CORPORATE HIERARCHY AND ORGANIZATIONAL LEARNING:
MEMBER TURNOVER, CODE CHANGE, AND INNOVATION IN THE MULTI-UNIT FIRM

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Abstract

This study examines how recombinant innovation is affected by member turnover and organizational learning within a corporate hierarchy. Most prior work has overlooked the role of organizational structure in organizational learning, focusing instead on the knowledge provided by individual new hires or on the disruption caused by individual departures. We address this gap by applying March’s (1991) mutual learning model to a corporate hierarchy. In doing so, we theorize how the contributions of corporate staff to socializing new employees and to learning from the organizational code may differ from those of the organization’s subunit members. Empirically, we examine the learning effects of aggregate corporate and subunit arrivals and departures on novel recombinant innovation by subunits. Using 24 years of Motorola company directories, we construct membership turnover measures for corporate and subunit employees and exploit patent data to capture recombinant innovation. Our results suggest that, whereas the influx of new ideas through arrivals may be critical, breaking the pattern of inertial behavior through departures is more important for recombinant innovation. Corporate departures matter most for recombinant innovation, a result that reflects not only corporate staff’s slower individual learning from the organizational code but also its ability to update that code more quickly. In a post hoc analysis, we also find different effects for technical and non-technical staff. Our study has strong implications for theories of organizational learning and strategic human capital and for the literature on organization design and innovation.

Keywords: organizational learning, organizational code, turnover, organizational structure, organizational design, knowledge, recombination, innovation
More than 25 years after the 1991 publication of “Exploration and Exploitation in Organizational Learning,” March’s work has become a part of the intellectual foundation of research concerned with organizational learning. His proposed model is one of mutual learning: organizational members learn from the organizational “code”—a store of beliefs, language, and practices that have accumulated over time (March, 1991: 74)—and the organizational code “learns” from members. This mutual learning model offers a means for explaining when collectives of individuals learn, and it has drawn attention to the idea that organizational learning occurs via the accumulation and flow of individual knowledge and the socialization of new organizational members (Argote and Miron-Spektor, 2011). March’s model has provided guidance for scholars seeking to elaborate theory accounting for the impact of turnover on organizational learning (Carley, 1992; Fang, Lee, and Schilling, 2010), as well as a basis for empirical research demonstrating how turnover affects innovation (Song, Almeida, and Wu, 2003; Cirillo, Brusoni and Valentini, 2014; Jain, 2016; Wang and Zatzick, 2019).

Yet, despite its rich contributions, most of this research theorizes membership turnover as being invariantly processed regardless of where members are located in the organizational structure. Thus, the literature implicitly assumes a unitary organization or “flat” structure. As a result, little is known about how organizational learning varies across levels within the firm (Puranam and Maciejovsky, 2017), which underscores a critical omission in March’s mutual collective learning model—namely, the corporate hierarchy. This lacuna is evident in modeling work that directly tests March’s theory (for an exception, see Carley, 1992) and also in empirical work on aggregate turnover (e.g., Wang and Zatzick, 2019), the mobility of star scientists (cf. Mawdsley and Somaya, 2016; Tzabbar and Cirillo, 2020) and executives (e.g., Wezel, Cattani and Pennings, 2006; Karim and Williams, 2012).

The implications of this omission for understanding learning and innovation are particularly significant for large technology companies, where members not only pursue innovation in specialized subunits but also are embedded in a hierarchical structure—so that their innovative behavior is often affected by a corporate office (Karim, 2012; Kunisch, Menz and Collis, 2020). Moreover, research points to the corporate hierarchy as an impediment to code change (Gavetti and Ocasio, 2015). Headquarters may
shape the socialization of new organizational members and play a prominent role in developing, maintaining, and circulating the organizational code (Gavetti, 2005); these factors make the corporate office the most likely unit to benefit from the existing code and also the least likely to change it (Tripsas and Gavetti, 2000). Empirical studies have begun to examine the role of hierarchy in innovation and to view subunit innovation as the consequence of a multi-level learning process (Csaszar, 2012; Gaba and Joseph, 2013; Karim, Carroll, and Long, 2016; Rhee, Ocasio, and Kim, 2019). However, still very little is known about how subunit innovation is associated with aggregate turnover patterns across a multi-unit hierarchical structure or about the comparative effects of turnover among subunit versus corporate staff.

Although we address this theoretical problem, we also consider another limitation of much of the extant research: the fact that it uses, as a measure of turnover, either the arrival or the departure of particular organizational members (for an exception, see Somaya, Williamson, and Lorinkova, 2008). These studies tend to focus either on “learning by hiring” (e.g., Song et al., 2003; Groysberg and Lee, 2009) or on “disruption from departures” (e.g., Wezel et al, 2006) of individuals, but not both. A common yet implicit assumption is that existing members who depart are replaced. In aggregate, however, there is usually a mismatch between the rates of member departures and arrivals. Organizations rarely hire as many members as those who depart, nor lose as many members as those who join (Hausknecht and Holwerda, 2013).

In this study, we address these gaps in the literature by building a theory of organizational learning that considers the corporate hierarchy. In doing so, we incorporate membership turnover of staff at both the corporate and subunit level. We also consider the implications of both arrivals and departures, all of which can affect the heterogeneity of learning within a firm. Our work conceptualizes this organizational learning and exploration as novel recombinant innovation, which includes both the combination of new technological components and new configurations of previously combined technological components (Fleming, 2001).

Our central thesis draws on March’s (1991) mutual learning model and posits that newcomers to the corporate office diversify the organizational code, thereby improving recombinant innovation, while the departure of corporate members may lead to revising or decay of the existing code—a dynamic that breaks inertial patterns in the subunits, promoting recombinant innovation. Our theory suggests that member
turnover among corporate staff plays a larger role in this process than does subunit-level staff turnover because, whereas individuals at the corporate level may learn more slowly (than subunit individuals) from the organizational code, they may update that code more quickly. Importantly, we theorize that aggregate corporate turnover plays a leading cross-level role in learning and subunit innovation.

The empirical analysis of our model is based on annual employee directories covering all of Motorola’s U.S. employees, from which we construct turnover measures, and on patent data during the period from 1974 to 1997, which we use to estimate recombinant innovation. In this way, we examine whether and how member arrivals and departures at the corporate office and also at the focal subunit (here, individual Motorola subunit locations), are associated with recombinant innovation at the subunit level. In line with our hypotheses, we find that the arrival and departure of staff members from the corporate office and from subunits have a positive relationship with recombinant innovation. In supplementary analysis we find that for newcomers (i.e., arrivals), this relationship holds only if they are from outside the firm. We also find that the arrival of technologists to a subunit has a positive association with recombinant innovation, while the departure of non-technical staff from within the firm is positively associated with the same. Most notably, corporate staff departures are the ones most strongly associated with recombinant innovation. Finally, we demonstrate the mutual learning mechanism in post hoc analyses based on internal corporate documents and the Linguistic Inquiry and Word Count (LIWC) lexicon (Pennebaker et al., 2007).

Our study makes three main contributions, of which the first is to the literature on organizational learning. Although empirical studies are of interest to scholars (e.g., Puranam and Swamy, 2016; Knott and Turner, 2019), contributions have lagged in their treatment of corporate structure—a deficiency that has limited development of theory and mechanisms (see Puranam and Maciejovsky, 2017). A few studies have distinguished corporate- and subunit-level learning from performance feedback (e.g., Gaba and Joseph, 2013; Rhee et al., 2019) or considered the effects of structural alternatives on balancing exploration and exploitation (e.g., Siggelkow and Levinthal, 2003; Csaszar, 2013; Wilson and Joseph 2015). However, we are not aware of studies that have offered a systematic treatment of turnover-driven learning at multiple levels or extended March’s (1991) mutual learning model to incorporate the role of corporate hierarchy.
Second, we contribute to the literature on organization design and innovation. Much of the organization design research on innovation (or search) examines the centralization of decision making (Siggelkow and Levinthal, 2003; Csaszar, 2012, 2013). Our theory suggests that the effect of hierarchy on innovation proceeds through turnover and the vertical division of labor, from which it follows that we can learn from revisiting turnover as a design problem. Scholars of corporate headquarters have indeed acknowledged the role of turnover in organization design (Kunisch et al., 2020); yet none have specifically examined how technological recombinant innovation is associated with corporate turnover. We address this gap and bring particular attention to the role of code change.

Third, we advance the literature on employee mobility and turnover (cf. Mawdsley and Somaya, 2016; Tzabbar and Crillo, 2020), most of which focuses on either the turnover of particular rank-and-file employees (e.g., Kehoe and Tzabbar, 2015) or executives (Karim and Williams, 2012; Bermiss and Murmann, 2015) but not on the turnover of all employees. Also absent are studies that have considered the simultaneous relevance of both aggregate arrivals and departures for innovation. Our unique data allows us to build and test theory on these facets of turnover, as well as conduct supplementary analyses which make distinctions between technical staff (e.g., scientists or engineers) and staff who occupy non-technical roles. In doing so, we offer a more complete picture of aggregate turnover on innovation in corporate hierarchies.

ORGANIZATIONAL LEARNING IN A CORPORATE HIERARCHY

Exploration frequently takes the form of recombinant innovation. Recombinant innovation reflects a search process that may range from exploratory, using completely new components and combinations, to exploitative, which uses familiar sets of components and combinations (March, 1991). As a result, recombinant innovation is a primary source of technological novelty and of firm heterogeneity (Katila and Ahuja, 2002; Karim and Kaul, 2015). Research has identified various drivers of novel and recombinant innovation: leadership (Davis and Eisenhardt, 2011), inventors (Gruber, Harhoff, and Hoisl, 2013), social networks (Godart, Shipilov, and Claes, 2014), structural recombination (Karim and Kaul, 2015), and—most importantly for our study—turnover (Song et al., 2003; Tzabbar and Cirillo, 2020).
Theories of organizational learning that view innovation as a recombinant process recognize the limits to innovation within complex organizations (Fang et al., 2010; Karim, 2012). In particular, hierarchies may create barriers to information processing and thereby limit the resources and attention allocated to new ideas (e.g., Csaszar, 2013; Keum and See, 2017). Most relevant, perhaps, for our study is that prior work has established the corporate office as a cognitive impediment to the pursuit of innovation (Gavetti, 2005; Gavetti and Ocasio, 2015)—a reflection of its role in maintaining the organizational code. This code is both the outcome of past organizational learning and the basis for future organizational learning (Levinthal and March, 1993; Gavetti, Greve, Levinthal and Ocasio, 2012).

Previous studies indicate that the organizational code exhibits remarkable persistence (Kotter and Heskett, 1992; March, Schultz, and Zhou, 2001) and is often a source of inertia that limits innovation among members (Tripsas and Gavetti, 2000). Because the code reflects past success and confidence in existing activities, it has the effect of limiting the search for new alternatives, even as the external environment changes. The ongoing operation of the code ultimately reinforces status quo behavior, which makes it difficult to alter when needed (Levinthal and March, 1993; Feldman and Pentland, 2003). Because the code serves as the decision premises for lower-level employees (Simon, 1976; Gavetti, 2005), it may constrain flexibility and limit new directions in subunits’ technological search. The canonical example of this phenomenon, offered by Tripsas and Gavetti (2000), is that of senior managers at Polaroid, whose entrenched beliefs based on the firm’s overwhelming success with photographic film compromised the efforts of lower-level managers to garner resources for developing digital technologies. Those beliefs delayed the firm’s entry into the digital market, damaging its financial performance. More generally, when current technologies are supported by corporate staff who are motivated to maintain the status quo, subunits may find it difficult to mobilize managerial support for novel technologies and to transform their initiatives into tangible outcomes in the form of recombinant innovation (Eggers and Kaplan, 2009).

Turnover may break the inertial grip of an existing organizational code. Situating March’s mutual learning model in a complex organization offers a lens through which we can better understand this possibility. March’s model reflects how individuals new to the firm rapidly learn from the organizational
code, which itself adapts rapidly to the knowledge of individuals. Because of rapid conformity to the code, the organization becomes more homogeneous in its held knowledge. The longer an individual is employed at the firm, the less impact their prior experience has (Dokko, Wilk and Rothbard, 2009) and the greater their convergence on the current code. This dynamic eventually creates a misfit with the external environment and limits exposure to external ideas and to exploration of those ideas. March’s model suggests that an organization learns by “ingesting” new members who have novel knowledge (Simon, 1991: 125). Thus, a key mechanism for introducing heterogeneity in organizational knowledge is membership turnover.

However, any such claims must recognize that the effect of corporate turnover on recombinant innovation may well differ from that of turnover in the firm’s subunits. Because most members of the corporate office do not participate in daily R&D activities (e.g., patent activity)—or even interact with lower-level technical staff—the effect of their turnover is seldom felt directly (Miller, Zhao, and Calantone, 2006; Fang et al., 2010), but is instead transmitted indirectly via changes in the organizational code (Gavetti et al., 2012). Given the cognitive constraints imposed by headquarters, we posit that corporate staff turnover may provide a way to overcome inertia and increase recombinant innovation at the subunit level.

We build our theory by linking aggregate member turnover, via the mechanisms of code updating and code breaking, to new recombinant innovation. We focus on aggregate turnover because turnover usually involves more than a single individual (e.g., corporate departure comprises not only high-ranking executives but also other corporate employees). Since no one individual has a full knowledge of a practice, turnover’s impact is often reflected in groups of individuals arriving and departing. For example, corporate activities reflect not only the agendas of new executives but also the efforts of new corporate staff who help translate those executives’ new agendas and strategy prescriptions into procedural routines (Bermis and Murmann, 2015). Similarly, innovation often reflects input not only from scientists and engineers directly associated with a technology, but also from other personnel who may help set the direction of technological development (e.g., sales personnel who bring customer information back to the firm).

Furthermore, because member turnover can affect several conditions conducive to organizational learning, especially relevant to recombinant innovation, we deconstruct turnover and consider arrivals and
departures separately at both the corporate and subunit levels. The respective rates of arrival and departure may not be equal and may offer distinct ways of affecting how organizations learn. In the following sections, we elaborate our conjectures, examine corporate and subunit arrivals and departures, and hypothesize how these arrivals and departures affect recombinant innovation.

**Corporate staff turnover and recombinant innovation**

Corporate newcomers may alter the organizational code in several ways that affect subunit recombinant innovation. First, new members of the corporate staff may introduce novel elements to the code. Technology firms often recruit from other firms. Such movement detaches organizational members from the organizational code at their old employer and they bring their beliefs, vocabularies, and routines, contributing to the code in the new setting (Cirillo et al., 2014). Second, when the arrival of newcomers disrupts ongoing activities, existing members may respond by reflecting on and re-evaluating the firm’s existing code. Both processes introduce greater variation into the code (Brown and Duguid, 2001).

In turn, corporate-driven code updating will increase recombinant innovation. Greater variation in corporate beliefs used in decision making is critical for recombinant innovation within subunits because such change entails greater variation in the decision premises for lower-level employees (Simon, 1976; Gavetti, 2005). This dynamic arises because greater variation in decision premises leads to additional variation in terms of which specific problems and opportunities require subunit attention, while also providing individual decision makers with new perspectives on possible solutions. Note that corporate beliefs do not necessarily have to be accurate to promote exploration—they only need to vary. Research shows that in hierarchies, variation in top managers’ mental representations of the environment can actually promote exploration by lower-level employees by limiting the negative impact of early negative feedback (Lee and Puranam, 2016), which often occurs when firms attempt to advance in new technological areas.

Concomitant with new beliefs is a greater variation in corporate vocabularies and routines. Newcomers to the corporate office may bring a new vocabulary from their previous employer and/or engage in discourse or rhetorical strategies to legitimize beliefs that differ from prevailing ones (Kaplan, 2008; Vaara and Monin, 2010; Oliveira, Argyres and Lumineau, 2021). Language serves as a lens for cognition
and is a category maker (Ocasio, Laamanen and Vaara, 2018: 160). New vocabularies create new categories and thus facilitate the creation of new ideas fitting those new categories. New corporate staff may encode new vocabularies into policies and goals, which serve as a source for variation in a corporation’s technology agenda (Loewenstein, Ocasio and Jones, 2012). Reprising these claims, research on discourse shows that a change in the language used in conversation is especially beneficial for ideational tasks (such as innovation) because it equips members with “new ways of interpreting shared problems and enables them to recombine ideas in new ways that yield novel solutions” (Lix, Goldberg, Srivastava and Valentine, 2021).

Finally, the addition of members at headquarters directly affects higher-order routines governing the use or recombination of lower-order routines. The latter refers to operational routines that correspond to innovation practices in the subunits, and the former refers to corporate meta-routines that directly modify the operational routines (March and Simon, 1958; Knott, 2001). Corporate newcomers in such roles as finance, human resources (HR), and general office management interact with incumbent members of the corporate office; the results of such interaction may include the addition or altering of meta-routines for a variety of complex processes such as recruiting or performance reviews and for initiatives aimed at training, quality, or innovation (Feldman and Pentland, 2003). An illustrative case in our setting is that starting in the 1980s, hundreds of newcomers to Motorola’s corporate training unit created a variety of new training programs for Motorola that dealt directly with technology development (Wiggenhorn, 1990). Such changes serve as managerial interventions that can disrupt subunits’ routinized activities related to technology development (Knott, 2001:432), prompting new technology trajectories.

In summary, we propose that the arrival of new members to the corporate staff leads to code updating, which in turn increases recombinant innovation. This suggests our first hypothesis:

Hypothesis 1a: A higher proportion of new staff members joining the corporate office is associated with a greater degree of novel recombinant innovation by a subunit.

Departures from the corporate office will also alter the code and increase recombinant innovation. However, unlike corporate arrivals, departures do not add new elements to the code directly. Rather, they provide opportunities for remaining members at the corporate office to modify the organizational code in
ways that were not possible prior to those departures. After corporate staff departures, dominant beliefs and corresponding vocabularies and routines may be altered as remaining members may revisit the current ways of doing business and to make changes that were previously unsupported by those who have departed. Thus, corporate departures function as a “release valve” that loosen constraints on the existing code. Departures provide opportunities for the members who remain to change the code by pursuing beliefs that were suppressed and actively adopting vocabularies and routines that were underutilized.

These corporate departure-driven code changes should increase recombinant innovation. Because departures may give remaining members an opportunity to express their beliefs about technologies that differ from the firm’s prevailing beliefs, it follows that the utilization of heterogeneous knowledge introduced by remaining members (particularly newer members who might be hesitant to raise novel or dissenting views against the corporate office) may sometimes occur only upon incumbent exit. Often these views are reflective of emerging technological areas that employees closer to the technological core recognize the importance of, but for which the corporate office has yet to embrace (Burgelman, 2002).

In these situations, subunit members have more freedom to pursue technological areas that were not supported by departing corporate staff. Tripsas and Gavetti’s (2000) analysis of Polaroid is illustrative. Turnover at Polaroid presaged a change in both beliefs and capabilities. Between 1996 and 1998, Polaroid saw a major departure of long-tenured top managers, and subsequently, the evolution of its capabilities and beliefs. The departing team’s “belief in large scale products with lengthy development cycles, had precluded investment in fast product development capability” (p. 1155). It was when the old corporate team departed that the firm became focused on rapid product development (Tripsas and Gavetti, 2000: 1157). Similarly, at Motorola, it was not until long-tenured executives left in in the mid-1990s that lower-level employees were able to significantly advance digital mobile phone technology. According to accounts at the time, “The rank and file were scared to death [to go against leadership]” (Bloomberg, 1998), and were unable to get their voices heard even as Nokia and Qualcomm’s digital phones took share from Motorola’s analog phones.

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Whereas such changes may occur through deliberate modifications of the current code, they may also occur through a less mindful but equally active process by which the current code is simply not maintained. In other words: with the departure of corporate members, components of the existing code may simply decay if decision makers forgo maintaining it. This is a form of forgetting which is defined as a loss of the code that is not planned or intended (Easterby-Smith and Lyles, 2011). For example, research shows that stories or narratives are prone to be forgotten following the dissolution of groups through which they circulated (Foroughi and Al-Amoudi, 2020). Feldman and Pentland (2003: 108) accordingly argue that, without proper maintenance (or continued performance) of existing routines, the associated standard operating procedures are likely to disintegrate. So even in the absence of any intentional efforts to change the code, the existing components of the code may deteriorate if many individuals depart.

Recombination may increase as a result because such deterioration through “forgetting” makes room for other unattended aspects of the code. That is, selective forgetting makes it easier for existing but underused vocabularies and routines to take hold. Forgetting may rid the organization of outdated corporate practices, and so remaining members can better engage in double-loop learning, which can provide a route to new avenues of research (Argyris, 1977; Easterby-Smith and Lyles, 2011). It is also the case that forgetting can make it easier for subunits to acquire “ownership” of the code and make it their own so that it fits their needs and interests (Hong, Easterby-Smith and Snell, 2006). In other words, forgetting may legitimize the adaptation and localization of code, which results in some loss of the original code and in the maintenance of variation in the code which may promote new knowledge recombinations.

In short, changes to the organizational code, which are a function of departures from the corporate office, lead to an increase in recombinant innovation. This suggests our next hypothesis:

**Hypothesis 1b:** A higher proportion of existing staff members departing the corporate office is associated with a greater degree of novel recombinant innovation by a subunit.

**Subunit staff turnover and recombinant innovation**

Our theorizing above suggests that arrivals and departures of corporate staff enhances recombinant innovation via changes to the organizational code. Next, we explain how turnover of staff in the subunit
fosters greater recombinant innovation. In particular, subunit arrivals may increase the diversity of knowledge available for technology and market development activities, and also prompt new interaction patterns among organizational members working on those technologies and activities (Miller et al., 2006).

Both technologists, which include engineers and scientists (inventors), and non-technical staff, which include a variety of subunit functional roles in manufacturing, marketing, sales, and distribution may impact the extent of recombination. Tasks related to a particular role can selectively activate different parts of the role occupants’ expertise and so influence the contributions to innovation that the role occupants make (Berg, 2016; Dahlander et al 2016; Higgins and Gulati 2016; Katila, Thatchenkery and Christensen, 2017).

New technologists bring with them knowledge that does not overlap the current technological knowledge of incumbent members (March, 1991). For example, Motorola recruited heavily from places, such as Bell Labs, Xerox, and IBM, in addition to hiring engineers directly out of college (Petrakis, 2003)—all of whom brought new knowledge to the firm. On top of that, new technologists are expected to find new solutions to the firm’s technology problems (and to find new technical problems). New technologists may bring and promote not only knowledge outside the firm’s core technologies, but also new routines for tackling problems within the firm’s core technologies which can help firms break from path dependent technology trajectories (Rosenkopf and Almeida, 2003; Song et al., 2003; Tzabbar, 2009).

New non-technical staff, who are co-located with technologists, may also serve as a source of new knowledge, although the expertise on which they draw is not necessarily technical (Fahrenkopf, Guo and Argote, 2020). Individuals in non-technical roles may bring unique customer perspectives and a more nuanced understanding of how the technology is used (Katila et al 2017). For instance, arriving members in non-technical roles may introduce new customers and a variety of new technical problems to the firm, which allows inventors to connect with new information, since new ideas often come from users of the technology (von Hippel, 1986). New non-technical staff may also create connections with new suppliers (Carnahan and Somaya, 2013), who can introduce new information associated with industry trends and competitive actions to increase organizational learning and open new avenues for innovation.
The arrival of newcomers can also disrupt existing subunit communication patterns between technical and non-technical staff. A disruption of such patterns creates opportunities for existing members to reflect on new ways of enacting their practices (Dittrich, Guérard, and Seidl, 2016), and may counter the inertia that can develop in firms that have deep experience with particular technologies (Sorensen and Stuart, 2000). For example, learning new technical grammar (Monteverde, 1995; Argyres, 1999)—communication about complex components and subsystems—creates new coordination patterns which may be especially useful in the pursuit of opportunities which involve novel recombination (Henderson and Clark, 1990). This dynamic is crucial for engineering discovery because the knowledge needed for recombinant innovation tends to be tacit and thus depends on close interactions (Miller et al., 2006).

In sum, the arrival of subunit staff, and their integration with existing staff, opens new avenues for recombination of technologies. These considerations motivate the following hypothesis.

**Hypothesis 2a:** A higher proportion of new members joining a subunit is associated with a greater degree of novel recombinant innovation in that subunit.

Irrespective of the arrival rate, the departure rate of subunit members can also increase the subunit’s output of recombinant innovations. Although this process does not introduce new knowledge, these departures may prompt remaining members to reflect upon and revise existing activities and knowledge. This may alter the direction of technology development as the subunit can advance new technology opportunities that were previously either not recognized or not supported.

For example, subunit departures can motivate a revision in routines. A subunit may update procedural routines involving the departed member’s task by replacing that task’s performer with another member or by omitting the task entirely (e.g., when there is no suitable replacement). When incumbent technologists see a colleague leave their subunit, they are conscious of the resulting operational gap and are motivated to adjust current tasks. In doing so, they re-examine current ways of doing things and, in the process, may find new technical problems and solutions. It is worth noting that recombinant innovation may benefit especially from disruptions to procedural routines, which can prevent exploitative practices from crowding out exploratory ones (Benner and Tushman, 2002).
Further, the loss of non-technical personnel may disrupt cozy external interfirm relationships, such as those with key suppliers or customers (Broshack and Block, 2014). This could have multiple effects on recombination. First, large customers often place stringent limits on the strategies and technologies that firms can and cannot pursue, inhibiting exploration (Christensen and Bower, 1986). The loss of customer-facing employees can disrupt those relationships and provide a window to reassess their technology portfolios. Second, because customer and supplier relationships may follow departing members, the loss of such employees can mean the loss of a potential source of uniqueness and differentiation. In turn, the focal subunit may face a loss of competitiveness and technological performance (Somaya et al., 2008), prompting remaining members to pursue new avenues of technology innovation to further differentiate their unit.

Finally, subunit departures may link previously unconnected individuals and create new communication partners—changes which enable interpersonal knowledge exchange and new knowledge combinations. Those who remain must find new communication patterns to address the communication gap created by departing members. This allows remaining members to access novel knowledge inputs from their peers and advance new technology combinations that may have previously been overlooked or rejected.

Hence, independent from our hypothesis about aggregate arrival of subunit staff and recombinant innovation, we posit the following hypothesis.

**Hypothesis 2b**: A higher proportion of staff members leaving a subunit is associated with a greater degree of novel recombinant innovation in that subunit.

**Corporate versus subunit turnover and recombinant innovation**

The aforementioned hypotheses suggest that both corporate and subunit member turnover (whether in the form of arrivals or departures) exhibit a positive association with recombinant innovation at the subunit level. Yet it may well be that the impact of turnover differs depending on where turnover occurs—that is, we should expect corporate and subunit turnover to have different magnitudes of effect on recombinant innovation. Because studies in this area typically ignore hierarchy altogether, we lack theory on how headquarters and subunits differentially affect the mutual individual–organizational learning needed to alter subunit-level innovative performance. Empirical studies often fail to detect how much of a subunit’s
performance is due to its own inputs versus those from corporate sources (McGahan and Porter, 1997). However, our data reveal turnover at both the corporate and subunit level, which allows us to compare the impact of both on recombinant innovation at the subunit level.

We argue that corporate turnover has a disproportionately stronger (positive) effect on recombinant innovation than does subunit turnover. This theoretical argument presupposes that corporate staff (in comparison with lower-level staff) learn more slowly from the organizational code but can update that code more rapidly. Slower learning benefits new corporate members because it prevents them from “converging” too soon on the existing code (March, 1991). That is, knowledge heterogeneity persists longer and so—in light of their slower learning—benefits recombinant innovation.

It is reasonable to expect that new corporate members (compared to new subunit members) may learn more slowly from the existing organizational code as they are separated from actual product markets and technological development activities and receive only aggregated data concerning those areas. Aggregation requires combining information at successive levels within the hierarchy which further abstracts from the details (March and Simon, 1958). Aggregation has been shown to foster more conservative decision-making behavior in organizations (Csaszar and Eggers, 2013), and may slow the learning process for individual (especially new) members of the corporate office.

Moreover, the corporate office can update the code more swiftly than can subunits because it has more control over the code’s components as well as the means to socialize newcomers. Departures from the corporate staff pave the way for previously frustrated existing corporate and subunit members to express their ideas; hence, such departures may have the greatest and swiftest impact on the existing code. Since remaining members may have greater legitimacy and are familiar with the inner workings of the firm and how to get things done (Karim and Williams, 2012), they can quickly change organizational features such as vocabularies (e.g., by emphasizing quality), roles (e.g., by adding a corporate sustainability executive), processes (e.g., by instituting a Six Sigma program), or resource allocation rules.

The corporate office may also facilitate diffusion of code changes by way of training, manuals, HR policies, and dedicated meetings. Such a top-down approach to code change is likely more influential than
an emergent process that originates through direct interactions within subunits. By leveraging hierarchical authority, corporate members can alter the criteria by which R&D efforts are evaluated and resourced. These interventions give corporate headquarters a greater ability to affect the direction and intensity of technological recombination, which leads to our final hypothesis.

**Hypothesis 3:** Corporate staff turnover is more strongly associated with novel recombinant innovation in a focal subunit than is staff turnover within that subunit.

**METHODS**

We test our hypotheses using aggregate employee turnover and patent data from Motorola for the period 1974–1997, during which the firm was a leading manufacturer of telecommunications electronics. Motorola offers an advantageous context for our research purposes in that the telecommunications sector is a high-velocity industry characterized by rapid innovation which dictates the need for recombinant innovations. In addition, this single-firm setting allows for variation in the conditions of interest (i.e., turnover, patenting) while controlling for common firm factors (e.g., incentives, propensity to patent, top management) and ensuring that the firm’s broad technological domain varies little over time. More significantly, this setting allows us to examine differential roles of corporate versus subunit turnover as well as code change (an underlying mechanism) by virtue of our unique access to intrafirm data spanning different levels of analysis (i.e., subunits and corporate) that would be otherwise unavailable in a multi-firm study.

During the study period, Motorola had a multi-level hierarchical structure that included a corporate office and seven business sectors, each of which developed communications-related technologies. Each sector included a variety of individual subunits (i.e., locations) spread throughout the United States, many of which were responsible for developing new technologies and served as our unit of analysis. This set-up provides assurance that variations in recombinant innovation by subunits reflect effects not only at the corporate level but also at the subunit level.

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2 We limit our observations to subunits that applied for at least one patent per year (i.e., “innovative” units) and that had been in existence for at least five years. In this way, we ensured that the included subunits experienced sufficient turnover and changes in innovation. We considered three years as the minimum existence period for subunits, and both three and five patents as the minimum number per year; our findings are robust to these alternative cut-offs. This sampling approach yielded 195 subunit–year observations.
Variables

Dependent variable: Novel recombinant innovation. Our dependent variable for all of the hypotheses is novel recombinant innovation at the subunit level. We follow the approach of Fleming and Sorenson (2004), who use patent data to observe recombination. Hsu and Lim (2014) adapt this approach to study recombinant innovation processes. The principal strength of this measure is that it allows us to characterize particular patterns of recombination as more or less novel; in other words, we can determine the extent to which the firm previously combined technological components. After collecting patent data from the National Bureau of Economic Research (NBER) patent database (Hall, Jaffe, and Trajtenberg, 2001), we used the information on the patents applied for by Motorola from 1963 to 1998 to create a panel data set for each of the firm’s subunit locations. Our dependent variable specifically reflects the extent to which the focal subunit applied for patents containing subclasses that were not likely to be combined with each other.

This variable was calculated in three stages, the first two of which followed Fleming and Sorenson (2004). First, as summarized in Equation (1), we computed the average likelihood \( E_c \) that an individual subclass \( c \) was combined with other subclasses per patent. Note that \( E_c \) is increasing in the average number of other subclasses with which subclass \( c \) is combined; put differently, \( E_c \) reflects the ease of recombining subclass \( c \) with other subclasses:

\[
E_c = \frac{\text{\# of subclasses previously combined with subclass } c}{\text{\# of previous patents in subclass } c}.
\]  

Second, we calculated a patent-level score indicating the extent to which patent \( j \) was created using subclasses that were not likely to be combined with others. We then averaged the \( E_c \) scores of all the subclasses on patent \( j \) and took the inverse, thereby creating the patent-level score \( K_j \); see Equation (2). The value of \( K_j \) increases with the extent to which the subclasses present in patent \( j \) are, on average, more difficult to combine with other subclasses. In essence, a high \( K_j \) score indicates that patent \( j \) is a novel recombinant patent because it combines subclasses that are unlikely to be combined with each other (Fleming and Sorenson, 2001, 2004):
\[ K_j = \frac{\# \text{of subclasses on patent } j}{\sum_{c \in j} E_c}. \] (2)

In the third stage of calculating this variable, we aggregated the Fleming and Sorenson (2004) measure at the subunit level of analysis; thus, we computed the extent to which patent applications belonging to a focal subunit were, on average, recombinant. We assigned patents to their respective primary subunits (their “home lab” location) by using information on the identity of the patent’s first listed inventor, in line with other research that has assigned patents to locations (Stolpe, 2002; Sorenson and Fleming, 2004). Motorola’s annual employee directories were used to identify inventors’ subunit affiliation. To calculate subunit-level recombinant innovation, we averaged the \( K_j \) scores of all patents applied for at a focal subunit \( i \) during year \( t \); see Equation (3). Recall that a high \( K_j \) value means that each patent applied for by focal subunit \( i \) consists of subclass combinations that are, on average, unlikely to occur. Simply put, a subunit with a high score in this dependent variable produces patents with novel recombinant innovation:

\[
(Novel \text{ recombinant innovation})_{i,t} = \frac{\sum_{j \in i} K_j}{\# \text{of patents by subunit } i \text{ in year } t}.
\] (3)

**Independent variables.** One of our study’s chief empirical tasks was to measure the aggregate turnover that occurred at the corporate office and within individual subunit locations. This task required us (a) to access data that tracked every individual’s annual personnel status during the observation period and then (b) to observe how many new members joined and how many existing members departed a focal unit (either the corporate office or subunit, as applies) in the sample every year. We obtained a set of annual directories of every Motorola employee working in the United States, which contained each person’s full name and affiliated location (i.e., corporate office or subunit location).³

After creating the complete list of employees working in the corporate office or in subunits each year, we generated 4 turnover variables for hypotheses testing and 8 variables for supplementary analyses. The construction of these variables followed an approach widely used in empirical studies on turnover (see

³ These directories listed only regular employees, so our turnover measure reflects the arrivals and departures only of permanent (i.e., not temporary) employees. Because we identify departure on the basis of directory data, we are unable to distinguish between voluntary and involuntary turnover; this is an issue common to prior studies on turnover (e.g., Kacmar et al., 2006; Ton and Huckman, 2008).
e.g., Kacmar et al., 2006; Ton and Huckman, 2008); the variables to test our hypotheses included arrival and departure rates at both the corporate office and the subunits. Corporate *arrivals* were defined as total number of individuals who were absent from the corporate staff directory in year t – 1 but appeared in the corporate directory in year t. Corporate *departures* were defined as total staff members who were listed by the corporate staff directory in year t – 1 but were absent from the entire directory in year t. Subunit *arrivals* were defined as total number of subunit members who were absent from the directory of a subunit location i in year t – 1 but were listed by subunit i’s directory in year t, while subunit *departures* were defined as all those who were listed by subunit i’s directory in year t – 1 but were absent from the entire directory in year t. Table 1 lists each of our turnover variables and the formula used to construct them.

Control variables. Our controls yield insights into alternative mechanisms that may be associated with recombinant innovation at individual subunits. The decision to incorporate these controls was motivated by our discussions with managers at Motorola, internal documentation, and the extant literature (e.g., Fabrizio, 2009; Kogan et al., 2017). To proxy for a focal subunit’s performance, we controlled for *subunit patent value*, the estimated value of patents applied for by a subunit in a given year. Controlling for subunit performance is necessary because it could affect both turnover and recombinant innovation. However, performance data (e.g., revenue, profit) were unavailable at the subunit level because many of the subunits involved in innovation do not directly generate revenue. The value of the technology these units create reflects their impact on the firm’s financial performance. We estimated subunit patent value using the measure developed by Kogan et al. (2017)—which estimates the market value of individual patents by examining the volatility of firm returns around patent announcement days—aggregated to the subunit–year.

We also controlled for *subunit age*, measured as the difference between the focal year and the year when a subunit was created, to accommodate the notion that older subunits are more likely to have learning experience (Argote and Miron-Spektor, 2011). We controlled for *subunit size*, calculated as the logarithm of the square footage of the subunit facility as listed in the corporate directories. While research widely uses the number of employees as proxy for organizational size, number of employees was already used as the
denominator of our turnover variables. Therefore, we instead followed prior studies adopting the square 
footage as a proxy for subunit-level size in their organizational setting (e.g., Shaw et al., 2013). Data on 
square footage was obtained from municipal property records. We also controlled for performance at the 
sector level (sector sales). A sector consists of multiple subunits and so is higher in the hierarchy than 
subunits. Controlling for sector sales is helpful because a subunit’s turnover and innovation activities are 
likely to be influenced by the resource availability of its upper-level organization.

Following the literature on patent innovation (e.g., Fabrizio, 2009), we included a number of 
controls that capture subunit-level patent characteristics. First, we operationalized star scientist presence as 
a dummy variable where subunits with at least one star scientist in a given year were coded as “1” and other 
subunits were coded “0” (The calculation of this variable is specified in Appendix A). Further, we 
controlled for the average number of citations to prior art (Average # of citations per patent)—or for the 
average “size” of a subunit’s patents, as patents that cite more prior art may be larger in their content and 
scale and so may take longer to develop. We also controlled for the average number of claims in a subunit’s 
patents (Average # of claims per patent) to adjust for variations in patent scope that may be reflected in the 
number of claims. Another control variable was for the total number of citations to the firm’s own patents 
within a subunit–year (# of self-citations in subunit–year). We employed a technology class–year-level 
control variable that considered changes in the industry’s technology area over time. Finally, we included a 
control for the total number of patents in the technology class: # of patents in technology class.

Model specification and estimation

We used a linear regression model to estimate the parameters. We also adopted a subunit random-effects 
model in light of the result of a Hausman test, which showed that unobserved time-invariant characteristics 
at the subunit level were not significantly correlated with our covariates in the regression model (Long and 
Freese, 2005). In addition, we conducted a Chow test to ensure that a subunit random-effects model yielded 
the best fit with our data (Long and Freese, 2005). The result of this test indicated that the relationship 
between turnover variables and our dependent variable was not sensitive to the regression’s inclusion of
subunit dummies. Although we report our results using a subunit random-effects model (see Table 3 in the next section), these results were robust to using a subunit fixed-effects model instead.

Because our data consisted of subunits with repeated observations over 24 years, the data structure was subject to serial autocorrelation. This issue was addressed by using robust standard errors clustered at the subunit level. It was also necessary to leave a time interval during which the effect of turnover could become manifest in the extent of recombinant innovation by subunits. We therefore estimated models with a one-year lag between our dependent variable and the covariates. Lagging by one year (rather than by a three-year or longer period) facilitates capturing a more direct effect of the code mechanism that stems from turnover. Our findings were also robust to the use of a two-year lag. Note that our dependent variable considers patent application date rather than issuance date.

RESULTS

Table 2 presents the mean values, standard deviations (SDs), and correlations among the variables included in our analyses. The mean score of our dependent variable is 0.52, which is slightly lower than the 0.63 observed by Fleming and Sorenson (2004) in their multi-industry sample. The low correlations between arrivals and departures indicate that these events occurred, for the most part, independently of each other at both the subunit level ($\rho = -0.17$) and the corporate office level ($\rho = -0.18$). At both of these levels, new members arrived at a higher average rate than departing members left. The implication is that we examined the company during a period of its overall growth, though firm performance varied over the period.

Table 3 reports the estimates of recombinant innovation across subunits during the observation period. We present 10 models to evaluate our hypotheses. The calculated mean variance inflation factor score, 2.13, in Model 10 indicates that our models did not have serious issues with multicollinearity.

Model 1 reflects how control variables are relevant for a focal subunit’s recombinant innovation. We test Hypothesis 1a in Model 2. This hypothesis proposes that corporate staff arrivals are associated with an increase in recombinant innovation by individual subunits. The positive and significant coefficient ($b = 1.855; p < 0.01$) for the corporate staff arrivals variable suggests that as the proportion of new staff
members in the corporate office increases, individual subunits become more likely to apply for patents involving combinations unlikely to occur among subclasses. Yet when corporate staff departures is included in Models 4 and 10, the coefficient for corporate staff arrivals becomes insignificant. In short, Hypothesis 1a was marginally supported.

We test Hypothesis 1b in Model 3. This hypothesis proposes that corporate staff departures contribute to recombinant innovation by subunits. We find the coefficient for corporate staff departures to be positive and significant ($b = 3.386; p < 0.01$). Even after controlling for corporate staff arrivals, we still find a positive and significant coefficient in Model 4 ($b = 2.679; p < 0.001$). In Model 10, a focal subunit experienced a $0.08 \times 2.813 = 22.50\%$ increase in the average level of novel recombinant innovation in patents applied for during year $t + 1$ when the rate of year $t$ corporate staff departures increased by 1 $SD$ (i.e., by 0.08). Thus, we find empirical evidence in support of Hypothesis 1b.

Model 5 is used to test Hypothesis 2a. This model examines the relationship between the rate of new members joining a focal subunit and the recombinant innovation by that subunit. We find that the coefficient for subunit member arrivals is not statistically significant ($b = 0.001; p = 0.997$). The coefficient of member arrivals was also non-significant in Models 7, 8, and 10, so Hypothesis 2a was not supported.

We use Model 6 to test Hypothesis 2b, which posits that a higher proportion of members leaving a subunit is associated with a greater extent of novel recombinant innovation in that subunit. In Model 7 the coefficient for subunit member departures remains both positive and significant ($b = 0.081; p < 0.001$). In model 10, subunits experience a $0.17 \times 0.081 = 1.37\%$ increase in the novelty of recombinant innovation—as reflected in the patents for which it applied during year $t$—when the member departure rate increases during year $t - 1$ by 1 $SD$, or by 0.17 (as when a subunit with 100 members loses 17 employees). We therefore find evidence in support of Hypothesis 2b.

According to Hypothesis 3, corporate staff turnover (both arrivals and departures) has a greater association with novel recombinant innovation by subunits than does the turnover of those subunits’ own members. To test this hypothesis, we first include all four turnover variables in Model 10 and compute “standardized” coefficients ($\beta$) for them in order to normalize the differences in the unit of measurement.
among those variables. Next, we conduct Wald tests to examine whether the standardized coefficient for corporate staff arrivals ($\beta = 0.063$; $p = 0.086$) differs significantly from that for subunit member arrivals ($\beta = 0.005$; $p = 0.442$) and whether the standardized coefficient for corporate staff departures ($\beta = 0.203$; $p = 0.000$) differs significantly from that for subunit member departures ($\beta = 0.026$; $p = 0.006$). The results of this test suggest that corporate staff departures are more strongly associated with novelty in recombinant innovation than are subunit member departures ($F = 13.18$; $p = 0.000$). However, we do not find empirical evidence that the coefficient of corporate staff arrivals on novel recombinant innovation differs meaningfully from that of the subunit member arrivals ($F = 2.89$; $p = 0.108$).

Figure 1 illustrates these results using the estimates derived from Table 3’s Model 10. In particular, the figure shows how novel recombinant innovation at a subunit changes in response to a 1 SD change in turnover at the subunit level and also at the corporate level. The vertical axis corresponds to values of our dependent variable (novel recombinant innovation) and the horizontal axis indicates the normalized range of each of the four turnover variables (i.e., from 1 SD below its mean to 1 SD above its mean). The slope of corporate staff departures (marked by diamonds) is the greatest. In accord with the standardized coefficient derived from Model 10, the magnitude of the improvement in the dependent variable is more strongly affected by corporate departures than by any other turnover variable—even though the extent of novel recombinant innovation also changes in concert with a change in the rate of subunit departures (marked by triangles). Consistent with the insignificant coefficients both for corporate staff arrivals (rectangles) and for subunit-level member arrivals (circles) in Model 10, neither factor has a statistically significant association with novel recombinant innovation. In sum, we find empirical evidence that the corporate-level effect, in terms of departures, is greater than the subunit-level effect. Therefore, Hypothesis 3 is supported.

Supplementary analyses: Organizational code as a mechanism

The key finding in this study is that corporate departures are most strongly associated with recombinant innovation by subunits. We have theorized that the role of corporate departures is driven by the code-breaking mechanism. To test this mechanism more directly, we used the Linguistic Inquiry and Word Count
(LIWC) lexicon (Pennebaker et al., 2007) to conduct an analysis of code change within the firm based on internal corporate memos written by corporate staff members.

Although the organizational code cannot be captured with a single variable, empirical studies have recognized the use of language as a realistic approach to measuring that code—if one assumes that corporate staff members’ thoughts and words reflect the organizational code (Goldberg et al., 2016; Srivastava et al., 2018). The LIWC lexicon is useful for coding textual data in terms of a pre-defined set of categories that represent affective, social, and cognitive processes. The LIWC has become a widely adopted textual analysis framework to capture meaning and linguistic style in natural text. To accurately capture the language aspect of the code, we assessed all memos \((n = 882)\) sent from Motorola’s corporate office to the “executive briefing” list, which included all executives at the vice-president level and above. These memos discuss a wide variety of organizational, operational, and strategic issues and cover the period 1979–1997.

With these Motorola data, we were able to test two relationships critical to our mechanism of code change: first, that the code does indeed change in response to corporate arrivals and departures; and second, that the relationship between corporate arrivals and departures and recombinant innovation is at least partially, if not fully, explained by code change. If the role of corporate turnover—especially corporate departure—for recombinant innovation is described by changes to the organizational code, then two things should be discovered: (1) corporate turnover should be a statistically significant predictor of code change; and (2) its relevance for recombinant innovation should weaken when included in a regression alongside our code change variable (Baron and Kenny, 1986). These theoretical possibilities were borne out in our data. The results of our analyses are presented in Figure 2 and Table 4.

Figure 2 plots the results from testing for whether corporate arrivals and departures predict code change. To measure a change in the language used by corporate staff members, we first “tokenized” all the corporate executive memos announced during year \(t\) into the LIWC’s 40 category frequencies—as an indicator of the yearly pattern of corporate staff language—and created a probability distribution with the normalized frequencies (cf. Srivastava et al., 2018). We then captured the degree of the change in that
frequency distribution by applying a measure of cosine similarity (Singhal, 2001). Finally, we created a variable, *corporate language dissimilarity*, by subtracting the cosine similarity score from 1. We used this variable as a proxy for code change. High values indicate that corporate staff language between years $t$ and $t + 1$ is dissimilar in terms of the LIWC vocabulary categories. Next, we conducted a path analysis to examine whether corporate arrivals and departures are associated with corporate language dissimilarity (i.e., code change). The turnover and code variables were all at the corporate level and so the number of observations was limited to the number of years in our study, which precluded our running a regression analysis. Figure 2 reveals that corporate departures predict the code change. Corporate language changed in response to member departures but not in response to new staff joining the corporate office.

Table 4 presents results from our testing for whether code change is significantly associated with recombinant innovation by subunits—including our corporate turnover measures, which we expect to weaken when incorporated with our code-change measure. In this table (as in Table 3), the dependent variable is novel recombinant innovation by subunits. Models 11 and 13 report, for purposes of comparison, the main effects of corporate staff arrivals and departures on novel recombinant innovation. The *corporate language dissimilarity* variable was significant both in Model 12 ($p < 0.01$) and in Model 14 ($p < 0.05$), which suggests that code change predicts novel recombinant innovation. Furthermore, we find diminished effect size for corporate departures when *corporate language dissimilarity* is included in the regression. Moving from Model 13 to Model 14, we can see that the coefficient for the corporate departure variable was substantially reduced in magnitude (from 12.957 to 0.839) when the language variable was included.

In sum, Figure 2 and Table 4 together suggest that: (1) corporate departures predict code change; (2) code change predicts recombinant innovation; and (3) the relationship between corporate departures and recombinant innovation is captured, in part, by changes to the corporate code. In short, this role of the code is consistent both with our theoretical mechanism and with March’s (1991) mutual learning model.

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4 Because the frequency distribution over the LIWC’s 40 categories was presented in the form of a 40-dimensional vector, we used the measure of cosine similarity to capture similarity—between the two frequency vectors (at years $t$ and $t + 1$)—in their respective orientations.
Supplementary analyses: External vs. internal arrivals

Although our preceding results support the relevance of the departures of corporate and subunit staff, the main effect of arrivals for Hypothesis 1a is not fully robust and we did not find support for Hypothesis 2a. We theorized that new staff members joining the firm increase novel recombinant innovation because they introduce new elements to the organizational code, while internal transfer of employees can effectively transfer existing knowledge within the firm (Stadler, Helfat, and Verona 2022). Given this rationale, it seems reasonable to expect that staff members who enter from outside the firm (rather than members who move internally) should have more impact on code updating and on recombinant innovation.

In a separate analysis, we found empirical evidence that shows that a higher proportion of new staff members at both the corporate and subunit levels joining from outside the firm is indeed associated with a greater extent of novel recombinant innovation by a subunit; Table 5 presents the results of this analysis. The positive and significant coefficient for corporate external staff arrivals ($p < 0.05$) in Model 15 indicates that, as the rate of new staff who join the corporate office from outside the firm increases, subunits produce recombinant innovation with a higher level of novelty. In Model 16, the coefficient for subunit external member arrivals is positive and significant ($p < 0.01$); in other words, as external newcomers become more prevalent in subunits, the novelty of recombinant innovation at those subunits increases.

Interestingly, we find that the effect for internal arrivals both for corporate staff and subunit members is negative. This result indicates that, as more employees join the corporate office or a focal subunit from inside the firm, the novelty of subunits’ recombinant innovation rather declines. Insiders may simply recirculate the current code and faithfully conform to existing agendas and strategic directions, which reinforces existing activities and thus constrains the pursuit of novel innovation by subunits. This finding is consistent with the argument of Karim and Williams (2012) that employees transferring within the firm retain “structural knowledge,” which leads them to move and work in the organization in accordance with familiar practices and routines. In sum, the supplementary analyses in Models 15 and 16 show that the benefit of newcomers for recombinant innovation is associated more with outsiders than with insiders.
Supplementary analyses: Technical vs. Non-technical member turnover

In line with our theory, we also conducted a supplementary analysis on subunit turnover in terms of technical versus non-technical members. Our findings on corporate-level turnover suggest that turnover affecting innovation is not necessarily driven only by employees who directly engage in patenting activities but also by non-technical employees who affect the code (i.e., corporate staff members). If our code mechanism indeed works, the role of turnover for innovation does not have to be explained only by members who participate in patent activities. That is, turnover (particularly, departures) of non-technical members at the subunit level may also have relevance for recombinant innovation by their subunit. Although non-technical members do not directly participate in patenting activities, their turnover should still play a role for technical members’ innovation by affecting code change at their subunit.

To explore this possibility more fully, we separated turnover for technical and non-technical members.\(^5\) We identified technical members as individuals who had patented at some point in their career at Motorola; in order to do so, we matched inventor names from all Motorola patents from 1963 onwards to the directories during our observation period. Subunit technical member arrivals were defined as technical members (i.e., employees who authored patents prior to the focal year) who joined the focal subunit during the year. Subunit technical member departures were defined as technical members who departed a focal subunit during the year. Non-technical members were employees who did not author any patents before the focal year. Subunit non-technical member arrivals were counted as non-technical members who joined a focal subunit during the year, while subunit non-technical member departures were defined as non-technical members who left the focal subunit during the year.

Models 17 and 18 in Table 5 present findings on technical and non-technical members’ arrivals and departures. Model 17 shows that as new technical members joined a focal subunit, recombinant innovation at that subunit increased as indicated by the positive, significant coefficient of subunit technical member arrivals \((p < 0.05)\). New non-technical members, however, were not relevant for novel innovation by their

\(^5\) We use the term “technical staff” in lieu of the more common term “scientist” given the focus on engineering at Motorola during our study period.
subunit, as indicated by the insignificant coefficient of *subunit non-technical member arrivals* in Model 18. This finding confirms the traditional idea in turnover research that the way new members spur innovation is by bringing new knowledge and perspectives. Because non-technical members do not bring new inputs directly relevant to patenting activities, their arrivals do not have relevance for subsequent innovation.

On the other hand, Model 18 indicates that the role of departures for novel innovation is explained by non-technical members rather than technical ones, as indicated by the positive, significant coefficient of *subunit non-technical member departures* (*p* < 0.001). This finding is well explained by our code mechanism, consistent with the finding that the departures of corporate staff, who also have a non-technical role, have a strong association with subunit recombination. To the extent that non-technical members form priorities, goals, and beliefs on R&D activities, their departures may allow remaining technical members to pursue technological agendas that were not supported by those leavers. However, the departures of technical members do not have relevance, as indicated by the insignificant coefficient of *subunit technical member departures* in Model 17. Technologist departures may change how remaining technical members conduct patenting activities in similar ways to non-technical member departures. But the departures of technical members may lead to the loss of knowledge specific to patenting activities, offsetting effects on code change.

**Endogeneity issues**

The analyses so far have sought to present empirical evidence in support of our hypotheses and in support of code change (by the departure of corporate staff members) as a primary mechanism through which turnover affects subunit recombinant innovation. Yet our findings could also support alternative explanations. For instance, prior studies suggest that a subunit with poor performance may change its own membership and thus be incentivized to promote novel innovation (Groysberg and Lee, 2009; Godart et al., 2014). Alternative explanations of this nature are driven by endogeneity (Stern et al., 2021), so we conducted additional analyses to address concerns about causal inference regarding the relationships between turnover (at both the subunit and corporate level) and recombinant innovation.
For these purposes, we started by considering the endogeneity of subunit-level turnover. To do so in a systematic fashion, we adopted the generalized propensity score (GPS) method (Imbens, 2000). The full description of the GPS method and results using this analysis are reported in Appendix B. In short, we found that our findings (particularly, Hypothesis 2b) are robust to the use of the GPS method.

We also considered the endogeneity of corporate-level turnover. One alternative explanation is that, when the corporate office had a strategic plan or intent to improve firm-level innovation, it may have directed staff turnover and thus impelled subunits to pursue innovation. We could not use econometric techniques because our data did not allow the corporate-level turnover variables to serve as dependent variables in a model with subunit-level covariates. However, we believe that our findings are less subject to such an alternative explanation. The corporate office, when seeking to “renew” the organization, is more likely to devise a hiring than a firing approach to spurring subunit-level innovation (cf. Karim and Williams, 2012), especially given Motorola’s family environment and emphasis on human resources during the period (Petrakis, 2003). Corporate layoffs normally occur when organizations wish to improve efficiency and save operating costs (Neinstedt, 1989). Consequently, if a third unobservable variable drives both corporate staff turnover and subunit-level recombinant innovation, that variable is more likely to affect corporate staff arrivals rather than departures. Thus, our key finding—the positive relationship between corporate departures and subunit innovation—is unlikely subject to endogeneity concerns.

DISCUSSION

This study examined how organizational learning and innovation is affected by member turnover within a corporate hierarchy. We found that aggregate corporate and subunit departures are positively associated with novel recombinant innovation. Our findings suggest that, although the influx of new ideas through arrivals may be important, breaking the pattern of inertial behavior through departures is even more important for the recombination of technological components. Moreover, it appears that the role of corporate departures is relevant for recombinant innovation more than that of the departures of rank-and-file organization members; we theorize that this outcome reflects corporate staff members’ slower individual learning and their ability to update the organizational code more quickly.
In a post hoc analysis, we examined the mechanism of code change. Using internal memos written by corporate executives and viewing their language as a component of the organizational code, we showed that corporate staff members changed the pattern of their language use (specifically, the frequency distribution of words across different LIWC vocabulary categories) when corporate departures occurred. Further, our textual data analysis revealed that such changes in language patterns explained some of the relationship between corporate departures and recombinant innovation, as we originally hypothesized. Both findings lend greater credence to our theoretical claim that the role of turnover (and corporate departures in particular) for innovation is explained, in part, by how much the organizational code changes in response to turnover. The theoretical validity of our code mechanism is further supported by the finding that the role of subunit member departures is explained by non-technical members, who did not participate in patenting activities, rather than by technologists (i.e., inventors). Our supplementary analysis was also informative, as it showed that corporate and subunit newcomers from outside the firm have a positive association with recombinant innovation, whereas newcomers from other units within the firm have a negative impact because they are simply recirculating commonly held knowledge.

With these findings, our paper makes several contributions. First, its examination of all Motorola U.S. employees from 1974 to 1997 enhances our understanding of how corporate hierarchies shape organizational learning in support of recombinant innovation. The salience of organizational learning in innovation is well established in the literature (see e.g., Argote and Miron-Spektor, 2011). However, much of that research abstracts from the concerns of multi-level firms and from the possible cross-level effects of headquarters on subunits. We address this gap in the research by advancing March’s (1991) mutual learning model, whereby turnover fuels learning between individuals and the organization in which they work; recombinant innovation is a function of such learning. While prior studies have improved on March’s model (e.g., Miller et al., 2006; Fang et al., 2010), neither agent-based models nor empirical work has theorized about or tested the corporate hierarchy’s role in terms of both aggregate arrivals and departures. This combination is crucial because it informs our theory of learning within a hierarchy. Proposing a theory of learning within corporate hierarchies, as we do in this study, requires consideration of the distinct learning
mechanisms attributed to arrivals and departures and of the differences in learning rates across the firm’s hierarchical levels. We argue that the corporate level has different learning properties than the subunit level. Learning is likely to be relatively slower at higher levels of the firm, given the greater aggregation of information at those levels (Csaszar and Eggers, 2013), their distance from the technological environment (Thompson, 1967), and the ambiguity of environmental signals (Gavetti, 2005). As a function of their roles, corporate staff can more swiftly update (than subunits can) aspects of the code that directly relate to recombinant innovation including beliefs, vocabularies, and routines. Our findings suggest that even though change may occur from the bottom up, it is more substantive when it happens from the top down (i.e., via corporate staff turnover). In this sense, we contribute more generally to research that emphasizes the considerable effect of managerial cognition on innovation (Eggers and Kaplan, 2009; Gavetti et al., 2012).

Second, by linking corporate hierarchy and turnover to innovation, our study contributes to the literatures on organization design and innovation. Research examines the link between organizational structure and performance and has identified the trade-offs, within complex organizations, between modularity and integration (Davis, Eisenhardt, and Bingham, 2009). One such line of inquiry views organizations as knowledge hierarchies that serve to manage exceptions and to match problems with solutions. More difficult or complex problems are referred up the hierarchy to be handled by specialized problem solvers. Another stream of research conceives of hierarchy as an information aggregation structure whose chief role is to validate proposals elevated within the organization in support of exploration and exploitation (Csaszar, 2012, 2013; Csaszar and Eggers, 2013; Keum and See, 2017). Most relevant to our research is the literature that takes cognition in hierarchical organizational forms as a central explanatory variable (Gavetti, 2005; Siggelkow and Rivkin, 2006; Jacobides, 2007). Of interest in these studies are the cross-level effects (a) that higher-level choice sets have on lower-level decisions (Siggelkow and Rivkin, 2006) and (b) that corporate-level interpretations and responses to feedback have on innovation-related outcomes at the subunit level (Gaba and Joseph, 2013; Joseph and Wilson, 2018).

Our paper complements these studies and offers new insights into how the cross-level effects between headquarters and subunits affect the latter’s behavior. By considering the role of corporate staff
turnover, we argue that a cross-level framework can help us identify a turnover mechanism that drives recombinant innovation at the subunit level. It follows that we can also learn from revisiting firm turnover as an organization design problem. Doing so points to a closer correspondence between Simon’s (1976) emphasis on hierarchy and decision premises and March’s (1991) emphasis on learning—thereby answering the call of scholars to reintegrate organizational structure into the behavioral foundations of the Carnegie tradition (Gavetti, Levinthal, and Ocasio, 2007).

We remark that our results align with previous research on strategic human capital (cf. Mawdsley and Somaya, 2016), inter-/intra-firm mobility (Tzabbar and Cirillo, 2020) and resource redeployment (Folta, Helfat and Karim, 2016), which has established that firms can access new knowledge through their hiring choices (Song et al., 2003; Fahrenkopf et al, 2020). For example, firms are more likely to draw on the technological knowledge of another firm after hiring inventors from that firm (Rosenkopf and Almeida, 2003), although this finding depends on the collaborative nature of those inventors (Tzabbar, 2009). An organization may also use the new knowledge provided by hires to re-evaluate aspects of its operations. In particular, our supplementary analysis, which highlights the benefits of external arrivals, strongly supports the conventional wisdom in this area of study. Further, the findings that the arrival of new technologists is beneficial suggest that while they may bring and advance new ideas – newly hired non-technical folks may not bring in new large customers or suppliers (although the departure of non-technical members can mean the loss of customers and suppliers). More generally, it suggests that managers may want to consider a broader range of membership changes when seeking to drive innovation and that scholars may want to consider different types of human capital more closely.

**Limitations and future research**

Like any study, this paper is subject to limitations which provide promising avenues for future research. First, we acknowledge that our empirical setting is a single firm which may limit generalizability. However, Motorola was a large firm that operated in multiple industries (e.g., semiconductors, telecommunications, automotive components) and, given the long period of observation, the variation we tracked in both left hand side and ride hand side variables was considerable. We also found, in separate
analysis, that Motorola was very similar to peer companies (e.g., AT&T, IBM, GE and Kodak) in terms of revenues and patenting rates over our observation period, which offers us greater confidence that the turnover and innovation patterns at Motorola may be more widely observed.

Second, we acknowledge that, notwithstanding the valuable code-updating and code-breaking insights offered here, more work needs to be done in this area. Research shows that a firm will monitor the work of departing inventors and can sometimes thereby leverage their knowledge even after they leave for another firm. For example, Godart et al. (2014) show that moderately weak ties with recently departed employees can be especially helpful in bringing new knowledge into the firm. Yet, unlike those authors, we focus on an organization that was a technology leader in most of the markets in which it competed. Hence, while some knowledge may have been acquired by departures, much of it was likely developed internally, and greater distinctions between code updating and code breaking are needed. We believe that our study is a useful start in this area, but more investigation is needed to refine these concepts.

Third, it is likely that old beliefs, language, and practices do not all update or deteriorate at the same rate and that these different rates affect the degree to which inertia affects technology decisions. While our data yielded insights on language change at the corporate level, they did not enable measurement of subunit language change or other code components; hence, scholars should view these as opportunities for further empirical research. Moreover, there is likely to be a threshold beyond which the rates of departures and arrivals become detrimental (because of their disruptive qualities) rather than beneficial. Although Motorola may have developed means of remaining below this upper bound, that possibility is not addressed by our empirical approach; yet it certainly merits exploration. Further, future research could profitably articulate the differences between voluntary and involuntary turnover or examine more closely the turnover rates associated with particular organizational roles.

Conclusion

Managing turnover is a vital capability for firms and a fundamental consideration for managers. It is therefore notable that the single most important move a firm can make to spur recombinant innovation is to regularly cull its corporate staff. Managers have long focused on downsizing corporate headquarters when
performance takes a turn for the worse. In most cases, these decisions are made in order to cut costs from non-revenue-generating areas or to improve the speed of decision making within a bureaucratic corporate apparatus. Yet, Motorola was growing during the period of our study, did not experience any major divestitures, and was generally successful; these facts indicate that the power of such layoffs may lie more in code breaking than in simply cutting costs. Thus, in addition to adding new scientists, corporate departures can become a mechanism for disrupting cognitive logjams in the innovation process as well as an indispensable component of managing human resources in technology-intensive firms.

REFERENCES


Table 1. Subunit and Corporate Turnover Variables and Formulas

<table>
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<tr>
<th>Variables</th>
<th>Formula ((i = \text{subunit}, t = \text{year}))</th>
<th>Variables</th>
<th>Formula ((i = \text{subunit}, t = \text{year}))</th>
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<td>Corporate staff arrivals (H1a)</td>
<td>Corporate arrivals(<em>i) _Corporate employees(</em>{i,t})</td>
<td>Subunit external member arrivals</td>
<td>Subunit Employees(<em>{i,t}) Internal subunit arrivals(</em>{i,t})</td>
</tr>
<tr>
<td>Corporate staff departures (H1b)</td>
<td>Corporate departures(<em>i) _Corporate employees(</em>{i,t})</td>
<td>Subunit internal member arrivals</td>
<td>Subunit Employees(<em>{i,t}) Internal subunit departures(</em>{i,t})</td>
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<td>Subunit member arrivals (H2a)</td>
<td>Subunit Arrivals(<em>i) Subunit Employees(</em>{i,t})</td>
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<td>Subunit Employees(<em>{i,t}) Technical subunit departures(</em>{i,t})</td>
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<td>Subunit member departures (H2b)</td>
<td>Subunit Departures(<em>i) Subunit Employees(</em>{i,t})</td>
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<td>External corporate arrivals _Corporate employees(_{i,t})</td>
<td>Subunit non-technical member arrivals</td>
<td>Subunit Employees(<em>{i,t}) Non-technical subunit departures(</em>{i,t})</td>
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Table 2. Descriptive Statistics and Correlations

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\( N = 195; \) \( \ddagger \) logged variable. Correlations greater than 0.19 are significant at \( p < 0.05; \) those greater than 0.26 at \( p < 0.01. \)
Table 3. OLS Regression of Turnover on Novel Recombination in Patents Applied for by Individual Subunits at Motorola, 1974–1997

<table>
<thead>
<tr>
<th>Variables</th>
<th>Baseline</th>
<th>Corporate Effect</th>
<th>Subunit Effect</th>
<th>Corporate and Subunit Combined</th>
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<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 3</td>
<td>Model 4</td>
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<td>1.855**</td>
<td>0.387 (0.583)</td>
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<tr>
<td>Corporate staff departures</td>
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<tr>
<td>Subunit age</td>
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<td>0.000</td>
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<tr>
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<tr>
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<tr>
<td>Star scientist presence</td>
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<td>0.063*** (0.016)</td>
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N = 195. ***p < 0.001, **p < 0.01, *p < 0.05, †p < 0.1. Robust standard errors (in parentheses) are clustered by subunits. Year dummies included. We use Model 10 as the full model; it includes the four main turnover variables, subunit arrivals and departures, and corporate arrivals and departures.
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<thead>
<tr>
<th>Variables</th>
<th>Model 11</th>
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<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td># of self-citations in subunit−year</td>
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<td>0.000</td>
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<td></td>
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<td>(0.000)</td>
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<td>-6.127*</td>
<td>-1.388*</td>
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<tr>
<td></td>
<td>(0.172)</td>
<td>(2.284)</td>
<td>(0.648)</td>
<td>(0.173)</td>
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N = 164, *** p < 0.001, ** p < 0.01, * p < 0.05, † p < 0.1. Robust standard errors (in parentheses) are clustered by subunits. Year dummies included. The models in this table present results from OLS regressions with recombinant innovation as the dependent variable. Note that the sample size has been reduced from 195 to 164; data on corporate executive memos were available only from 1979, so observations for 1974–1978 were omitted.
Table 5. Supplementary Analyses

<table>
<thead>
<tr>
<th>Variables</th>
<th>External vs. Internal Arrivals</th>
<th>Technical vs. Non-technical Turnover</th>
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<tbody>
<tr>
<td></td>
<td>Model 15</td>
<td>Model 16</td>
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<tr>
<td>Corporate external staff arrivals</td>
<td>0.291*</td>
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<td>Corporate internal staff arrivals</td>
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</tr>
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<td></td>
<td>(0.131)</td>
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<tr>
<td>Subunit external member arrivals</td>
<td>0.108**</td>
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<tr>
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</tr>
<tr>
<td>Subunit internal member arrivals</td>
<td>-0.130*</td>
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<tr>
<td></td>
<td>(0.061)</td>
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<tr>
<td>Subunit technical member arrivals</td>
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</tr>
<tr>
<td>Subunit technical member departures</td>
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</tr>
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<td></td>
<td>(0.233)</td>
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</tr>
<tr>
<td>Subunit non-technical member arrivals</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.001</td>
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<tr>
<td>Subunit non-technical member departures</td>
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<tr>
<td>Subunit age</td>
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</tr>
<tr>
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<td>Subunit size</td>
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<td>-0.015*</td>
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<tr>
<td>Subunit patent value</td>
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<td>Sector sales</td>
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<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
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<tr>
<td>Star scientist presence</td>
<td>0.063***</td>
<td>0.051**</td>
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<td></td>
<td>(0.018)</td>
<td>(0.017)</td>
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<td>Average # of citations per patent</td>
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<td>0.006</td>
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<tr>
<td></td>
<td>(0.005)</td>
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<tr>
<td>Average # of claims per patent</td>
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<td>-0.000</td>
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<td>(0.000)</td>
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<tr>
<td>Constant</td>
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<td>0.626***</td>
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<td></td>
<td>(0.132)</td>
<td>(0.094)</td>
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</tbody>
</table>

N = 195. *** p < 0.001, ** p < 0.01, * p < 0.05, † p < 0.1. Robust standard errors (in parentheses) are clustered by subunits. Year dummies included. The models in this table present results from OLS regressions with recombinant innovation as the dependent variable. The eight supplementary turnover variables analyzed in this table were calculated following the formulas in Table 1.
Figure 1. Comparing Effect Size of Corporate and Subunit Turnover on Novel Recombinant Innovation by Subunits

![Graph showing the effect size of corporate and subunit turnover on novel recombinant innovation.]

Figure 2. Path Analysis of Corporate Arrivals and Departures Predicting Code Change

![Path diagram showing the relationship between corporate arrivals, departures, and code change.]

Notes: This diagram is used to analyze whether corporate arrivals and departures during year \( t \) explain a change in corporate staff language between years \( t \) and \( t+1 \). This result is estimated based on a path analysis with 500 bootstrapping replications, where robust standard errors are clustered by years. **\( p < 0.01 \)**