control). Note that all our results hold when we measure *Network Resilience* merely with employees' contacts to prior business units, as is reported in Appendix B1.

$$\mathrm{NR}_{i,t} = \frac{\sum \bigcap (\mathrm{Net}_{i,t-2}, \mathrm{Net}_{i,t-1}, \mathrm{Net}_{i,t})}{\sum \mathrm{Net}_{i,t-2}}$$

where NR represents *Network Resilience* for individual i in time t, which is the total number of overlapped email recipients between current month (Net_t), prior month Net_{t-1}, and two months ago (Net_{t-2}), divided by the total number of initial email recipients (Net_{t-2}).

Post Move. We capture the mobility event by setting *Post Move* to 1 in the month the employee moves jobs and subsequently. It is set to zero prior to the move.

Women. This variable represents the mover's gender which was self-reported to Big Bank. Employees could provide one of three responses for gender: female, male, or decline to identify. As we are interested in gender differences between women and men, we exclude those employees who declined to identify from our analyses (0.15% of the sample). This variable is set to 1 when the mover was recorded as women and 0 for men.

Brokerage. As one possible mechanism, we expect *Network Resilience* to be associated with *Brokerage*. To test this expectation empirically, we measure *Brokerage* as the inverse of the square root of Burt's *Network Constraint* measure. *Network Constraint* is commonly used to measure network cohesion around an individual (Burt, 1992). Conceptually, it calculates the level of concentration of contacts who are also connected—which also coincides with the lack of structural holes in an incumbent's communication network—as the sum of constraint posed by each of the contacts in the network. More specifically, this variable is a function of the direct communication between focal employee A and a contact C and the extent to which C also communicates with A's other contacts D (detailed in Burt, 1992). Monotonically transforming the *Network Constraint* measure to a *Brokerage* measure facilitates interpretation of the results without introducing bias to measure (Kleinbaum, 2018). Our results are also robust to other measures of brokerage, such as *Betweenness Centrality* (see Appendix B2).

Network Size and ***New Contacts.*** These two variables are controls that address concerns regarding movers' new ties could be underlying the performance effect, rather than persistent ties from their prior roles. There are two variables that can potentially be helpful in this regard, namely *Network Size* and *New Contacts*. *Network Size* in each month counts the total number of email recipients in the individual's network during that calendar month. This variable helps us to account for the movers' overall activity. *New Contacts* in each month counts the total number of "new" contacts in the network of that month—those who were not contacted by the focal sender in the prior three months. This variable helps us to capture the movers' activities to establish relationships with current coworkers. We log-transform both variables to account for their right-skewed distribution. To avoid modeling issues with multicollinearity, in the models reported below we only include the variable *Network Size* because it is correlated with *New Contacts* ($r = 0.81$, $p < 0.01$, see Table B1 in Appendix B), but the results also hold when we instead control for *New Contacts*.

MODELING STRATEGY

Using the panel data constructed from employees who have experienced intra-organizational mobility, we employ a *pre-post* design to compare the communication networks and performance of movers before and after a change of working business units. With a dummy variable *Post Move* that is equal to 1 for observations occurring after a job change and 0 otherwise, we estimate the main effect of *Post Move* and the interaction term *Post Move* × *Gender* on two outcomes of interest: *Individual Sales Performance* in the subsequent month for Hypothesis 1 and Hypothesis 3, and *Network Resilience* for Hypothesis 2. As *Network Resilience* essentially captures network changes comparing current month and past months, we do not lag independent variables in testing Hypothesis 2. All other variables are lagged by one month when we estimate *Individual Sales Performance*.

To identify the effect of mobility on individual performance, we adopt a *within-person* fixed effect approach. The within-person fixed effect model compares each mover with her own past records (in terms of communication networks and performance) and then estimates whether the variation of communication networks, namely *Network Resilience,* can be explained by *Post Move* × *Gender,* which, in turn, affects *Individual Sales Performance*. The mover fixed effect allows us to account for time-invariant differences across individuals, such as unobserved individual ability. This approach precludes estimation of the main effect of employee gender because it is collinear with the person fixed effect (in this data set, gender is time-invariant for all observations), so we also estimate models for the sub-samples of men and women. Across all the models, we include monthly fixed effects to account for possible time-specific variation. We also include business unit fixed effects to control for location factors that might affect performance.

We report fixed effect models with additional control variables in Appendix B3, and all results are consistent with those reported below. More specifically, we control for individuals' demographic variables for each month (i.e., age, organizational tenure, and job experience), the characteristics of the employee's business unit such as its size, proportion of men as well as the work group's network characteristics (i.e., communication density and centralization within the business units). Although fixed effects help to account for unobserved heterogeneity, they do not fully account for endogenous mobility. To better account for this endogeneity, we estimate two additional sets of models. The first analyzes a subset of people whose mobility was induced by the closure of their business unit; the second employs a matched "control group" of non-movers. For parsimony, we lead with the simpler models, but results remain consistent and significant across these two additional modeling approaches, which appear in the Appendixes C and D respectively.

RESULTS

Among the 1,137 employees in the sample, 682 (60%) employees are women, which corresponds to the proportion of women in the entire retail sales department employee sample (66.42%) (see Table B1 for all descriptive statistics and their correlations for the sample).

The Effect of Network Resilience on Performance

Table 1 presents results for *Network Resilience* on *Individual Sales Performance,* again using the within-person, pre-post approach. Note that as individual fixed effects are included, the models in Table 1 present the relative change of *Individual Sales Performance* for the same employee. In line with prior research (Groysberg and Lee, 2009; Groysberg et al., 2008), movers experience significant performance decline during the transition to a new job; in Model (1), *Post Move* is significantly negative for *Individual Sales Performance* ($\beta = -0.25$, $p < 0.01$), suggesting that on average, movers experience a 22.11% decrease in performance following job mobility. The main effect of *Post Move* remains significant ($\beta = -0.09$, $p < 0.01$), while *Network Resilience* has a significant and positive effect on *Individual Sales Performance* ($\beta = 1.70$, $p < 0.01$) in Model (2). Model (3) adds the interaction term *Post Move* × *Network Resilience,* and consistent with our first hypothesis, it shows that *Network Resilience* improves performance following a job change ($\beta = 2.05$, $p < 0.01$). In other words, retaining 21% of ties to former co-workers (one standard deviation) is associated with a 46.5% marginal increase in *Individual Sales Performance*. To ensure that the variation in performance is driven by *Network Resilience* rather than just network expansion, we estimate effects accounting for *Network Size* in Model (4), and the effects of *Network Resilience* and the interaction term remain consistent. The effects of *Network Resilience* also hold when we include *New Contacts* instead of *Network Size*. Models (5) and (6) estimate the effect of *Post Move* × *Network Resilience* separately for women and men movers and indicate that the benefit of *Network Resilience* does not differ by gender.

[TABLE 1 ABOUT HERE]

Together, the findings from Table 1 demonstrate that *Network Resilience* mitigates performance declines following a job change. The positive interaction effect of *Post Move* and *Network Resilience* supports Hypothesis 1. These results also provide initial evidence for the mediating role of *Network Resilience* proposed in Hypothesis 3; comparing Model (1) to the subsequent models in Table 1 shows that the negative effect of *Post Move* on *Individual Sales Performance* is reduced when we account for *Network Resilience*.

The Effect of Gender on Network Resilience

Table 2 presents models with *Network Resilience* as the dependent variable to examine Hypothesis 2, which argues that following a job change women will retain more ties to former colleagues than men. In Model (1), the coefficient of *Post Move* is negative and statistically significant ($\beta = -0.079$, $p < 0.01$). Interacting a time-invariant variable, *Women*, with a time-variant variable, *Post Move*, permits us to examine the effects of gender within fixed effect models. As such, Model (2) includes the term *Post Move* × *Women* and demonstrates that women movers exhibit significantly greater *Network Resilience* ($\beta = 0.078$, $p < 0.01$) than men movers, providing support for Hypothesis 2. After a move, women movers' *Network Resilience* is 8.11% greater than men movers.

[TABLE 2 ABOUT HERE]

The Effect of Gender on Performance through Network Resilience

To test that gender differences in *Network Resilience* mitigates women's performance disruption after a job change as proposed in Hypothesis 3, we examine whether the effect of *Post Move* × *Women* on *Individual Sales Performance* is mediated by *Network Resilience*. We first examine *Network Resilience* as a mediator according to the recommendation of Baron and Kenny (1986) and then test the mediation employing the Imai, Keele, and Yamamoto (2010) approach. Following the steps recommended by Baron and Kenny (1986), if *Network Resilience* mediates the effect of *Post Move* × *Women* on *Individual Sales Performance*, then three conditions should be met in the regressions presented in Table 2: (a) *Post Move* × *Women* should have a significant coefficient in Model (4); (b) *Network Resilience* should have a significant coefficient in Model (5); and (c) the coefficient of *Post Move* × *Women* should either become insignificant or decrease in magnitude in Model (5) compared with Model (4).

Models (3) - (7) in Table 2 estimate the effect of *Post Move* and *Gender* on *Individual Sales Performance*. As shown in Model (4), women movers exhibit a significantly greater *Individual Sales Performance* ($\beta = 0.125$, $p < 0.01$) than men movers, despite the fact that *Individual Sales Performance* of all movers decreases after job changes ($\beta = -0.330$, $p < 0.01$). Model (5) shows *Network Resilience* is positively associated with *Individual Sales Performance* ($\beta = 1.637$, $p < 0.01$). Importantly, in Model (5) the *Post Move* × *Women* interaction term is no longer statistically informative, which is indicative of the mediating role of *Network Resilience*.

Because *Network Resilience* might have different performance implications before and after job mobility and our theory concerns post-move relationship between *Network Resilience* and performance, we also run models including the interaction term *Post Move* × *Network Resilience*. As is shown in Model (6), the inclusion of the interaction term *Post Move* × *Network Resilience* demonstrates that *Network Resilience* benefits post-move performance. The coefficients for *Post Move* × *Women* in both Models (5) and (6) are no longer significant ($\beta = 0.012$, $p > 0.5$ in Model 5, and $\beta = 0.014$, $p > 0.5$ in Model 6, respectively) after the inclusion of *Network Resilience* in the models, indicating that *Network Resilience* mediates the relationship of *Post Move* × *Women* on *Individual Sales Performance*. Model (7) further controls for *Network Size*, and all results remain robust. Next, we confirmed the mediating effect of *Network Resilience* using the method proposed by Imai, Keele, and Yamamoto (2010) and calculate the confidence intervals based on 5,000 bootstrap samples. This analysis confirms that the effect of *Post Move* × *Women* on *Individual Sales Performance* almost entirely flows through *Network Resilience* (ACME = 0.11, $p < 0.01$; proportion of variation explained: 0.89, 95% CI [0.50, 1.27], $p < 0.01$). Consequently, these results together demonstrate support for Hypothesis 3.

Given that we included fixed effects for movers in models presented in Table 2, we cannot estimate the main effect of gender. As such, we also ran multilevel linear random-effects models with individual-level observations nested within business units and present the estimates in Table 3. All results align with those presented in Table 2.

[TABLE 3 ABOUT HERE]

DYADIC-LEVEL ANALYSES ON TIE PERSISTENCE

Thus far, we have provided evidence that network resilience is associated with a reduction in the performance decline after a move and that women retain a higher proportion of ties to former colleagues than men, leading them to perform better in their new units than men, *ceteris paribus*. An empirical question thus arises: why are women's networks more resilient? We herein conduct a set of dyad-level analyses to estimate the factors that help explain *the likelihood of a tie being retained* after a move. The models aim to provide a complementary analysis for the underlying factors for Hypothesis 2 that women's (v. men's) networks will exhibit greater *Network Resilience* and Hypothesis 3 on the differential effects between women and men movers on *Network Resilience* and *Individual Sales Performance*.

To do so, we construct a cross-sectional dataset comprised of 16,384 communication ties from the 1,137 movers in the three months before their job changes. Supposing a mover changes her business unit in month t; as long as a contact received one email from her between month t-3 and t-1, the mover-contact dyad will be included in the sample. The key dependent variable, *Tie Persistence,* is set to 1 when mover sent at least one email to person j in month t+1, month t+2, or month t+3; otherwise it is 0.

Given that each dyad represents a tie to a prior colleague, *Tie Persistence* is a dyadic representation of high *Network Resilience*. In the subsequent analyses, we focus our attention on the gender of the mover (the sender of the email) and the sender-receiver relationship, particularly *Tie Strength* and *Common Contacts*, and their implication for *Tie Persistence*. If our proposed theory on gender and network resilience holds, women will be more likely to continue sending emails to prior contacts after making job changes because their dyad communications will tend to be stronger and more embedded than men's communications.

We first estimate effects of gender on *Tie Strength* and *Common Contacts*, and the results are reported in Table 4. Next, we estimate the effect of gender on *Tie Persistence* and investigate whether or not the effect of gender could be explained by the differential network characteristics of men and women movers. We report these analyses in Table 5. Both tables include controls for other homophily variables that have been found to affect tie formation or persistence in the literature (Dahlander and McFarland, 2013; Kleinbaum, 2018), including *Same Gender* (set as 1 when both parties have the same gender, and 0 otherwise), *Same Department* (set as 1 when both parties work in the same department, and 0 otherwise), and the differences between the movers and contacts working and organizational experience. We also control for the *Network Degree* and *Brokerage* of the mover and the contact (receiver). And finally, in the estimation of *Tie Persistence*, we additionally control for post-move geographic *Distance (logged).* All the regressions are estimated with two-way clustering on both the movers and their contacts, accounting for the interdependence among network observations in calculating the standard errors (Cameron et al., 2011; Kleinbaum et al., 2015).

Models (1) and (2) in Table 4 report the effect of a mover's gender on *Tie Strength* operationalized in two ways: *Reciprocity* (the percentage of messages that received a reply) and *Response Interval* (the average time between emails sent and received). Model (1) shows that communications initiated by women are more likely to be reciprocated than those initiated by men ($\beta = 0.082$, $p = 0.02$). On average 56.2% emails received replies, and the percentage of reciprocated emails was eight percentage points higher for women senders. Model (2) shows that women's emails tend to also recieve significantly quicker responses ($\beta = -0.164$, $p < 0.01$) than those of men, indicating a higher frequency of communication and shorter turnaround time between email changees of women and their contacts. Models (3) and (4) in Table 4 report the effect of gender on *Common Contacts* operationalized as *Structural Similarity* and *Simmelian Tie. Structural Similarity* variable measures the level of equivalence of the mover and contact by calculating the number of common contacts among them between month *t-3* and month *t-1* divided by the average contact count for both parties. To illustrate, *A* and *B* are structurally similar if they both have communication ties to the same people (e.g., *C* and *D*) and likewise lack ties to the same others (e.g., *E* and *F*). A related way to measure common contacts is *Simmelian Tie*, a binary indicator of the presence of at least one shared third party (Krackhardt, 1999). Model (3) shows that the women mover ties are more likely to share third-party contacts ($\beta = 0.067$, $p < 0.01$), and Model (4) demonstrates that ties to women movers are much more likely to be Simmelian ($\beta = 0.329$, $p < 0.01$) than those ties to men. The likelihood of women being embedded in Simmelian ties is 40% higher than that of men. Notably, our results do not suggest *Same Gender* is a significant factor in explaining either *Tie Strength* or *Common Contacts*. Nor do we find that the interaction between *Gender* and *Same Gender* to be significant. This findings suggests that the gender of the mover, rather than the gender homophily of pairs, serves as the key determinant affecting network resillience. Taken together, these results show that overall women's ties tend to be stronger and exhibit greater closure than men's ties, which parallels prior research on network differences by gender (Brass, 1985; Ibarra, 1992; Singh et al., 2010). In the subsequent set of analyses, we show that all these features increase the likelihood of *Tie Persistence*.

[TABLE 4 ABOUT HERE]

Table 5 reports the models estimating *Tie Persistence*. Model (1) demonstrates that ties initiated by women are more likely to be retained after a mover changes jobs ($\beta = 0.216$, $p < 0.01$). In Models (2) and (3), the effect of gender remains significant with the inclusion of mobility and homophily related variables ($\beta = 0.283$ and $\beta = 0.265$ respectively, $p < 0.01$ in both models). *Reciprocity* ($\beta = 0.254$, $p < 0.01$) in Model (4), *Response Interval* ($\beta = -0.914$, $p < 0.01$) in Model (5), *Structural Similarity* ($\beta = 0.409$, $p < 0.01$) in Model (6), and whether or not the tie is a *Simmelian Tie* ($\beta = 1.744$, $p < 0.01$) in Model (7) all appear to mediate the gender effect on the likelihood of a tie's persistence after the move. The mediation effects are further confirmed by the Imai, Keele, and Yamamoto (2010) approach: the effect of *Gender* on *Tie Persistence* flows through its effects on *Reciprocity* ($p < 0.01$), *Response Interval* ($p < 0.01$), *Structural Similarity* ($p < 0.01$), and *Simmelian Tie* ($p < 0.01$).

[TABLE 5 ABOUT HERE]

Taking the two sets of analyses together, we complement our main analyses for Hypothesis 2 by providing consistent evidence that women's communication ties to prior colleagues are stronger and are more likely to be structurally embedded than the ties of men. These properties give rise to women's network resilience that in turn helps them to mitigate the performance consequences of mobility.

MECHANISM EXPLORATION: NETWORK RESILIENCE AND BROKERAGE

We suggested two possible mechanisms the performance effect of *Network Resilience.* And although we cannot examine social support with these data, we are able to investigate structural network changes, specifically *Brokerage*. That is, network resilience promotes post-move performance by facilitating creating a brokerage opportunity for the mover by which they derive their performance improvements. To assess this possibility empirically, we tested whether the effect of *Post Move* × *Network Resilience* on *Individual Sales Performance* is partially mediated by *Brokerage*.

[TABLE 6 ABOUT HERE]

We first show that *Post Move* × *Network Resilience* positively associates with *Brokerage*. Models (1) – (4) in Table 6 estimate the effect of *Post Move* and *Network Resilience* on *Brokerage;* Models (5) and (6) provide analyses with men and women movers separately. As shown in Model (1), *Post Move* alone is not significantly meaningful for *Brokerage*. Model (2) includes the main effect of *Network Resilience*, which has a positive, significant effect on *Brokerage* ($\beta = 2.125$, $p < 0.01$). Model (3) adds the interaction term *Post Move* × *Network Resilience* and shows a positive association between *Post Move* × *Network Resilience* and *Brokerage* ($\beta = 2.437$, $p < 0.01$).

We then regress *Brokerage* on *Individual Sales Performance* in Models (7) – (9). As is shown in Model (7), and consistent with voluminous prior research (e.g., Burt, 1992), *Brokerage* significantly increases performance ($\beta = 0.537$, $p < 0.01$), demonstrating that spanning disconnected groups benefits employees' performance. Models (8) and (9) include *Brokerage* in the models estimating effects of *Post Move* × *Network Resilience* on *Individual Sales Performance*. As is shown in Model (8), An increase of one standard deviation in *Brokerage* corresponds to 43.3% of marginal increase in *Individual Sales Performance*. More important is the effect of *Post Move* × *Network Resilience* on *Individual Sales Performance*. The effect of *Post Move* × *Network Resilience* remains significant when we include

Brokerage in the model ($\beta = 1.572$, $p < 0.01$), suggesting *Brokerage* only partially mediates the effect. Testing the mediating effects of *Brokerage* based on the method detailed by Imai, Keele, and Yamamoto (2010) and calculating the confidence intervals based on 5,000 bootstrap samples, we find evidence for partial mediation (ACME = 0.46, $p < 0.01$; proportion of variation explained: 0.23, 95% CI [0.17, 0.30], $p < 0.01$). This set of analyses complements our main analyses on Hypotheses 1 and 3 by showing that brokerage is one mechanism through which network resilience facilitates performance. The partial mediation also indicates that other mechanisms may explain the effect of network resilience, including social support via persistent ties.

ACCOUNTING FOR ENDOGENEITY CONCERNS WITH MOBILITY

Although we take advantage of the longitudinal nature of our data and include individual fixed effects in our main analyses, as with many mobility studies, there are reasons to be concerned about endogeneity introduced by unobserved variables. Specifically, the underlying reasons why employees might choose to change jobs may be driving both their social networking behavior and their post-move performance. Moreover, it is possible that unobservable differences between women and men movers exist that may be underlying both their mobility and their post-move differences. We attempt to address this endogeneity concern with two different analytical strategies: using a subsample of movers from business units that were officially closed and using a "matched" sample of movers to their observationally equivalent non-movers.

Subsample Analyses of Employees from Business Units that Were Closed. We identified a sample of employees for whom—even if it were possible to maintain prior network ties—there exists no strong reason to do so. Specifically, we examined the effects of *Network Resilience* and *Individual Sales Performance* on a sample of employees who moved due to the closure of their business units (N=165). The primary reason provided as to why these Big Bank business units closed was the shift to mobile banking and associated changing consumer demand for in-person service. These external factors made employees move within Big Bank involuntarily and potentially less prepared than other movers who were hired into their new job through official applications. And although the changes in technology and consumer demand were evident, the timing of the closure was uncertain, making the mobility of these employees plausibly exogenous. This closure-driven sample not only helps to mitigate concerns about endogeneity arising from employees' motives for moving, but also allow us to examine a case wherein employees would need to significantly reshape their social networks in a relatively short amount of time and with little preparation. We run the same set of analyses as presented in Tables 2 and 3 with this sub-sample, and all findings remained robust despite the greatly decreased sample size. We report the results of these analyses in Appendix C.

Triple-Differences Approach with "Matched" Movers and Non-Movers. Instead of comparing movers with their past selves, we might also compare movers to an observationally equivalent set of employees who do not change jobs to assess the differences in variables of interest, then compare the magnitude of effects between men and women. Essentially, doing this helps account for the possible selection effect of mobility and addresses the concern that movers are potentially different from employees who stay in their positions. Of course, this approach relies on a strong assumption of comparability between movers and their observationally equivalent, non-moving counterparts.

We adopt a *differences-in-differences-in-differences* (triple differences) approach and report the analyses in Appendix D. This triple-differences approach can be understood as a two-step analysis: first estimating differences-in-differences (diff-in-diff) for women and for men separately and then comparing the effect sizes. In other words, the basic diff-in-diff analysis examines the outcomes of employees who experience mobility with the outcomes of those who do not experience mobility. That is, how do women movers perform relative to similar women employees who did not change jobs? And we make the same comparison for men. The diff-in-diff analysis in essence controls for the average outcome in the control group (non-movers) from the average outcome in the treatment group (movers), thereby eliminating confound effects arising from stable differences between groups and from the trend.

We adopt an additional differencing into the diff-in-diff estimator to purge our results of factors correlated with mobility, resulting in a triple-differences approach. With the triple-differences estimator, we seek to compare the trajectories of movers with a matched set of controls (observationally equivalent employees who do not move). The triple-differences analysis then represents differences between these differences, to arrive at an estimate of how the effect of intra-organizational mobility depends on gender. The analyses, therefore, account for the selection in who moves and focuses on variations in the effects of intra-organizational mobility as a function of gender (Rogan and Sorenson, 2014). Together these differences provide an estimate of the effect of intra-organizational mobility, conditional on gender. Results of these analyses, which appear in Appendix D, are fully consistent with the main results in Tables 2, 3 and 4, lending further credence to our conclusions.

DISCUSSION AND CONCLUSION

Understanding network changes arising from job mobility is particularly important to inform theory on how individual network differences come about and accumulate over time (Ahuja et al., 2012; Borgatti and Halgin, 2011). Building on a theoretical foundation to explore network dynamics and careers, we extend understandings of the network dynamics of tie maintenance in the face of mobility. Our findings show that following a job move, network resilience*,* the degree to which individuals preserve prior network ties, creates an opportunity for brokerage, which in turn helps to offset the performance challenges that occur during mobility. Furthermore, we demonstrate systematic gender difference in movers' network resilience; women are more likely than men to retain ties to former co-workers, and under these mobility conditions, women are able to benefit from brokerage and experience less of a performance disruption than men movers.

This paper offers four contributions to the literature. First, this study speaks to previous work on mobility and organizational social networks. A long line of work has examined the role of networks in changing jobs and performance in a job (Borgatti and Halgin, 2011; Burt, 1992; Kilduff and Brass 2010; Podolny and Baron, 1997; Tortoriello et al., 2012). Heading calls for an increased focus on network dynamics (Ahuja et al., 2012), our research presents how mobility alters intra-organizational networks and how these network changes are conditioned on the employee's network charactistics prior to the move. Introducing the concept of network resilience as a means of obtaining a brokerage position, we advance the literature on the antecedents of individual network structures (Burt and Merluzzi, 2016;

Kleinbaum et al., 2015; Kleinbaum, 2012; Sasovova et al., 2010; Singh et al., 2010). While the preponderance of network scholarship has focused on tie formation, our research also contributes to the growing literature on tie decay (Burt, 2001; Dahlander and McFarland, 2013; Jonczyk et al. 2016; Kleinbaum, 2018) and substantiates findings that women are more willing to maintain distant ties than men (Dunbar and Spoors, 1995; Roberts and Dunbar, 2015). Nevertheless, these gender differences seem to be a by-product of the network structures women find themselves.

Second, our attempt to investigate how women's and men's network dynamics differ in response to intra-organizational mobility builds on and extends research that links social network and gender differences. Scholars studying gender differences increasingly acknowledge the critical role that social networks and social interactions play in organizations (Brands and Kilduff, 2014; Brands et al., 2015; Mehra et al., 1998; Merluzzi, 2017; Ibarra et al., 2005; Singh et al., 2010). As women strive to pursue their professional goals by changing their networks, they are likely to experience challenges associated with freeing themselves from the "super-strong and sticky" social relationships within which they were previously embedded (Ibarra, 1992; Krackhardt, 1999). By demonstrating that women could improve their performance by maintaining persistent communication ties following a job change, our work provides an important contingency through which women might be able to reap the benefits of brokerage for themselves and their organizations without the penalization (Brands and Kilduff, 2014; Brands et al., 2015). That is, while women may not benefit from networks in the same way as their male counterparts (Brands and Kilduff, 2014; Brands and Mehra, 2019), we add to the growing research that suggests alternative network arrangements by which women might find similar or better outcomes to men (Ody-Brasier and Fernandez-Mateo, 2017; Obukhova and Kleinbaum, 2020; Yang et al., 2019)

Third, network scholars have documented substantial descriptive network differences between men and women. Compared to men, women tend to have smaller (Dunbar and Spoors, 1995) and less diverse networks (Brass, 1985; Ibarra, 1992; Mehra et al., 1998; Singh et al., 2010), which tend to be weaker in providing career-related information, resources, and opportunities compared with those of their men counterparts (Ibarra, 1992; Ody-Brasier and Fernandez-Mateo, 2017). Despite ample evidence underscoring gendered network differences (Burt, 1992; Ibarra, 1992; Singh et al., 2010), there has been little investigation into how women might benefit from their networks (cf. Obukhova and Kleinbaum, 2020; Ody-Brasier and Fernandez-Mateo, 2017; Yang et al., 2019). Our paper suggests that intra-organizational mobility, the process by which employees move between business units within the same organization (Bidwell and Keller, 2014; Keller, 2018), may dynamically create opportunities that are advantageous to women. Put simply, the very network structures that constrain women's performance in the cross-section seem to benefit them when they experience mobility. This conclusion underscores the need for more dynamic analyses of organizational networks.

Lastly, our investigation contributes to the question of how gender role stereotypes interact with characteristics of networks to affect performance outcomes and possibly career advancement. According to the gender-stereotype literature, women who are seen to be violating prescribed gender roles elicit punishment such as hostility and antipathy from their peers (Eagly, 2005; Eagly and Karau, 2002). Because brokerage in workplace networks is associated with striving to get ahead, the kind of agency it involves tends to be associated with stereotypical expectations for men rather than women (Barbulescu and Bidwell, 2013; Brands et al., 2015). Hence, prejudice against women as brokers of relationships in organizations is evident in the literature on subjective performance evaluation and leadership (Brands et al., 2015; Brands and Kilduff, 2014; Brands and Mehra, 2019). Our work shows a contingent context in which women benefit from brokerage: women movers could overcome prejudice in the social realm and perform well by leveraging relationships to their prior colleagues. Future research should more fully explore precisely why building brokerage positions through the combination of mobility and tie maintenance provokes less judgement than other, more agentic approaches.

Despite these contributions, our work presents opportunities for further investigation. Following other case study approaches common in this type of research, we study these network dynamics following job mobility within a single organization (Burt and Merluzzi, 2016; Kleinbaum, 2012; Kneeland, 2018; Sasovova et al., 2010). Focusing on a single firm enables us to gather a wide range of rich data, but also limits the extent to which we can generalize our findings to organizations beyond those similar to the one we examine. And although we have no reason to believe that this firm or this empirical context are idiosyncratic in ways that contribute to these results, our data cannot speak to the role that network resilience plays in this particular intra-organizational market. We leave it for future research to identify the conditions under which the benefits of network resilience outweigh its costs.

Our results are based on the email exchanges of the women in our sample rather than the perceptions of the women's networks. Although this approach importantly provides objective, unbiased, longitudinal network data, we cannot directly speak to whether or not their colleagues are aware of the brokerage positions that women movers occupy, nor can we identify how others' awareness and perceptions affect the benefits that women movers could obtain. Accordingly, future research should directly measure perceptions of employees who move and further explore if brokerage via ties to former colleagues is perceived as role congruent for women.

In closing, social networks are dynamic structures influenced not only by individual differences but also organizational circumstances and events. Incorporating past social network characteristics, individual differences, and workplace changes illuminates the complexity in understanding the antecedents of social structure.

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TABLES

Table 1: Effects of Mobility and Network Resilience on Performance

	Individual Sales Performance (t+1, logged)					
	(1)	(2)	(3)	(4)	(5)	(6)
					Women Subsample	Men Subsample
Post Move	− 0.254*** (0.033)	− 0.093** (0.031)	− 0.092* (0.031)	− 0.075* (0.031)	− 0.074 (0.037)	− 0.081* (0.039)
Network Resilience		1.703*** (0.071)	− 0.235** (0.078)	− 0.582*** (0.076)	− 0.556*** (0.104)	− 0.610*** (0.134)
Post Move × Network Resilience			2.053*** (0.147)	2.232*** (0.145)	2.027*** (0.176)	2.552*** (0.250)
Network size (logged)				0.881*** (0.031)	0.808*** (0.038)	0.986*** (0.053)
Observations	12,161	12,161	12,161	12,161	7,637	4,523
Adjusted R^2	0.111	0.130	0.283	0.364	0.336	0.327
Unit Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mover Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

Standard errors clustered by movers are in parentheses

Table 2: Effects of Mobility and Gender on Individual Network Resilience and Performance (Fixed Effects Models)

	Network Resilience		*Individual Sales Performance (t+1, logged)*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post Move	− 0.079*** (0.004)	− 0.125*** (0.006)	− 0.254*** (0.033)	− 0.330*** (0.034)	− 0.091** (0.031)	− 0.087* (0.031)	− 0.071* (0.031)
Post Move × Women		0.078*** (0.008)		0.125* (0.051)	0.012 (0.052)	0.014 (0.051)	0.017 (0.051)
Network Resilience					1.637*** (0.071)	− 0.235** (0.078)	− 0.582*** (0.076)
Post Move × Network Resilience						1.972*** (0.147)	2.287*** (0.145)
Network Size (logged)							0.880*** (0.031)
Observations	12,161	12,161	12,161	12,161	12,161	12,161	12,161
Adjusted R^2	0.191	0.221	0.111	0.118	0.130	0.284	0.364
Business Unit Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mover Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Standard errors clustered by movers are in parentheses

Table 3: Effects of Mobility and Gender on Individual Network Resilience and Performance (Random Effects Models)

	Network Resilience		*Individual Sales Performance (logged)*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post Move	− 0.117*** (0.004)	− 0.168*** (0.008)	− 0.493*** (0.034)	− 0.601*** (0.053)	− 0.363*** (0.049)	− 0.124* (0.067)	− 0.085 (0.066)
Women		0.016*** (0.002)		− 0.144 (0.097)	− 0.124 (0.087)	− 0.120 (0.084)	− 0.130 (0.073)
Post Move × Women		0.112*** (0.007)		0.176*** (0.067)	0.006 (0.062)	0.011 (0.061)	0.019 (0.060)
Network Resilience					1.652*** (0.062)	− 0.503*** (0.069)	− 0.404*** (0.069)
Post Move × Network Resilience						3.548*** (0.133)	3.607*** (0.131)
Network Size (logged)							0.817*** (0.026)
Constant	0.385*** (0.010)	0.379*** (0.011)	9.927*** (0.182)	10.016*** (0.192)	9.850*** (0.190)	10.121*** (0.190)	7.121*** (0.205)
Observations	12,161	12,161	12,161	12,161	12,161	12,161	12,161
Log Likelihood	4,217.78	4,220.56	− 33,842.57	− 33841.82	− 30,488.24	− 30,309.22	− 29,863.44
Business Unit Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Standard errors clustered by movers are in parentheses

Mover Nested in Business Unit Random Intercepts are included in all the models

Table 4: Effects of Gender on Tie Strength and Common Contacts

	Tie Strength		*Common Contacts*	
	(1) *Reciprocity*	(2) *Response Interval*	(3) *Structural Similarity*	(4) *Simmelian Tie*
	Linear (Standardized Coefficients)			Logistic
Women	0.082* (0.033)	− 0.164*** (0.029)	0.067** (0.028)	0.329*** (0.062)
Mover Job Tenure (T1)	− 0.007 (0.015)	0.043** (0.013)	− 0.046** (0.013)	− 0.074** (0.028)
Mover Org Tenure (T1)	0.007* (0.003)	0.001 (0.003)	− 0.009** (0.003)	− 0.006 (0.007)
Mover Indegree (logged, T1)	0.049 (0.027)	− 0.202*** (0.025)	0.299*** (0.024)	0.482*** (0.055)
Mover Brokerage (T1)	− 0.045** (0.013)	0.039** (0.011)	− 0.113*** (0.011)	− 0.182** (0.025)
Receiver Indegree (logged, T1)	0.064** (0.022)	− 0.308*** (0.020)	0.057** (0.019)	0.508*** (0.045)
Receiver Brokerage (T1)	0.006 (0.009)	− 0.084*** (0.008)	− 0.030** (0.008)	− 0.022 (0.017)
Same Department	− 0.034 (0.036)	− 0.192*** (0.032)	0.510*** (0.031)	0.352*** (0.069)
Same Gender	0.033 (0.031)	− 0.035 (0.028)	0.063* (0.027)	0.027 (0.059)
Job Tenure Difference (Sender – Receiver, T1)	− 0.009 (0.007)	− 0.007 (0.006)	0.004 (0.006)	0.027* (0.013)
Org Tenure Difference (Sender – Receiver, T1)	− 0.005* (0.002)	0.0003 (0.002)	0.003 (0.002)	− 0.001 (0.004)
Observations	16,384	16,384	16,384	16,384
Log Likelihood	− 18,608.229	− 17,942.773	− 17,709.680	− 13,676.687
Monthly Fixed Effects	Yes	Yes	Yes	Yes

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

Standard errors clustered by senders and receivers are in parentheses

Table 5: Effects of Gender and Network Resilience on Tie Strength and Common Contacts

	Tie Persistence (T1 to T2)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Women	0.216** (0.081)	0.283** (0.082)	0.265** (0.097)	0.186* (0.098)	0.109 (0.097)	0.184 (0.099)	0.175 (0.099)
Distance (logged)		− 0.051*** (0.010)	− 0.057*** (0.011)	− 0.058*** (0.011)	− 0.058*** (0.012)	− 0.045** (0.011)	− 0.051** (0.011)
Mover Job Tenure (T1)			0.097* (0.041)	0.101* (0.042)	0.145** (0.041)	0.116** (0.041)	0.134** (0.041)
Mover Org Tenure (T1)			− 0.010 (0.010)	− 0.013 (0.011)	− 0.006 (0.010)	− 0.003 (0.010)	− 0.005 (0.010)
Mover Indegree (logged, T1)			0.471*** (0.089)	0.304** (0.087)	0.386*** (0.090)	0.333** (0.090)	0.369*** (0.089)
Mover Brokerage (T1)			− 0.141** (0.038)	− 0.083* (0.041)	− 0.067 (0.038)	− 0.092* (0.040)	− 0.068 (0.039)
Receiver Indegree (logged, T1)			0.752*** (0.072)	0.724*** (0.072)	0.566*** (0.077)	0.721*** (0.074)	0.676*** (0.074)
Receiver Brokerage (T1)			0.185*** (0.026)	0.181*** (0.026)	0.144*** (0.028)	0.160*** (0.028)	0.155*** (0.028)
Same Department			0.542*** (0.104)	0.549*** (0.104)	0.393** (0.110)	0.331*** (0.108)	0.367*** (0.108)
Same Gender			0.062 (0.091)	0.055 (0.091)	0.060 (0.091)	0.029 (0.091)	0.041 (0.091)
Job Tenure Difference (Sender – Receiver, T1)			− 0.026 (0.021)	− 0.013 (0.021)	− 0.028 (0.022)	− 0.026 (0.021)	− 0.027 (0.021)
Org Tenure Difference (Sender – Receiver, T1)			0.007 (0.007)	0.009 (0.007)	0.003 (0.007)	0.005 (0.007)	0.005 (0.007)
Reciprocity (T1)				0.254*** (0.060)			
Response Interval (T1)					− 0.914*** (0.052)		
Structural Similarity (T1)						0.409*** (0.044)	
Simmelian Tie (T1)							1.744*** (0.109)
Constant	− 0.061*** (0.297)	− 2.634*** (0.314)	− 5.212*** (0.442)	− 5.077*** (0.442)	− 5.278*** (0.461)	− 5.494*** (0.455)	− 5.287*** (0.459)
Observations	16,384	16,384	16,384	16,384	16,384	16,384	16,384
Log Likelihood	− 12,251.004	− 12,224.954	− 11,777.418	− 11,657.232	− 11,593.483	− 11,619.516	− 11,623.376

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

Standard errors clustered by senders and receivers are in parentheses; Monthly Fixed Effects are included.

Table 6: Effects of Mobility and Network Resilience on Performance via Brokerage

	Brokerage						*Individual Sales Performance (t+1, logged)*		
	(1)	(2)	(3)	(4)	(5) Women Subsample	(6) Men Subsample	(7)	(8)	(9)
Post Move	– 0.052 (0.058)	0.137* (0.058)	0.108* (0.054)	0.118* (0.055)	0.115* (0.056)	0.128* (0.059)		– 0.078* (0.033)	– 0.100** (0.034)
Network Resilience		2.125*** (0.106)	– 0.349** (0.108)	– 0.157 (0.107)	– 0.192* (0.090)	– 0.096 (0.097)		– 0.232** (0.077)	– 0.575*** (0.076)
Post Move × Network Resilience			2.437*** (0.338)	2.068*** (0.334)	2.082*** (0.242)	2.034*** (0.254)		1.572*** (0.147)	1.844*** (0.145)
Network size (logged)				0.468*** (0.007)	0.470*** (0.008)	0.461*** (0.011)			0.870*** (0.032)
Brokerage							0.537*** (0.051)	0.368*** (0.050)	0.107* (0.050)
Observations	12,161	12,161	12,161	12,161	7,637	4,523	12,161	12,161	12,161
Adjusted R^2	0.105	0.133	0.138	0.281	0.289	0.276	0.221	0.313	0.378
Unit Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mover Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Standard errors clustered by movers are in parentheses

Appendix A: The Effect of Brokerage and Gender on Individual Sales Performance

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 *Brokerage* affects *Individual Sales Performance* and whether the effect differs by gender. This full sample consists of 138,241 individual-month observations for 12,914 individuals who were working in the retail-sales department at Big Bank between November 2014 to April 2016. The total number of employees in the retail sales department ranges between 7,568 and 7,796 across the nineteen sampled months. All variables other than our dependent variable, *Individual Sales Performance*, were lagged by one month.

In the models, we include individual *Brokerage* (as measured in the main manuscript) and *Network Size*. We also include individual demographical variables, including their *Age*, *Gender*, *Organizational Tenure* (in years), *Job Role Tenure* (in years). All employees at Big Bank are assigned a job level, which corresponds with tenure in particular business unit and organization. Job levels range from 8 to 22. In 28.5% of the cases where employees moved to a new work group or business unit, they also changed job level. Nevertheless, women and men do not differ in their likelihood of a job level change (see Figure A). Although not reported in final models, the interaction term between *Gender* and *Job Level* is not significant in estimating performance. Across all the models, we include job level fixed effects to account for possible level-specific variation.

[FIGURE A ABOUT HERE]

Additionally, we control for variation between business units to account for the contextual differences among them, including *Size*, *Average Organizational Tenure*, *Average Role Tenure* (in the prior financial quarter), *Proportion of Male* employees, and *Total Numbers of Job Levels*. *Communication Density* and *Centralization* are also included to capture the possible network variations among business units. All models include fixed effects for *months*, *business units*, and *job levels*. The standard errors are clustered by employee. In this way, the analyses essentially estimate the effect of an employee's extensive 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 level. In Table A1, we report analyses with individual fixed effects. Table A2 presents models with individual random effects and embeds individual effects in the business units where they are working, to allow the probability of interest to vary across different employees.

[INSERT TABLES A1 AND A2 ABOUT HERE]

In Table A1, Model (1) shows a positive and significant main effect of *Brokerage* on *Individual Sales Performance* (β = 0.525, p <0.001). Model (2) further includes *Network Size*, which also positively influences performance. Model (3) demonstrates that the *Brokerage* effect on *Individual Sales Performance* differs between men and women. We find that *Brokerage* positively relates with *Individual Sales Performance*; the positive association between *Brokerage* and *Individual Sales Performance* is stronger for men employees (β = 0.28, p < 0.01) than women employees ($\beta_{Women \times Brokerage} = -0.13$, p < 0.01), which is consistent with prior research (Brands and Kilduff, 2014; Brands et al., 2015). Importantly, the effects of *Brokerage* remain robust with the inclusion of additional controls in Model (6). The results in Table B2 parallel those in Table A1. These analyses provide evidence that improves performance within our setting for retail sales employees, in line with prior research (Burt, 1992).

Table A1: Effects of Brokerage on Individual Sales Performance (Fixed-effect Models)

	Individual Sales Performance (logged, t+1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Brokerage	0.525***	0.144***	0.198***	0.219***	0.228***	0.276***
	(0.017)	(0.018)	(0.019)	(0.020)	(0.020)	(0.020)
Network Size (logged)		0.737***	0.603***	0.587***	0.600***	0.706***
		(0.018)	(0.017)	(0.017)	(0.019)	(0.019)
Women × Brokerage			− 0.090**	− 0.106**	− 0.112***	− 0.126***
			(0.032)	(0.031)	(0.032)	(0.032)
Age (years, logged)				0.499		0.083
				(0.538)		(0.539)
Org Tenure (years)				− 0.363***		− 0.354***
				(0.033)		(0.034)
Job Tenure (years)				0.076**		0.062*
				(0.027)		(0.027)
Unit Size (logged)					− 0.300***	− 0.204***
					(0.043)	(0.043)
Average Org Tenure					0.008	− 0.009
					(0.006)	(0.006)
Average Job Tenure					− 0.177***	− 0.039*
					(0.017)	(0.017)
Proportion of Men					− 0.068	− 0.068
					(0.073)	(0.073)
Unit Total Job Levels					0.094***	0.059***
					(0.006)	(0.006)
Within-Unit Communication Density					0.143+	0.161*
					(0.077)	(0.077)
Within-Unit Centralization					− 0.285***	− 0.223***
					(0.054)	(0.053
Observations	138,241	138,241	138,241	138,241	138,241	138,241
Job Level	Included	Included	Included	Included	Included	Included
Adjusted R^2	0.191	0.221	0.232	0.271	0.264	0.286

**p*<0.05; ***p*<0.01; ****p*<0.001 (two-tailed tests).
All models include individual, month, business units, and job level fixed effects.

Table A2: Effects of Brokerage on Individual Sales Performance (Random-effect Models)

	Individual Sales Performance (logged, t+1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Brokerage	0.414*** (0.015)	0.142*** (0.015)	0.190*** (0.016)	0.159*** (0.017)	0.303*** (0.017)	0.346*** (0.017)
Network Size (logged)		0.687*** (0.015)	0.686*** (0.015)	0.634*** (0.016)	0.749*** (0.017)	0.704*** (0.017)
Women			0.074 (0.068)	0.121 (0.065)	0.107 (0.065)	0.117 (0.065)
Women × Brokerage			− 0.087** (0.025)	− 0.082** (0.025)	− 0.097*** (0.025)	− 0.131*** (0.032)
Age (years, logged)				0.207*** (0.054)		0.171*** (0.050)
Org Tenure (years)				0.049*** (0.003)		0.044*** (0.003)
Job Tenure (years)				0.359*** (0.012)		0.327*** (0.012)
Unit Size (logged)					− 0.170*** (0.031)	− 0.179*** (0.030)
Average Org Tenure					0.019*** (0.004)	0.008+ (0.004)
Average Job Tenure					0.111*** (0.012)	0.074*** (0.012)
Proportion of Men					− 0.189*** (0.051)	− 0.187*** (0.051)
Unit Total Job Levels					0.017*** (0.005)	0.025*** (0.005)
Within-Unit Communication Density					0.162* (0.066)	0.171* (0.065)
Within-Unit Centralization					− 0.027 (0.046)	− 0.063 (0.046)
Constant	8.479*** (0.229)	− 2.722** (0.861)	7.424*** (0.227)	5.860*** (0.313)	6.884*** (0.260)	6.246*** (0.315)
Observations	138,241	138,241	138,241	138,241	138,241	138,241
Job Level	Included	Included	Included	Included	Included	Included
Log Likelihood	− 206497.0	− 204398.8	− 204228.1	− 202422.6	− 193491.8	− 191608.8

*$p<0.05$; **$p<0.01$; ***$p<0.001$ (two-tailed tests).
All models include *mover nested in business unit random intercepts, month, job level, and business unit fixed effects.*

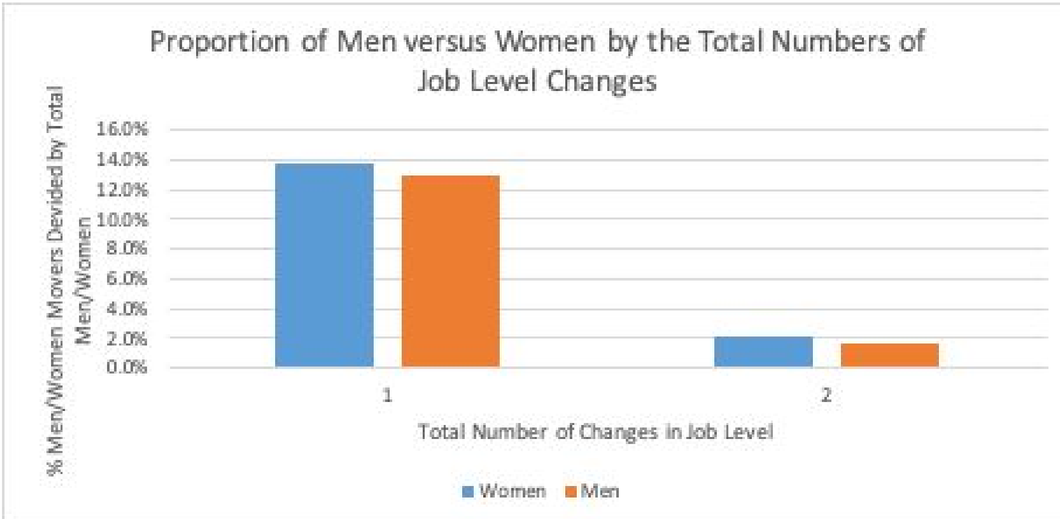

Figure A: The proportion of male movers (divided by all male employees) and the female movers (divided by all female employees) by job level.

Appendix B: Supplemental Analyses

We report descriptive statistics and correlation matrix in Table B1.

[INSERT TABLE B1 HERE]

Appendix B1: Alternative Measure of Network Resilience

Our results hold when we measure Network Resilience (Prior Colleagues) focusing exclusively on employees' contacts in prior business units. The models (as in Tables 2 and 3 in the main manuscript) estimated with this different measure of *Network Resilience (Prior Colleagues)* are reported in Tables B2 and B3. $\mathrm{NR}_{\mathrm{i,t}} = \frac{\sum \mathrm{Net}_{\mathrm{i,t,Unit1}}}{\cap \sum \mathrm{Net}_{\mathrm{i,t-1,Unit1}} \mathrm{Net}_{\mathrm{i,t-2,Unit1}}}$

where NR represents *Network Resilience* for individual *i* in time *t*, which is the total number of overlapped email recipients working in movers' prior business units in month *t*, divided by the total number of unique colleagues in prior business units with whom the mover has contacted two months prior to the move. Analyses in Tables B2 and B3 show consistent results with Tables 1 and 2. All hypothesized effects remain robust.

[INSERT TABLES B2 AND B3 HERE]

Appendix B2: Alternative Measure of Brokerage (Betweenness Centrality)

Our results are robust to other measures of brokerage, specifically *Betweenness* centrality in the whole intra-organizational network and are reported in Table B4. Note that as the distribution of *Betweenness* centrality is right-skewed, we log transformed it. The results show consistent patterns compared with analyses that we report in Tables 6. In other words, the proposed effects remain robust to different measures of brokerage.

[INSERT TABLE B4 HERE]

Appendix B3: Fixed Effect Models with Control Variables

We present supplementary analyses on *Network Resilience* and *Individual Sales Performance* with individual level and the group level control variables in Tables B5 and B6. More specifically, we also include individual demographical variables, including their *Age*, *Gender*, *Organizational Tenure* (in years), *Job Role Tenure* (in years). We also control for demographics of the business units to account for the contextual differences among the employees, including *Size*, *Average Organizational Tenure*, and *Average Role Tenure* in the prior financial quarter, the *Proportion of Male* employees, and the *Total Numbers of Job Levels*, *Communication Density*, and *Centralization* to capture the variations among business units. In addition, the fixed effects of *month* and *business units* are included in all of the models. Across all the models, we include job level fixed effects to account for possible level-specific variation. All hypothesized effects remain robust.

[INSERT TABLE B5 and B6 HERE]

Table B1: Descriptive Statistics (1,137 Intra-Organizational Movers, 682 Women Movers)

		Mean.	Std.	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Age (years)	34.70	11.49	21	74															
2	Org Tenure (years)	4.26	6.23	0.67	44.90	0.54*														
3	Job Tenure (years)	1.11	1.21	0.34	11.70	0.32*	0.34*													
4	Unit Size (logged)	2.26	0.62	0.69	7.17	0.04*	0.06*	0.09*												
5	Unit Average Org Tenure	5.61	3.79	0.03	16.9	0.21*	0.43*	0.17*	0.25*											
6	Unit Average Job Tenure	1.94	1.21	0.03	9.21	0.17*	0.23*	0.26*	0.26*	0.58*										
7	Within-Unit Proportion of Men	0.34	0.21	0	1	—0.13*	-0.16*	0	—0.09*	—0.32*	—0.18*									
8	Unit Total Jobs Levels	2.75	1.59	1	7	0.05*	0.07*	0.10*	0.69*	0.31*	0.33*	0.07*								
9	Within-Unit Communication Density	0.12	0.06	0.02	1	—0.15*	—0.16*	—0.20*	—0.10*	—0.04*	—0.06*	—0.03*	0.10*							
10	Within-Unit Communication Centralization	0.31	0.13	0	1	0.08*	0.13*	0.13*	0.09*	0.08*	0.08*	—0.04*	0.09*	—0.48*						
11	Network Resilience	0.40	0.21	0	1	0.04*	0.06*	0.10*	0.02*	0.06*	0.05*	—0.05*	0.02*	0.04*	0.06*					
12	Network Resilience (prior colleagues)	0.39	0.21	0	1	0.09*	0.09*	0.13*	0.02*	0.08*	0.06*	—0.06*	0.02*	0.01*	—0.04*	0.75*				
13	Brokerage	2.51	0.89	1	8.16	0.20*	0.20*	0.29*	0.15*	0.03*	0.06*	0.09*	0.16*	—0.55*	0.19*	—0.05*	—0.04*			
14	New Contacts (logged)	2.26	0.99	0	7.78	0.17*	0.17*	0.25*	0.16*	0.07*	0.08*	0.01	0.18*	—0.35*	0.15*	—0.32*	—0.17*	0.59*		
15	Network size (logged)	3.36	1.02	0.69	7.82	0.17*	0.17*	0.24*	0.12*	0.05*	0.06*	0.02*	0.13*	—0.56*	0.14*	0.08*	0.08*	0.65*	0.81*	
16	Individual Sales Performance (logged)	10.08	2.26	0	13.83	0.15*	0.20*	0.23*	0.07*	0.09*	0.10*	—0.02*	0.08*	—0.36*	0.16*	0.17*	0.12*	0.29*	0.35*	0.39*

*$p < 0.05$ (two-tailed tests)

Table B2: Effects of Mobility and Network Resilience (Focusing on Prior Colleagues)

	Individual Sales Performance (t+1, logged)					
	(1)	(2)	(3)	(4)	(5) Women Subsample	(6) Men Subsample
Post Move	− 0.254*** (0.033)	− 0.143** (0.033)	− 0.069* (0.033)	− 0.052 (0.033)	− 0.048 (0.037)	− 0.145* (0.039)
Network Resilience (Prior Colleagues)		1.877*** (0.071)	− 0.481** (0.072)	− 0.513*** (0.076)	− 0.595*** (0.093)	− 0.521*** (0.134)
Post Move × Network Resilience (Prior Colleagues)			1.903*** (0.161)	1.821*** (0.159)	1.819*** (0.189)	1.849*** (0.278)
Network size (logged)				0.881*** (0.031)	0.808*** (0.038)	1.033*** (0.054)
Observations	12,161	12,161	12,161	12,161	7,637	4,523
Adjusted R^2	0.111	0.142	0.271	0.369	0.374	0.358
Unit Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mover Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

Standard errors clustered by movers are in parentheses

Table B3: Effects of Mobility and Gender on Individual Network Resilience (Focusing on Prior Colleagues) and Performance

	Network Resilience (Focusing on Prior Colleagues)		*Individual Sales Performance (t+1, logged)*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post Move	− 0.108***	− 0.089***	− 0.254***	− 0.330***	− 0.139**	− 0.068*	− 0.041
	(0.004)	(0.006)	(0.033)	(0.034)	(0.031)	(0.031)	(0.031)
Post Move × Women		0.099***		0.125*	0.020	0.017	0.021
		(0.008)		(0.051)	(0.052)	(0.052)	(0.052)
Network Resilience (prior colleagues)					1.877***	− 0.480**	− 0.513***
					(0.071)	(0.078)	(0.077)
Post Move × Network Resilience (prior colleagues)						1.886***	1.735***
						(0.161)	(0.158)
Network Size (logged)							0.922***
							(0.031)
Observations	12,161	12,161	12,161	12,161	12,161	12,161	12,161
Adjusted R^2	0.214	0.274	0.111	0.118	0.142	0.284	0.368
Business Unit Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mover Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Standard errors clustered by movers are in parentheses

Table B4: Effects of Mobility and Network Resilience on Individual Betweenness and Performance

	Betweenness (logged)				*Individual Sales Performance (t+1, logged)*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post Move	− 0.005 (0.035)	− 0.024 (0.035)	− 0.094 (0.068)	− 0.103+ (0.061)		− 0.093* (0.033)	− 0.106** (0.033)
Network Resilience (prior colleagues)		− 0.430*** (0.073)	− 0.869*** (0.082)	1.094* (0.053)		− 0.254*** (0.077)	− 0.310** (0.100)
Post Move × Network Resilience (prior colleagues)			1.817*** (0.158)	0.461** (0.141)		1.776*** (0.147)	1.714*** (0.147)
New Contacts (logged)				1.714*** (0.026)			0.656*** (0.031)
Betweenness (logged)					0.323*** (0.007)	0.124*** (0.008)	0.067*** (0.008)
Observations	12,161	12,161	12,161	12,161	12,161	12,161	12,161
Adjusted R^2	0.121	0.133	0.142	0.258	0.184	0.333	0.371
Business Unit Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mover Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Standard errors clustered by movers are in parentheses

Table B5: Effects of Mobility and Gender on Network Resilience with Controls

	Network Resilience (t+1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Post Move	− 0.079***	− 0.125***	− 0.187***	− 0.180***	− 0.184***	− 0.176***
	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Post Move × Women		0.078***	0.207***	0.192***	0.181***	0.163***
		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Job Level Change			0.035*			0.019
			(0.015)			(0.015)
Working Group Change			− 0.088***			− 0.075***
			(0.005)			(0.005)
Age (years, logged)				0.522***		0.489***
				(0.132)		(0.132)
Org Tenure (years)				0.049***		0.051***
				(0.005)		(0.005)
Job Tenure (years)				0.020***		0.013**
				(0.004)		(0.004)
Unit Size (logged)					− 0.026**	− 0.006
					(0.008)	(0.008)
Average Org Tenure					0.001	0.001
					(0.001)	(0.001)
Average Job Tenure					0.009**	0.004
					(0.003)	(0.003)
Proportion of Men					0.012	− 0.001
					(0.014)	(0.014)
Total Unit Levels					− 0.007***	− 0.002+
					(0.001)	(0.001)
Within-Unit Communication Density					0.069**	0.106***
					(0.019)	(0.019)
Within-Unit Centralization					− 0.064***	− 0.064***
					(0.015)	(0.016)
Observations	12,161	12,161	12,161	12,161	12,161	12,161
Adjusted R^2	0.191	0.221	0.268	0.252	0.329	0.367

*p<0.05; **p<0.01; ***p<0.001 (two-tailed tests).
All models include individual, month, business units, and job level fixed effects.

Table B6: Effects of Mobility and Gender on Individual Performance with Controls

	Individual Sales Performance (logged, t+1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post Move	− 0.254***	− 0.330***	− 0.285***	− 0.295***	− 0.131**	− 0.112*	− 0.044
	(0.033)	(0.034)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Post Move × Women		0.125*	0.115*	0.123*	0.141**	0.153**	0.018
		(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)
Network Resilience							− 0.195***
							(0.077)
Post Move × Network Resilience							1.858***
							(0.147)
Job Level Change			− 0.042**			− 0.068***	− 0.031*
			(0.013)			(0.013)	(0.013)
Working Group Change			− 0.078**			− 0.050*	− 0.043+
			(0.024)			(0.024)	(0.024)
Age (years, logged)				1.070		1.201	0.410
				(1.169)		(1.169)	(1.088)
Org Tenure (years)				0.418***		0.313***	0.263***
				(0.048)		(0.048)	(0.046)
Job Tenure (years)				0.032		− 0.019	− 0.001
				(0.038)		(0.038)	(0.038)
Unit Size (logged)					− 0.069	− 0.243**	− 0.192**
					(0.063)	(0.063)	(0.064)
Average Org Tenure					− 0.003	− 0.006	− 0.002
					(0.009)	(0.009)	(0.009)
Average Job Tenure					0.029	0.001	0.168
					(0.026)	(0.026)	(0.026)
Proportion of Men					− 0.049	− 0.048	− 0.073
					(0.112)	(0.112)	(0.112)
Total Unit Levels					0.043**	0.044***	0.038***
					(0.011)	(0.011)	(0.011)
Within-Unit Communication Density					0.944***	0.899***	0.762***
					(0.161)	(0.161)	(0.161)
Within-Unit Centralization					− 1.133***	− 1.124***	− 1.059***
					(0.128)	(0.128)	(0.128)
Observations	12,161	12,161	12,161	12,161	12,161	12,161	12,161
Adjusted R^2	0.111	0.118	0.177	0.238	0.266	0.286	0.371

*p<0.05; **p<0.01; ***p<0.001 (two-tailed tests). All models include individual, month, business units, and job level fixed effects.

Appendix C: Subsample Analyses with Employees from Business Units that Were Closed

We previously outlined why it is unlikely that networks could be created with strategic intent and concomitantly affect mobility and performance. Nonetheless, we return to our consideration about the exogeneous aspects of job mobility. We identified a subsample of employees whose mobility was spurred by the closure of their business unit, rather than individual volition, and examined the effects *Network Resilience* and *Individual Sales Performance* on this subsample. Comparing the employees who remain working at Big Bank and find other jobs in the firm (N=165) to those who left the company following the closure of their business units (N = 379), we found no significant differences in either their *Brokerage* or *Individual Sales Performance* in the month before closure; we also find no significant difference in gender and the likelihood of staying. Hence the subsample of employees moving from business units that were closed permit us to account for endogeneity concerns associated with unobserved reasons for mobility.

With the individual-month observations on the small sample of employees who moved due to business units that closed, we run the same set of analyses with this sub-sample, and all findings remained robust despite the greatly decreased sample size. The results are reported in Tables C1-C3. All interpretations remain.

[INSERT TABLES C1-C3 HERE]

Table C1: Effects of Mobility and Network Resilience on Individual Brokerage

	Brokerage			
	(1)	(2)	(3)	(4)
Post Move	0.070*	0.045*	0.024	0.017
	(0.022)	(0.022)	(0.040)	(0.039)
Network Resilience		− 0.276***	− 0.314**	− 0.090
		(0.045)	(0.045)	(0.045)
Post Move × Network Resilience			1.938***	1.007***
			(0.150)	(0.151)
Network Size (logged)				0.490***
				(0.019)
Observations	1,789	1,789	1,789	1,789
Adjusted R^2	0.112	0.124	0.262	0.263
Business Unit Fixed Effects	Yes	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes	Yes
Mover Fixed Effects	Yes	Yes	Yes	Yes

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

Standard errors clustered by movers are in parentheses

Table C2: Effects of Mobility and Network Resilience on Individual Brokerage and Performance

	Individual Sales Performance (logged)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post Move	– 0.101***	– 0.054	– 0.078*	– 0.071*		– 0.075*	– 0.100**
	(0.039)	(0.034)	(0.031)	(0.033)		(0.034)	(0.034)
Network Resilience		0.575**	0.116	– 0.435*		0.116	– 0.417*
		(0.187)	(0.184)	(0.183)		(0.184)	(0.178)
Post Move × Network Resilience			2.919***	2.530***		2.137***	1.816***
			(0.378)	(0.371)		(0.377)	(0.369)
Network size (logged)				0.789***			0.957***
				(0.080)			(0.085)
Brokerage					0.292***	0.171**	0.141*
					(0.053)	(0.054)	(0.055)
Observations	1,789	1,789	1,789	1,789	1,789	1,789	1,789
Adjusted R^2	0.103	0.171	0.235	0.265	0.165	0.296	0.355
Unit Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mover Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Standard errors clustered by movers are in parentheses

Table C3: Effects of Mobility and Gender on Individual Network Resilience and Performance

	Network Resilience		*Individual Sales Performance (logged)*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post Move	— 0.072***	— 0.109***	— 0.101***	— 0.170*	— 0.064	— 0.062*	-0.056
	(0.011)	(0.019)	(0.039)	(0.066)	(0.033)	(0.031)	(0.033)
Post Move × Women		0.062*		0.044*	0.018	0.015	0.012
		(0.023)		(0.019)	(0.019)	(0.020)	(0.020)
Network Resilience					0.577***	-0.216	-0.431*
					(0.167)	(0.184)	(0.183)
Post Move × Network Resilience						2.789***	2.413***
						(0.378)	(0.371)
Network Size (logged)							0.787***
							(0.080)
Observations	1,789	1,789	1,789	1,789	1,789	1,789	1,789
Adjusted R^2	0.258	0.282	0.111	0.121	0.134	0.286	0.329
Business Unit Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mover Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Standard errors clustered by movers are in parentheses

Appendix D: Triple Diff-in-Diff Analyses on the Gender, Network Resilience, and Performance

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

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

To generate an appropriate comparison set (similar individuals who remain in the same business unit), we construct a sample that matches the movers (cases) with a set of counterfactual movers (controls), movers who could have moved but that did not. For the movers, we followed a "Coarsened Exact Matching" (CEM) approach (Iacus et al., 2012), choosing individuals from the complete employee lists that matched the movers on several observable characteristics including demographics, such as age and gender; tenure, such as the time one has spent in one's current job; geography, such as the primary market of focus; and job characteristics, such as one's job level in the organizational structure. Each mover is matched to several observationally equivalent employees who remain not moved in month *t* when the job change occurs. After the matching, for both the mover and the matched non-movers, their performance between month *t-3* and month *t+5* are included in the sample. The final matching sample includes 60,295 individual-month observations on 835 movers who have changed job locations and 4,073 observationally equivalent employees who remain not moved.

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

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

(Equation 1)

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

(Equation 2)

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

(Equation 3)

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

(Equation 4)

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

To test for the proposed mediated moderation, we adopt the Baron and Kenny (1986) original approach. The sufficient conditions are checked accordingly and explained as follow: essentially, we estimate the above Equations 2, 3, and 4 and test for two conditions. The first condition is met when the moderation of the overall treatment effect exists ($\beta_{Mover\ x\ Post\ Move\ x\ Gender} \neq 0$). The second condition is met when the moderation of the mobility effect in Equation 5 is smaller than the moderation of the overall treatment effect in Equation 2 ($\beta_{33,\ Mover\ x\ Post\ Move\ x\ Gender} < \beta_{13,\ Mover\ x\ Post\ Move\ x\ Gender}$). For the second condition to occur, the indirect paths from the diff-in-diff estimator via the mediator to the dependent variable must be moderated ($\beta_{35} \neq 0$).

[TABLE D1 ABOUT HERE]

We provide the results in Table D1. In Models 1 and 2, we show that there is a negative effect of *post move* on *Network Resilience* ($\beta_{Mover\ x\ Post\ Move}$= -0.495, p < 0.001), indicating that changing location leads to an average 49.5% decrease in individual's proportion of persistent communication ties to prior colleagues. Social networks do respond to formal positional job changes. This effect of intra-organizational mobility also depends on gender ($\beta_{Mover\ x\ Post\ Mover\ x\ Gender} = -0.163$, p < 0.01), suggesting the decrease in the proportion of persistent communication ties is 60.8% for men and 44.5% for women. On average, male employees maintain persistent communication with 19.93 other employees, thus male movers drop 12.06 persistent communication contacts; female employees maintain persistent communication with 18.93 other employees, thus average female movers drop 7.67 persistent contacts, respectively. Women's networks do respond relatively slowly to positional changes.

Models 3-5 estimate the effects on *Individual Sales Performance*. Model 3 shows that there is an overall effect of the diff-in-diff estimator ($\beta_{Mover\ x\ Post\ Move} = -0.402$, p < 0.001), indicating that intra-organizational mobility in the form of changing job locations leads to a 40% decrease in individual performance. We proceed to estimate the gender difference. We examine the effect of the interaction between *Gender* and the diff-in-diff estimator on *Individual Sales Performance* as reported in Model 4. To assist illustration, the performance effect is plotted in Figure E1. As is shown in Model 4 in Table E1, the overall effect of intra-organizational mobility depends on gender ($\beta_{Mover\ x\ Post\ Move} = -0.305$ and $\beta_{Mover\ x\ Post\ Move\ x\ Gender} = -0.213$, p < 0.001).

[FIGURE D1 ABOUT HERE]

In Model 5 which includes *Network Resilience* on estimating individual performance, the interaction effect size between intra-organizational mobility and gender is no longer significant. And the effect of this three-way interaction in Model 5 is smaller than the interaction effect in Model 4 ($abs(\beta_{33,\ Mover\ x\ Post\ Move\ x\ Gender}) = 0.287 < abs(\beta_{13,\ Mover\ x\ Post\ Move\ x\ Gender}) = 0.306$). The indirect path from intra-organizational mobility and gender interaction via *Network Resilience* to the performance outcome is significant. Indeed, moderation of the intra-organizational mobility effect is observed along the path from *Network Resilience* to the *performance* outcome ($\beta_{Network\ Resilience\ x\ Post\ Move} = 0.193, p < 0.001$). Taken all together, the results suggest that women suffer a smaller performance disruption when making intra-organizational moves, and that the gender difference can be explained by women's relatively high network resilience.

Table D1: Effects of Gender and Network Resilience on Individual Sales Performance

	Network Resilience		*Individual Sales Performance* (logged, t+1)		
	(1)	(2)	(3)	(4)	(5)
Women	0.116***	0.130***	0.162	0.180	0.140
	(0.024)	(0.024)	(0.093)	(0.097)	(0.094)
Mover	0.093***	0.069***	0.078*	0.059	0.028
	(0.017)	(0.017)	(0.033)	(0.035)	(0.034)
Post Move	0.013	0.007	0.144***	0.121***	0.074***
	(0.010)	(0.011)	(0.016)	(0.016)	(0.016)
Mover × Post Move	− 0.495***	− 0.445***	− 0.402***	− 0.305***	− 0.287***
	(0.024)	(0.024)	(0.039)	(0.039)	(0.040)
Women × Mover		0.079*		0.071	0.030
		(0.037)		(0.072)	(0.071)
Women × Post Move		0.032		0.124**	0.073
		(0.025)		(0.039)	(0.039)
Women × Mover × Post Move		− 0.163**		− 0.213***	− 0.107
		(0.051)		(0.083)	(0.080)
Network Resilience					− 0.079***
					(0.007)
Network Resilience × Mover					0.001
					(0.005)
Network Resilience × Post Move					0.021*
					(0.009)
Network Resilience × Mover × Post Move					0.193***
					(0.013)
Job Level Change	0.163***	0.163***	− 1.144***	− 1.345***	− 1.144***
	(0.021)	(0.021)	(0.033)	(0.033)	(0.033)
Working Group Change	− 0.214***	− 0.214***	− 0.621***	− 0.372***	− 0.621***
	(0.015)	(0.015)	(0.024)	(0.024)	(0.024)
Org Tenure (years)	0.009***	0.009***	0.044***	0.032***	0.044***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
Job Tenure (years)	0.012***	0.010***	0.005	0.005	0.005
	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)
Constant	0.027	0.027	10.628***	10.678***	10.628***
	(0.103)	(0.103)	(0.343)	(0.335)	(0.343)
Observations	60,295	60,295	60,295	60,295	60,295
Log Likelihood	− 79633.14	− 79635.01	− 116,721.9	− 106,422.3	− 116,721.9

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

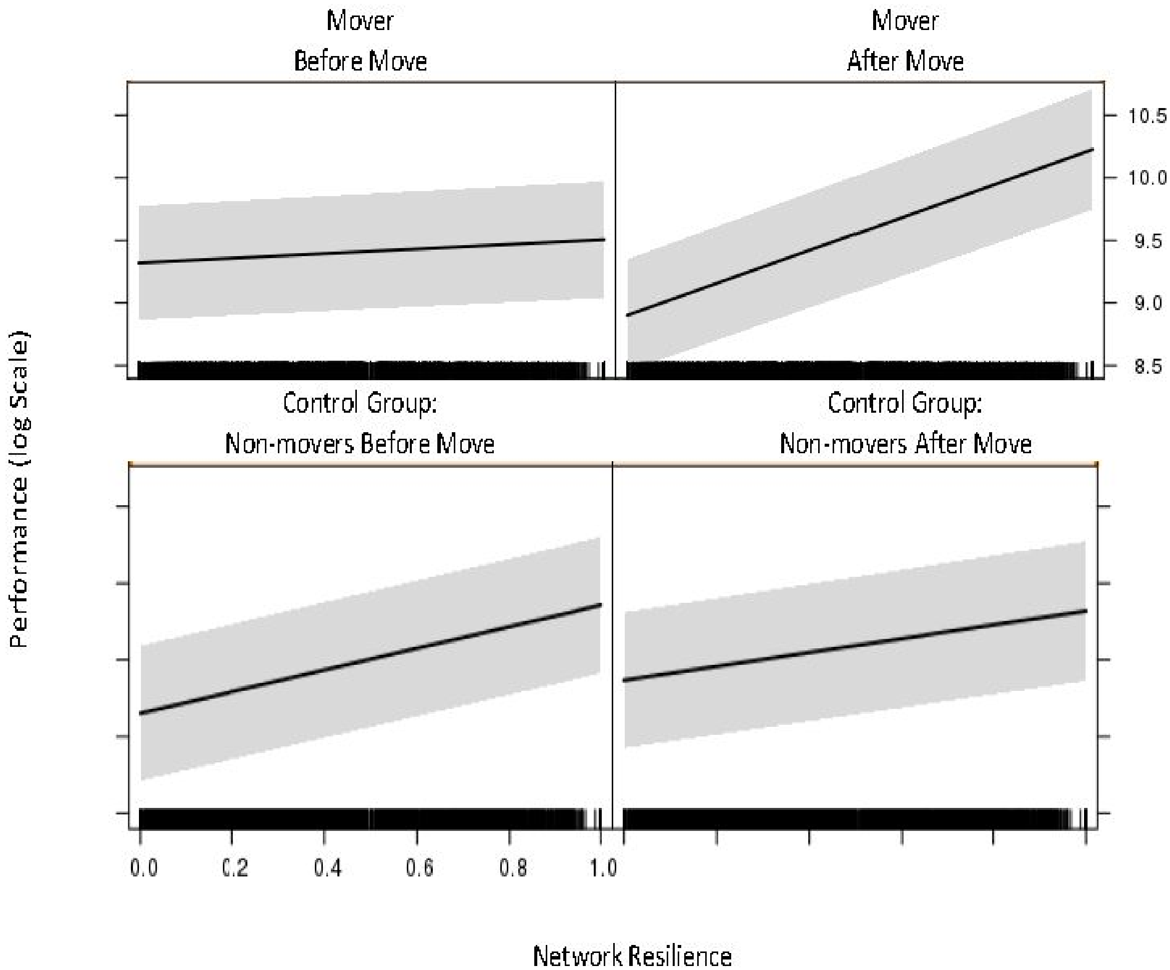

Figure D1: The Effect of Network Resilience on Individual Performance