Team Composition Responses to Employee Mobility Threats

ABSTRACT

How do firms respond when employees' mobility barriers weaken? While strategic human capital research has emphasized retention mechanisms that prevent departures, we propose that firms also *insure* against the disruption-induced departures by increasing compositional redundancy – structuring teams so that members possess overlapping knowledge portfolios. We test this proposition using a quasi-natural experiment: the American Competitiveness in the Twenty-First Century Act (AC21) of 2000, which increased job mobility for H-1B visa holders. Analyzing 31,769 patent-teams in the U.S. electronics industry (1996–2005), we find that teams with greater exposure to the mobility shock exhibit significantly higher knowledge similarity among members post-treatment. This effect is attenuated when potentially mobile inventors have extensive prior collaborative relationships with teammates, suggesting that relational embeddedness substitutes for compositional redundancy as an alternative insurance mechanism. Our findings advance strategic human capital theory by identifying a novel firm response to mobility threats that operates through proactive team restructuring rather than retention or replacement, revealing how organizations can cultivate resilience against human capital risks they cannot prevent.

Keywords:

Compositional Redundancy, Employee Mobility, H-1B Visa Portability, Strategic Human Capital, Innovation.

INTRODUCTION

Knowledge-intensive firms face a fundamental vulnerability: the human capital that generates their most valuable innovations can walk out the door. When key employees depart, they carry with them not only codified expertise but also the tacit knowledge, collaborative routines, and relational capital that enable productive teamwork (Coff, 1997; Grant, 1996; Groysberg, Lee & Nanda, 2008; Awate, Khanna, & Kannan, 2025). The consequences can be severe – disrupted projects, degraded team performance, and competitive knowledge spillovers to rivals (Oettl, 2012; Somaya, Williamson, & Lorinkova, 2008; Tzabbar & Kehoe, 2014). Strategic human capital scholarship has devoted considerable attention to how firms respond to this threat, documenting mechanisms ranging from compensation policies and deferred incentives to legal instruments such as non-compete agreements and intellectual property protections (Campbell, Coff, & Kryscynski, 2012; Ganco, Ziedonis, & Agarwal, 2015; Marx, Strumsky, & Fleming, 2009). Yet these studies share a common premise: that the primary strategic response to mobility threats is prevention, erecting barriers that deter departure or replacement, finding substitute talent after departure occurs. This focus on retention and replacement, while valuable, leaves a critical question unaddressed: how do firms adapt when mobility barriers weaken and prevention becomes less feasible?

We propose that firms can strategically respond to heightened mobility threats not by preventing departures, but by insuring against the disruption that departures cause. Drawing on organizational reliability theory (Weick & Roberts, 1993) and research on knowledge integration in teams (Grant, 1996; Taylor & Greve, 2006), we introduce the concept of compositional redundancy, the deliberate structuring of teams such that members possess overlapping rather than strictly differentiated knowledge portfolios. When team members share overlapping expertise, the departure of any single individual is less likely to create an irreplaceable gap in the team's collective capability. We argue that when external conditions elevate mobility threats, firms will systematically increase compositional redundancy within their knowledge production teams, accepting efficiency costs in exchange for resilience against potential disruption. This insurance logic represents a departure from prevailing theoretical frameworks that emphasize either ex ante retention mechanisms or ex post replacement strategies, instead highlighting how firms can proactively restructure ongoing knowledge production activities to mitigate the consequences of mobility rather than its occurrence.

We further theorize that compositional redundancy operates as one element within a broader portfolio of insurance mechanisms. Specifically, we examine how relational embeddedness, the extent to which potentially mobile employees have established collaborative relationships with teammates, serves as a substitute form of insurance. When team members have extensively collaborated, they develop shared understanding and transactive memory that can partially compensate for a colleague's departure (Lewis, 2003; Reagans, Argote, & Brooks, 2005). We predict that firms will deploy compositional and relational redundancy as substitutes: teams in which potentially mobile members are already embedded in dense collaborative networks will exhibit smaller increases in knowledge similarity, as the marginal value of insurance provided by compositional redundancy diminishes when relational insurance is already present.

Additionally, we examine how competitive intensity amplifies insurance investments. Drawing on competitive dynamics research (Chen, 1996), we argue that when firms operate in highly contested technological domains, the costs of knowledge production disruption escalate – delays create opportunities for rivals to preempt markets, and departing employees are more likely to transfer valuable knowledge to competitors. Under these conditions, the insurance value of compositional redundancy increases, leading firms to invest more heavily in redundant team structures.

We test our predictions using a quasi-natural experiment created by the American Competitiveness in the Twenty-First Century Act (AC21) of 2000, which substantially increased job mobility for H-1B visa holders by allowing them to change employers while their permanent residency applications were pending. Focusing on patent teams in the U.S. electronics industry from 1996 to 2005, we employ a difference-in-differences design that compares changes in team knowledge similarity between teams with higher proportions of inventors likely affected by the policy (those with Indian and Chinese surnames, who comprise the majority of H-1B holders in technical occupations) and teams with lower proportions of such inventors. This name-based identification approach, now standard in research on immigrant inventors and their contributions (e.g., Kerr, 2008; Kerr & Lincoln, 2010; Choudhury & Kim, 2019), allows us to proxy for likely visa status in the absence of direct visa data. We employ a number of safeguards and checks including placebo effects to ensure that our results are not a consequence of ethnicity of inventors but rather are caused by the inventors' increased job mobility. This setting offers a reasonable identification strategy: the policy change exogenously increased mobility options for a subset of inventors while leaving the mobility constraints of domestic inventors unchanged, allowing us to isolate firm responses to differential mobility threats within the same organization. Our results support the core theoretical proposition: following the AC21 provision, affected teams exhibit significantly higher knowledge similarity among members – an approximate 8 percent increase relative to the pre-treatment mean. Consistent with our substitution hypothesis, this effect is attenuated for teams in which potentially mobile inventors have more extensive prior collaborative relationships with teammates. We find no support for the competitive intensity amplification hypothesis across alternative operationalizations.

This study makes three primary contributions to strategic management research. First, we advance the strategic human capital literature by identifying a novel organizational response to mobility threats that operates through team composition rather than retention incentives or replacement hiring. While prior work has extensively documented how firms attempt to prevent departures (Marx et al., 2009) or cope with their aftermath (Tzabbar & Kehoe, 2014), our insurance framing reveals how firms can proactively restructure knowledge production activities to render themselves more resilient to departures that cannot be prevented. This perspective complements the influential work of Campbell et al. (2012) on human capital-based competitive advantage by specifying organizational design choices that affect how vulnerable such advantages are to employee mobility. Second, we contribute to research on team composition and innovation by demonstrating that team structure responds endogenously to external labor market conditions. Studies of R&D team composition have typically treated team structure as reflecting capability requirements or managerial preferences (Taylor & Greve, 2006; Huckman, Staats, & Upton, 2009); our findings reveal that team composition also reflects strategic responses to human capital risks, suggesting that observed team structures may be jointly determined by productive efficiency and resilience considerations. Third, we contribute to the broader literature on organizational responses to uncertainty by documenting how compositional and relational mechanisms serve as substitutes in providing insurance against disruption, extending reliability theory from operational contexts to knowledge production settings.

THEORY AND HYPOTHESES

Knowledge Production in Teams and the Challenge of Employee Mobility

Knowledge-intensive firms depend critically on the collaborative efforts of specialized individuals to produce innovations (Kogut & Zander, 1992; Grant, 1996). In R&D settings, invention rarely emerges from solitary effort; rather, it arises from teams that integrate diverse expertise, coordinate interdependent tasks, and synthesize distributed knowledge into novel combinations (Hargadon & Sutton, 1997; Taylor & Greve, 2006). This team-based character of knowledge production renders firms vulnerable to disruption when key members become mobile. Unlike physical assets that remain with the firm, human capital walks out the door when employees depart (Coff, 1997).

The challenge of employee mobility has long occupied strategic management scholars. When employees leave, they take with them not only the explicit knowledge codified in documents and procedures, but also the tacit knowledge embedded in skills, routines, and relationships that is difficult to articulate and transfer (Polanyi, 1966; Nonaka, 1994). For knowledge production teams, the departure of a member disrupts more than the stock of knowledge available to the firm – it disrupts the ongoing *flow* of knowledge creation. Team members who have developed shared understanding, complementary expertise, and coordination routines must suddenly compensate for the loss of a contributor whose role was integrated into the collective process of invention (Argote, 2013; Lewis, 2003).

These disruptions are particularly consequential because knowledge production is time-sensitive. Innovation races reward speed; delays in development allow competitors to preempt markets, establish standards, and capture first-mover advantages (Eisenhardt & Tabrizi, 1995; Lieberman & Montgomery, 1988). When a key team member departs mid-project, the remaining members face difficult choices: redistribute work among themselves, integrate a replacement who lacks project-specific context, or abandon the endeavor entirely. Each path imposes costs. Redistributed work strains remaining members and may exceed their expertise; new members require time to develop the shared understanding necessary for effective collaboration; and abandoned projects represent sunk investments that yield no return (Huckman, Staats, & Upton, 2009).

Given these vulnerabilities, how do firms respond when the threat of employee mobility escalates? Prior research has emphasized mechanisms that firms employ to *prevent* departures – compensation policies, noncompete agreements, firm-specific investments, and relational inducements that raise the costs of exit (Campbell et al., 2012; Marx et al., 2009; Wang, He, &

Mahoney, 2009). Yet prevention is inherently incomplete. Labor markets are imperfect but not frozen; legal constraints on mobility vary across jurisdictions and evolve over time; and employees retain agency over their careers regardless of firm preferences (Somaya et al., 2008). When external conditions shift to facilitate mobility – as occurs when legal barriers weaken or labor market competition intensifies – firms face the prospect that prevention-oriented strategies may prove insufficient.

We propose that firms can respond to heightened mobility threats by *insuring* against the disruption that departures cause. Insurance, in this context, means structuring knowledge production activities such that the departure of any individual member, while still costly, does not catastrophically impair the team's ability to continue its work. The logic parallels organizational reliability theory, which emphasizes redundancy as a mechanism for maintaining function in the face of component failure (LaPorte & Consolini, 1991; Weick & Roberts, 1993). Just as high-reliability organizations build backup systems to ensure continued operation when primary systems fail, knowledge-intensive firms can build redundancy into team structures to ensure continued knowledge production when key members depart. Applied to knowledge production teams, this implies composing teams such that multiple members possess overlapping knowledge portfolios, not because duplication is efficient under stable conditions, but because overlap provides resilience when disruption occurs.

Compositional Redundancy as Insurance Against Disruption

We introduce the concept of *compositional redundancy* to characterize teams in which members possess overlapping rather than strictly differentiated knowledge portfolios. In teams with high compositional redundancy, multiple members hold similar expertise, have experience with similar technical problems, and can draw upon similar knowledge domains. In teams with low compositional redundancy, each member occupies a distinct knowledge niche, and the collective capability emerges from the combination of non-overlapping specializations. Importantly, compositional redundancy is not merely an incidental feature of team composition but can be a *strategic choice* – a deliberate investment in resilience that trades off against efficiency.

The distinction between compositional redundancy and related constructs warrants clarification. Transactive memory systems (TMS) research has emphasized the value of *differentiation* – team members specializing in distinct knowledge domains and developing accurate awareness of "who knows what" (Wegner, 1987; Lewis, 2003; Ren & Argote, 2011). Such differentiation enables efficient division of cognitive labor, expands the team's aggregate knowledge capacity, and avoids duplicative investment in knowledge acquisition. These benefits are well-documented and substantial. However, differentiation also creates vulnerability: when the sole expert in a domain departs, the team loses not only the knowledge itself but also the capacity to continue work in that domain until a replacement is found and integrated.

Compositional redundancy addresses this vulnerability by ensuring that critical knowledge domains have multiple stewards. The trade-off parallels the broader organizational tension between efficiency and slack. Organizational theorists have long recognized that some redundancy – whether in resources, capabilities, or personnel – provides adaptive capacity that proves valuable when environments shift or disruptions occur (Cyert & March, 1963; Bourgeois, 1981). Nohria and Gulati (1996) demonstrated that moderate levels of slack enhance innovation by providing resources for experimentation and buffering against setbacks. Compositional redundancy extends this logic to the domain of team knowledge structures: overlap in knowledge portfolios may reduce efficiency in stable conditions but provides the slack necessary to absorb disruption when key members depart. This framing clarifies when differentiation's benefits will be outweighed by redundancy's insurance value. When employee departure is unlikely and replacement is easy, differentiation dominates – firms can maximize their knowledge frontier confident that any losses can be readily restored. But when departure probability rises and replacement becomes difficult, the calculus shifts. The expected costs of disruption increase, and the insurance value of redundancy rises correspondingly. Under such conditions, rational firms will accept some sacrifice in efficiency to purchase resilience.

The insurance value of compositional redundancy derives from three mechanisms. First, when team members share overlapping expertise, they can more readily absorb the responsibilities of a departed colleague. Remaining members possess the foundational knowledge necessary to continue work in the departed member's domain, even if they lack the same depth or recent engagement (Smith & Hou, 2015). The team need not wait for a replacement to restore capacity – it can reallocate work internally and maintain momentum. Second, overlapping knowledge facilitates the integration of replacement members when they do arrive. New entrants joining a team with redundant knowledge structures can draw upon multiple colleagues for orientation and knowledge transfer, accelerating their productive contribution. Third, redundancy enables more effective real-time coordination. When multiple members understand a domain, they can evaluate each other's contributions, identify errors, and suggest improvements – coordination benefits that operate continuously, not only in response to turnover.

How do firms increase compositional redundancy in practice? The primary mechanism operates through *project staffing decisions* , i.e., the assignment of inventors to specific teams and projects. R&D managers and project leaders, when assembling teams for new initiatives, can select inventors whose knowledge portfolios overlap rather than inventors whose portfolios are maximally differentiated. Firms can also adjust compositional redundancy through *hiring decisions*, recruiting inventors whose expertise complements existing team members in the sense of providing backup rather than extending into entirely new domains. Finally, *reassignment* of existing inventors across projects can reshape team composition to increase overlap where mobility threats are most acute. While individual inventors may not perceive these staffing decisions as strategic responses to mobility threats, the aggregate pattern of team composition reflects managerial choices about the efficiency-resilience trade-off.

We argue that firms will strategically increase compositional redundancy within teams when external conditions elevate the threat of employee mobility. When mobility barriers weaken, the expected probability of departure rises, increasing the expected costs of disruption and thereby increasing the insurance value of redundancy. This general theoretical proposition yields a specific empirical prediction in our research context. The American Competitiveness in the Twenty-First Century Act (AC21) of 2000 provides a compelling setting to examine this mechanism. Prior to AC21, H-1B visa holders faced substantial frictions when changing employers: the prospective employer had to file a new petition, and the worker typically could not begin the new position until approval – a process that could take months. This institutional arrangement created de facto mobility barriers that bound H-1B workers to their sponsoring employers. AC21's portability provision eliminated this barrier by allowing H-1B holders to begin working for a new employer immediately upon petition filing. The policy change thus represented an exogenous shock that selectively weakened mobility barriers for one population of workers (foreign-born inventors from countries heavily represented in the H-1B program, principally India and China) while leaving another population (domestic inventors) unaffected.

We expect that teams with greater exposure to this mobility shock – those with higher proportions of inventors whose mobility barriers weakened under AC21 – will exhibit increased compositional redundancy following the policy change. Firms employing these affected inventors face heightened departure risk and will respond by composing teams with greater knowledge similarity among members. Note that this prediction reflects strategic firm response, not mere selection effects. If the effect were driven by selection, highly specialized affected inventors departing, leaving behind more similar inventors, we would observe the pattern regardless of firm intent. However, the strategic response interpretation implies that firms *actively adjust* team composition to insure against increased mobility risk, a mechanism we explore through moderating conditions below.

> **Hypothesis 1:** *When employee mobility barriers weaken, teams with greater exposure to the mobility increase will exhibit higher knowledge similarity among members.*

Relational Embeddedness as a Substitute Mechanism of Insurance

The preceding argument treats compositional redundancy as the primary mechanism through which firms insure against knowledge production disruption. However, firms may have access to alternative insurance mechanisms that serve similar protective functions. We theorize that prior collaborative relationships among team members constitute one such alternative – what we term *relational embeddedness* – and that compositional redundancy and relational embeddedness function as *substitutes* in providing insurance against disruption.

Relational embeddedness refers to the extent to which team members have established working relationships through prior collaboration. When inventors have previously worked together on patents, they have developed shared experiences, mutual understanding, and coordination routines that transcend any single project (Reagans et al., 2005; Huckman et al., 2009). These relationships represent accumulated investments in team-specific human capital – knowledge about how teammates think, communicate, and approach problems that facilitates coordination and knowledge sharing.

We argue that relational embeddedness provides insurance against mobility-induced disruption through two primary mechanisms. First, when team members have extensively collaborated with a potentially mobile colleague, they possess rich knowledge about that colleague's expertise, working style, and contributions – knowledge that persists even after departure. Remaining team members who have extensively collaborated with the departed colleague possess not only awareness of *what* the colleague knew but also insight into *how* that colleague approached problems, communicated ideas, and integrated with the team's workflow. This relational knowledge enables more effective redistribution of responsibilities. In essence, prior collaboration embeds knowledge *about* the potentially mobile inventor within the remaining team's collective memory, providing insurance that does not require duplicating the individual's technical expertise (Argote, 2013).

Second, relational embeddedness supports the development and maintenance of transactive memory, the team's collective awareness of who knows what and how to access distributed expertise (Wegner, 1987). When team members have collaborated extensively, they develop accurate mental models of each other's knowledge domains, capabilities, and working styles. These mental models enable efficient coordination by directing inquiries to the appropriate experts and facilitating knowledge integration across specialized domains. Importantly, transactive memory structures persist even after a member departs, enabling the remaining team to reconstruct or compensate for lost capabilities more effectively than would be possible without such shared history. The team retains a "map" of the departed member's knowledge that guides both redistribution of work and integration of replacements.

Given that relational embeddedness and compositional redundancy both provide insurance against disruption, albeit through different mechanisms, we expect firms to deploy these mechanisms as substitutes. When teams already possess high relational embeddedness, i.e., when potentially mobile inventors are deeply integrated into collaborative relationships with their teammates, the marginal insurance value of increasing compositional redundancy diminishes. The firm has already invested in one form of protection through the accumulated history of collaboration; additional investment in an alternative form yields decreasing returns. Conversely, when relational embeddedness is low, i.e., when potentially mobile inventors have limited collaborative history with teammates, compositional redundancy becomes the primary available insurance mechanism, and firms will invest more heavily in knowledge overlap.

This substitution logic generates a specific empirical prediction about how the main effect of mobility threats on compositional redundancy will vary with relational embeddedness. Teams in which affected inventors have extensive prior co-patenting relationships with their teammates should exhibit weaker responses to the mobility shock than teams in which such relationships are absent. The pre-existing relational embeddedness has already purchased the insurance that compositional redundancy would otherwise provide. Importantly, this moderation effect provides evidence for the *strategic* nature of firm responses: if the main effect were driven entirely by selection, we would not expect it to vary systematically with the availability of substitute insurance mechanisms.

> **Hypothesis 2:** *The positive effect of weakened mobility barriers on team knowledge similarity will be attenuated for teams in which potentially mobile members have more extensive prior collaborative relationships with their teammates.*

Competitive Intensity as an Amplifier of Insurance Investments

Having examined an internal boundary condition – the availability of substitute insurance mechanisms within the team – we now turn to an external boundary condition: the competitive intensity of the firm's technological environment. We theorize that competitive intensity amplifies the insurance value of compositional redundancy, leading firms facing more intense competition to respond more aggressively to mobility threats.

Competitive intensity refers to the degree to which a firm faces rivals operating in proximate technological spaces. In highly competitive environments, multiple firms pursue similar innovations, develop overlapping capabilities, and compete for similar market opportunities. Low competitive intensity characterizes environments in which firms occupy distinct technological niches with limited direct rivalry. We measure competitive intensity at the level of specific technology domains, recognizing that firms may face varying degrees of competition across different areas of their innovative activity. Competitive intensity elevates the costs of knowledge production disruption through two primary mechanisms. First, competitive intensity compresses the time available for successful innovation. When rivals are numerous and similarly capable, the window during which an innovation can capture market value narrows. Delays caused by team disruption allow competitors to reach market first, establish standards, build customer relationships, and capture returns that would otherwise accrue to the focal firm (Eisenhardt & Tabrizi, 1995; Chen, 1996). The time-based advantages documented in research on first-mover effects are larger when competition is intense, because more rivals stand ready to capitalize on any firm's setbacks (Lieberman & Montgomery, 1988). In less competitive environments, the consequences of delay are attenuated because fewer rivals are positioned to exploit the focal firm's disruptions.

Second, competitive intensity increases the likelihood that departing employees will transfer valuable knowledge to rivals. Research on employee mobility has documented that knowledge flows follow people across firm boundaries, benefiting destination firms at the expense of origin firms (Almeida & Kogut, 1999; Song, Almeida, & Wu, 2003). When competition is intense, more potential destination employers exist for mobile employees, and those destinations are more likely to be direct rivals who can immediately exploit transferred knowledge. The competitive damage from losing an employee thus compounds: the firm loses not only the employee's contribution to its own innovation efforts but also faces the prospect of that contribution enriching a rival's capabilities.

Competitive intensity may also increase the efficiency costs of redundancy, i.e., firms facing intense competition cannot afford to sacrifice any frontier innovation capacity. However, we argue that disruption costs dominate efficiency costs when competition is intense. The reason is temporal asymmetry: efficiency losses from redundancy are ongoing but incremental, whereas disruption losses are sudden and potentially catastrophic. A team operating at 95% of its potential innovation frontier due to redundancy may be marginally disadvantaged relative to a maximally efficient competitor, but a team whose knowledge production halts entirely due to key member departure faces far more severe consequences. When competition is intense, the probability that rivals will capitalize on any production halt is high, making the catastrophic downside of disruption particularly salient. Risk-averse firms will trade modest ongoing efficiency losses for substantial reduction in disruption risk.

Furthermore, competitive intensity (which implies greater number of competitor firms which operate in proximate technologies), also increases the mobility opportunities for inventors. Therefore, as other forms of mobility barriers reduce, the threat of departures is likely to increase more for firms that face greater competitive intensity.

These arguments suggest that competitive intensity should amplify the insurance value of compositional redundancy. When competition is intense, the costs of disruption are higher, and therefore the benefits of insuring against disruption are greater. The logic parallels insurance theory in economics: demand for insurance increases with both the probability of loss and the magnitude of loss conditional on occurrence (Ehrlich & Becker, 1972). The weakening of mobility barriers (as occurred under AC21) increased the probability of departure for affected inventors. Competitive intensity increases the magnitude of loss conditional on departure. Firms facing both elevated probability and elevated magnitude should exhibit the strongest insurance response.

> **Hypothesis 3:** *The positive effect of weakened mobility barriers on team knowledge similarity will be amplified for teams operating in more competitively intense technological domains.*

DATA AND METHODS

Empirical Setting - The H-1B Visa Program and Mobility Constraints

The H-1B visa program, established under the Immigration Act of 1990, permits U.S. employers to temporarily employ foreign workers in "specialty occupations" requiring specialized knowledge and at least a bachelor's degree. The program has become the primary pathway for high-skilled foreign workers to enter the U.S. labor market, particularly in science, technology, engineering, and mathematics (STEM) fields. By the late 1990s, H-1B holders constituted approximately 24% of the U.S. science and engineering workforce with bachelor's degrees and nearly 47% of those with doctorates (Kerr & Lincoln, 2010). The program is heavily concentrated among workers from India and China, who together have consistently accounted for over 60% of H-1B approvals since the program's inception—a share that has grown to exceed 85% in recent years.

A defining feature of the H-1B program is that it ties the worker's legal status to a specific employer. The sponsoring firm files the H-1B petition and must specify the individual worker, position, and work location. Unlike U.S. citizens or permanent residents who enjoy at-will employment mobility, H-1B holders cannot simply accept a job offer from a new employer. Prior to October 2000, changing employers while on H-1B status required the prospective employer to file a new H-1B petition, and, critically, the worker had to wait for that petition to be approved before beginning the new position. Given processing times that could extend to six months or longer, this created substantial friction in the job-switching process. Workers faced extended periods of uncertainty during which they could neither work for the new employer nor, in many cases, safely leave their current position. If the petition was ultimately denied, the worker risked falling out of legal status and potentially having to leave the country. These institutional features created a de facto mobility barrier that bound H-1B workers to their sponsoring employers far more tightly than the at-will employment relationship experienced by domestic workers.

We exploit a quasi-natural experiment created by the American Competitiveness in the Twenty-First Century Act (AC21) of 2000 to examine how firms strategically restructure knowledge production teams in response to weakened employee mobility barriers. Prior to AC21, H-1B visa holders faced significant constraints on job mobility because changing employers required the prospective employer to file a new H-1B petition, and the worker typically could not begin the new position until that petition was approved – a process that could take many months. Section 105 of AC21 provision introduced 'portability,' allowing H-1B holders to begin working for a new employer immediately upon the filing of a new petition. This seemingly technical change had profound implications for labor market mobility: it transformed the effective switching cost from months of uncertainty and income loss to a matter of days required for petition preparation and filing. This policy change substantially reduced the mobility barriers facing foreign-born inventors from countries heavily represented in the H-1B program – particularly India and China – while leaving domestic inventors unaffected. Importantly, AC21 affected only temporary visa holders; it had no impact on the mobility of U.S. citizens or permanent residents, who could always change jobs freely under at-will employment. This differential impact across worker populations creates the identifying variation we exploit.

The electronics industry (3-digit SIC 367) provides an ideal empirical context for several reasons. First, this sector has historically employed a disproportionate share of H-1B visa holders in technical and R&D roles. Second, knowledge production in electronics relies heavily on collaborative inventor teams, making it particularly susceptible to disruption from key employee departures. Third, the industry exhibits substantial variation in competitive intensity across technology domains, enabling examination of moderating effects. We situate our study in the electronics industry (3-digit SIC code 367), which includes firms manufacturing electronic components, semiconductors, circuit boards, and related products. This empirical context offers several advantages for testing our theoretical predictions. First, the electronics industry has historically employed a disproportionate share of H-1B visa holders in technical and R&D roles. Kerr (2008) documents that Chinese and Indian inventors are particularly concentrated in electronics patenting, reflecting both the technical skill requirements of the industry and its aggressive recruitment of foreign talent. This ensures sufficient treatment intensity to detect firm responses to the mobility shock. Second, knowledge production in electronics relies heavily on collaborative inventor teams. Unlike industries where innovation is often the product of individual effort, electronics R&D typically requires integrating specialized knowledge across multiple technical domains such as circuit design, materials science, software, and manufacturing processes, necessitating team-based work. This makes the industry particularly susceptible to disruption when key team members depart, and thus particularly likely to exhibit strategic responses aimed at protecting against such disruptions. Third, the electronics industry exhibits substantial variation in competitive intensity across technology domains. Some firms compete head-to-head in commodity semiconductor segments, while others occupy specialized niches with limited direct competition. This variation enables examination of whether competitive intensity moderates firm responses to the mobility threat. Fourth, focusing on a single industry allows us to hold constant many unobserved factors – technology trajectories, regulatory environments, labor market institutions – that might confound cross-industry comparisons. The AC21 provision affected all industries equally, but its relevance varied with H-1B utilization rates. By restricting attention to electronics, we ensure our treatment and control groups operate in similar technological and competitive environments.

Sample and Data

We construct our sample from PatentsView, which provides comprehensive data on U.S. utility patents including disambiguated inventor identities, patent texts, technology classifications, and application dates. We link patent data to Compustat for firm-level financial characteristics using DISCERN 2 (Arora et al., 2023). Our sample includes all U.S. utility patents granted to publicly traded firms in SIC 367 between 1998 and 2003. We defined team-based patents as those comprising at least two inventors. We impose several restrictions to isolate the phenomenon of interest. First, we retain only patents where all listed inventors have U.S. addresses, ensuring we observe teams operating under U.S. labor market conditions. Second, we exclude single-inventor patents because our theoretical focus is on team-level knowledge redundancy – a concept requiring multiple team members. Third, we identify inventors whose first patent in the U.S. fall within a six-year window prior to the shock to ensure that the inventors in the treated group are indeed on a temporary H-1B visa. These restrictions yield a final sample of 31,769 patent-teams from 150 unique firms. To identify inventors likely affected by the AC21 provision, we use ethnic name classification algorithms validated in prior research to classify inventors as Indian or Chinese based on their names (Torvik & Agarwal, 2016; Ross et al., 2022; Wapman et al., 2022).

Patent records do not directly identify inventors' visa or immigration status, precluding direct observation of H-1B holders. Following established methodological practice in research on immigration and innovation, we infer likely exposure to the visa portability provision using name-based ethnicity classification. This approach, pioneered by Kerr (2008) and subsequently employed in labor economics as well as strategic management, applies ethnic-name databases to inventor surnames to identify likely country of origin. Kerr (2008) demonstrates that surnames such as Chang or Wang reliably indicate Chinese ethnicity, while names like Acharya or Gupta indicate Indian ethnicity among U.S.-based inventors. This methodology has been validated and adopted across the innovation and strategy literatures, including studies of ethnic community knowledge and inventor innovativeness (Almeida, Phene, & Li, 2015), ethnic migrant inventors and knowledge codification (Choudhury & Kim, 2019), and the supply-side effects of H-1B visa policy (Kerr & Lincoln, 2010; Kerr, Kerr & Lincoln, 2015). The validity of this proxy rests on the stark concentration of H-1B visas among nationals from these two countries: India and China together account for approximately 60–70 percent of all H-1B visas granted in STEM occupations during our study period, with Indian nationals alone comprising roughly half of all H-1B recipients (Kerr & Lincoln, 2010). Consequently, inventors with Indian or Chinese surnames working in U.S. high-technology sectors are substantially more likely to hold H-1B visas and thus to have been affected by the AC21 portability provision than inventors from other ethnic backgrounds. In our difference-in-differences estimation, explained in detail below, we focus on Indian and Chinese inventors (Choudhury & Kim, 2019) because among patent-teams in our sample, approximately 41% include at least one Indian or Chinese inventor meeting the aforementioned criteria, with a mean proportion of affected inventors of 0.207 across all teams. While this proxy introduces measurement error, as not all Indian and Chinese inventors are H-1B holders and some may be U.S. citizens or permanent residents, this attenuation bias works against finding significant effects, making our estimates conservative. Moreover, the difference-in-differences design addresses this concern by comparing changes in outcomes for teams with higher versus lower proportions of these inventors, with any constant measurement error differencing out across treatment and control groups. Further, as we describe in more detail below, we employ placebo effects to rule out the possibility that the effects we estimate arise purely from the ethnicity of the team composition.

Dependent Variable

Team knowledge similarity. Our primary dependent variable captures the extent to which team members possess overlapping knowledge portfolios, operationalizing the concept of compositional redundancy as insurance against knowledge production disruption. We measure knowledge similarity using text-based analysis of inventors' prior patent portfolios. For each focal patent, we identify all patents filed by each team member during the preceding five years. We combine the title, abstract, claims, and summary text of each historical patent and apply TF-IDF (Term Frequency-Inverse Document Frequency) vectorization (Aizawa, 2003), which weights terms by their distinctiveness across the patent corpus. TF-IDF algorithm has found increasing adoption in management research utilizing text data (Guo, Sengul, Yu, 2021; Song, 2026). We fit the TF-IDF vectorizer on 78,028 historical patents from 1991–2004, yielding a vocabulary of 97,528 terms by excluding terms appearing in fewer than 2 documents (to ensure statistical reliability) or in more than 90% of documents (to remove ubiquitous terms lacking discriminative power). TF-IDF represents each patent as a vector where each dimension corresponds to a term in the vocabulary, weighted by how frequently the term appears in that patent relative to how common it is across all patents. Terms that are frequent in a given patent but rare across the corpus receive higher weights, capturing the distinctive technical content of each patent. Cosine similarity between two inventors' TF-IDF vectors thus measures the extent to which their historical patents emphasize similar technical vocabulary – inventors whose prior work describes similar components, processes, or methods will have vectors pointing in similar directions, indicating overlapping knowledge domains. For each pair of inventors on a focal patent, we calculate the cosine similarity between the TF-IDF vectors representing their respective historical patent portfolios. When an inventor has multiple historical patents, we compute all pairwise similarities with each historical patent of their teammate and take the mean. Our team-level similarity measure is the average of these pairwise inventor similarities across all inventor dyads on the focal patent. This measure ranges from 0 (no textual overlap in prior patents) to 1 (identical knowledge portfolios), with a sample mean of 0.179 and standard deviation of 0.185.

Treatment Variable

Affected team. We construct an intensity-based treatment indicator that equals 1 if the proportion of Indian or Chinese inventors on the team exceeds the sample mean (0.207), and 0 otherwise. This operationalization identifies teams where the policy shock created meaningful exposure to increased inventor mobility, rather than treating any foreign inventor presence as equivalent treatment intensity.

Post. We define the post-treatment period as patent application years 2001–2003, following the October 2000 enactment of AC21. The pre-treatment period encompasses 1998–2000. This symmetric three-year window balances adequate statistical power against potential confounds from time-varying factors.

Moderating Variables

Prior co-patenting (Embeddedness). We measure the organic embeddedness of potentially mobile inventors within the team by counting their prior collaborative patents with teammates. For each focal patent, we identify all dyads involving at least one Indian or Chinese inventor and their non-ethnic teammates. We then count the number of patents these inventor pairs co-authored within the same firm during the five years preceding the focal patent. Our team-level measure is the average prior co-patent count across all such dyads. Higher values indicate that affected inventors have deeper collaborative relationships with teammates, potentially providing alternative insurance through relational rather than compositional redundancy.

Competitive intensity. We construct measures of competitive intensity in the focal patent's technology space based on the prevalence of highly similar competitor patents. For each focal patent, we identify all patents filed by other firms in SIC 367 during the preceding five years. We compute the TF-IDF-based cosine similarity between the focal patent and each competitor patent using a vocabulary of 143,753 terms fitted on 107,855 industry patents. We then establish global similarity thresholds at the 90^{th} percentile of the cross-firm similarity distribution (threshold of 0.106). Our primary measures for competitive intensity correspond to *Competitor knowledge similarity*, number of *Competitor patents in* 90^{th} *percentile* and unique *Competitor firms in the 90th percentile* similarity threshold, capturing how many close rivals exist in the focal technology domain.

Control Variables

We include several team-level and firm-level controls that may correlate with both treatment status and team composition decisions. *Technology domain overlap* measures technological overlap using the Jaccard similarity of inventors' CPC technology class portfolios, capturing categorical rather than substantive knowledge overlap (Sears & Hoetker, 2014). *Team technology diversity* measures the dispersion of team members' collective technology experience across CPC subclasses (Chang, 2023). *Novice team* is an indicator for teams where no inventor has prior patenting history. *Team size* controls for the number of inventors on the focal patent (Choudhury & Haas, 2018). At the firm level, we control for *Firm size* as the annual revenue to account for firm scale, *R&D intensity* (R&D expenditure divided by revenue) to control for innovation investment, *Number of Patents* to capture overall patenting activity, and *Firm Technological Diversity* as a CPC subclass-based HHI measure to control for firm-level technological diversification.

Estimation Strategy

We employ a difference-in-differences research design that compares changes in team knowledge similarity between affected teams (those with above-average proportions of Indian/Chinese inventors) and unaffected teams, before versus after the AC21 policy implementation. Our baseline specification takes the form:

$$Y_{ijt} = \beta_0 + \beta_1 Affected_{ijt} \times Post_t + \beta_2 Affected_{ijt} + \beta_3 Post_t + \gamma X_{ijt} + \alpha_j + \delta_t + \varepsilon_{ijt}$$

where Y_{ijt} is team knowledge similarity for patent-team i in firm j at time t; $Affected_{ijt}$ indicates treatment status; $Post_t$ indicates the post-AC21 period; X_{ijt} represents time-varying controls; α_j captures firm fixed effects; and δ_t captures year fixed effects. The coefficient of interest is β_1, which estimates the differential change in team knowledge similarity for affected teams following the policy shock.

Because our dependent variable is bounded between 0 and 1, we estimate our primary models using fractional logit (generalized linear model with binomial family and logit link) (Papke & Wooldridge, 1996), which appropriately handles proportional outcomes without the boundary problems of OLS. We also report OLS estimates with firm fixed effects absorbed using the *reghdfe* procedure (Correia, 2016) for comparability and computational efficiency with high-dimensional fixed effects. All standard errors are clustered at the firm level to account for within-firm correlation across patent-teams.

To test moderating hypotheses, we extend the baseline model with three-way interactions:

$$Y_{ijt} = \beta_0 + \beta_1 Affected_{ijt} \times Post_t \times Moderator + [Lower\ order\ terms] + \gamma X_{ijt} + \alpha_j + \delta_t + \varepsilon_{ijt}$$

where *Moderator* represents either prior co-patenting embeddedness or competitive intensity. The three-way interaction β_1 captures how the treatment effect varies across levels of the moderating variable.

The validity of our difference-in-differences design rests on the parallel trends assumption: absent the AC21 policy change, affected and unaffected teams would have exhibited similar trends in knowledge similarity. We assess this assumption through an event study specification that estimates separate treatment effects for each year relative to the policy implementation:

$$Y_{ijt} = \sum_{\tau} \beta_\tau \times Affected_{ijt} \times 1[t = \tau] + \gamma X_{ijt} + \alpha_j + \delta_t + \varepsilon_{ijt}$$

We normalize $\beta_{2000} = 0$ (the year immediately before AC21 implementation) and plot the β_τ coefficients with 95% confidence intervals. Parallel trends would be supported by pre-treatment coefficients that are statistically indistinguishable from zero, with divergence emerging only in post-treatment periods. Figure 1 presents the event study analysis assessing the parallel trends assumption. The pre-treatment coefficients for 1998 and 1999 are small in magnitude and statistically indistinguishable from zero, supporting the assumption that affected and unaffected teams were on similar trajectories prior to the policy shock. The treatment effect emerges gradually: the 2001 coefficient is positive but not statistically significant, while coefficients for 2002 and 2003 are both positive and significant. This pattern is consistent with the realistic timing of organizational responses—teams working on patents filed in 2001 were likely assembled before firms fully internalized the implications of the October 2000 policy change. Team composition decisions reflect project planning, hiring pipelines, and assignment processes that precede patent application dates by months or longer, so an immediate effect would be implausible. The gradual divergence supports the validity of our identification strategy by ruling out coincidental shocks precisely at the policy date while demonstrating sustained treatment effects as firms adjusted their practices.

Insert Figure 1 about here

Further, we implement two placebo tests to further assess the validity of our research design. The idea behind these placebo effects is that if the effects we observe is due to ethnicity of inventors rather than due to increased mobility caused by changes to immigration law, then we should see the same effects at other time periods as well (i.e., even if we "imagine" the shock to have occurred at some other time). In other words, if we do not see any effects at other times when we conduct a similar test, it implies that it is not the ethnicity of the inventors that cause the effects but rather the effects are caused by the changes in the institutional environment in 2001 that increased the mobility of inventors with Indian or Chinese ethnicity.

First, we conduct a *pre-shock placebo* using data from 1996–2001 with a fictitious treatment date in 1999 (coded as Pre = 1996–1998, Post = 1999–2001). Finding a significant "treatment" effect in this specification would suggest pre-existing differential trends across different ethnicities rather than a causal effect of AC21. Second, we conduct a *post-shock placebo* using data from 2000–2005 with a fictitious treatment date in 2003 (coded as Pre = 2000–2002, Post = 2003–2005). A significant effect in this specification would suggest continued divergence unrelated to the initial policy shock, potentially indicating time-varying confounds. Tables 1 and 2 present results from the *pre-shock placebo* and *post-shock placebo* mean difference-in-differences respectively. The difference-in-differences coefficients are neither positive nor statistically distinguishable from zero in both placebo tests, suggesting that the effects reported in our main findings indeed emerge from the visa portability provision of AC21.

<< Insert Table 1 and 2 about here >>

Besides the mean difference-in-differences, Table 3 reports regression results from the pre-shock and post-shock placebo samples following identical specification as used to report our main findings (Table 6, Model 2). The interactions terms in both regression models in Table 3 contain negative and non-significant coefficients suggesting that the effects reported in our main findings indeed emerge from the visa portability provision of the AC21 Act.

<< Insert Table 3 about here >>

RESULTS

Table 4 presents descriptive statistics and correlations for our analysis sample of 31,769 patent-teams. The mean team knowledge similarity is 0.18 (SD = 0.18), indicating substantial variation in the extent to which team members possess overlapping knowledge portfolios. Approximately 38% of patent-teams in our sample include an above-average proportion of Indian or Chinese inventors (our treatment group), and 57% of observations fall in the post-AC21 period. The average team has approximately 3 inventors, with 11% of teams consisting entirely of novice inventors without prior patenting history. The correlation matrix reveals several patterns worth noting. Team knowledge similarity exhibits a strong positive correlation with Technology domain overlap, confirming that these text-based and categorical measures capture related but distinct aspects of knowledge redundancy. Team knowledge similarity is negatively correlated with novice team status, as expected given that novice teams lack the historical patent portfolios needed to generate high similarity scores. Notably correlations of key variables are moderately to low suggesting that multicollinearity is not a concern (VIF = 1.97).

<< Insert Table 4 about here >>

Table 5 presents the mean difference-in-differences analysis comparing team knowledge similarity across treatment status and time periods. Before the AC21 policy implementation, affected teams exhibited slightly *lower* average knowledge similarity than unaffected teams (0.111 vs. 0.118; difference = -0.007, $p < .05$). This pattern reverses in the post-period: affected teams display *higher* average knowledge similarity than unaffected teams (0.113 vs. 0.105; difference = 0.008, $p < .10$). The difference-in-differences estimate is 0.015 ($p < .01$), indicating that affected teams experienced a significant increase in knowledge similarity relative to unaffected teams following the policy shock. Given the sample mean of 0.18, this represents approximately an 8% relative increase in team knowledge similarity.

<< Insert Table 5 about here >>

Table 6 reports results from our regression specifications with firm and year fixed effects. Model 1 presents a controls-only baseline using fractional logit estimation. Model 2 adds the difference-in-differences interaction terms. The coefficient on Affected Team × Post is positive and statistically significant ($\beta = 0.101$, $p < .01$), supporting our central hypothesis that firms respond to weakened mobility barriers by increasing knowledge redundancy within affected teams. The coefficient on Affected Team (the main effect) is negative and marginally significant ($\beta = -0.036$, $p < .10$ in Model 2), indicating that prior to the policy change, teams with higher concentrations of Indian/Chinese inventors exhibited somewhat lower knowledge similarity—consistent with the pre-period difference in Table 5. The negative coefficient on Post ($\beta = -0.135$, $p < .05$) suggests a general decline in team knowledge similarity over this period for unaffected teams, perhaps reflecting broader trends toward specialization in the electronics industry. Model 3 replicates this specification using OLS with absorbed firm fixed effects; the interaction coefficient remains positive and significant (β = 0.014, $p < .01$), demonstrating robustness to alternative estimation approaches.

<< Insert Table 6 about here >>

Moderating Role of Prior Collaboration

Table 7 examines whether the effect of visa portability on team knowledge similarity varies with the embeddedness of potentially mobile inventors within existing collaborative relationships. We operationalize embeddedness as the average number of prior co-patents between Indian/Chinese inventors and their teammates on the focal patent. Our theoretical expectation is that prior collaboration provides an alternative mechanism of redundancy – relational rather than compositional – potentially substituting for the need to increase knowledge similarity. The three-way interaction (Affected Team × Post × Prior collaboration) is negative and significant across both estimation approaches (β = -0.004, $p < .01$ in fractional logit; β = -0.032, $p < .01$ in OLS). This finding supports the interpretation that compositional redundancy and relational embeddedness function as substitute mechanisms for insuring against knowledge production disruption. When affected inventors are already embedded in strong collaborative relationships with teammates – evidenced by a history of joint patenting – firms have less need to increase compositional redundancy within the team. The redundancy provided by established working relationships and tacit coordination routines serves a similar protective function.

<< Insert Table 7 about here >>

Moderating Role of Competitive Intensity

Table 8 examines whether competitive intensity in the focal patent's technology domain moderates the treatment effect. We employ three measures of competitive intensity: (1) average similarity to competitor patents, (2) count of competitor patents exceeding the 90th percentile similarity threshold, and (3) count of competitor firms with patents exceeding this threshold. We expect that firms facing more intense competition to be more responsive to the mobility threat, investing more heavily in knowledge redundancy when the costs of knowledge production disruption are highest. Contrary to our expectations, the three-way interactions with competitive intensity measures are not statistically significant. The interaction with average competitor similarity (Model 1: β = -2.088, SE = 1.905), competitor patent count (Model 2: $\beta = -0.000$, SE = 0.000), and competitor firm count (Model 3: $\beta = -0.001$, SE = 0.001) all fail to reach conventional significance levels. The Affected Team × Post main effect remains positive and significant across all specifications (Model 1: $\beta = 0.209$, $p < .05$; Model 2: $\beta = 0.132$, $p < .05$; Model 3: $\beta = 0.208$, $p < .10$), indicating that the baseline treatment effect is robust to the inclusion of competition-related interactions. The null findings for competitive intensity moderation admit several interpretations. First, all firms in our sample operate in the highly competitive electronics industry (SIC 367), potentially restricting range on competitive intensity and limiting our ability to detect moderation effects. Second, the costs of knowledge production disruption may be sufficiently high across all competitive contexts that firms respond similarly to the mobility threat regardless of the intensity of product market competition. Third, competitive intensity may affect other dimensions of firm response to mobility threats – such as compensation adjustments or non-compete enforcement – rather than team composition decisions specifically.

<< Insert Table 8 about here >>

Taken together, our results provide strong support for the core theoretical proposition that firms strategically increase team knowledge redundancy in response to weakened employee mobility barriers.

DISCUSSION AND CONCLUSION

This study examined how firms strategically restructure knowledge production teams when employee mobility barriers weaken. Drawing on a quasi-natural experiment created by the AC21 visa portability provision of 2000, we found that teams with greater exposure to the mobility shock, those with higher proportions of inventors whose external mobility options expanded under the policy, exhibited significantly increased knowledge similarity among members in the post-treatment period. This effect supports our core theoretical proposition that firms respond to heightened mobility threats by investing in compositional redundancy as insurance against knowledge production disruption. Our analysis further revealed that relational embeddedness serves as a substitute insurance mechanism: teams in which potentially mobile inventors had established extensive prior collaborative relationships with teammates exhibited attenuated increases in knowledge similarity, consistent with the logic that firms deploy compositional and relational redundancy as alternative means of achieving resilience.

We found no evidence for competitive intensity as an amplifier of insurance investments across alternative operationalizations, suggesting boundary conditions that warrant further investigation.

Our study makes three primary contributions to strategic management theory. First, and most fundamentally, we advance the strategic human capital literature by identifying and theorizing a novel organizational response to mobility threats that operates through ex ante team composition rather than retention incentives or ex post replacement. The dominant paradigm in strategic human capital research has emphasized how firms create and appropriate value from human capital by either preventing employee departure through isolating mechanisms – compensation policies, deferred incentives, non-compete agreements, and firm-specific skill development (Coff, 1997; Campbell et al., 2012; Marx et al., 2009), or by managing the consequences of departure through replacement hiring and knowledge transfer protocols (Tzabbar & Kehoe, 2014). Our insurance framing introduces a third strategic logic: rather than preventing mobility or replacing departed employees, firms can proactively restructure ongoing activities to render themselves more resilient to departures that cannot be prevented. This perspective is particularly relevant in contexts where legal or institutional constraints limit firms' ability to erect mobility barriers, where talent scarcity makes replacement difficult, or where the tacit and collaborative nature of knowledge production makes seamless replacement infeasible even when substitute talent is available. The insurance logic we develop also contributes to resolving a tension in the knowledge-based view of the firm regarding the relative merits of specialization versus redundancy in team composition. Influential work on transactive memory systems has emphasized the performance benefits of differentiation – team members specializing in distinct knowledge domains and developing shared awareness of "who knows what" (Wegner, 1987; Lewis, 2003; Ren & Argote, 2011). This perspective implies that redundancy represents inefficiency, as overlapping expertise means underutilized specialization potential. Yet research on organizational reliability has documented contexts in which redundancy is essential for maintaining performance under uncertainty (Weick & Roberts, 1993; LaPorte & Consolini, 1991). Our framework reconciles these perspectives by specifying the conditions under which the insurance value of redundancy outweighs the efficiency benefits of differentiation.

Second, we contribute to research on team composition and innovation by demonstrating that team structure responds endogenously to external labor market conditions. Prior studies of R&D team composition have primarily examined how team characteristics affect innovative outcomes, exploring, for instance, how team diversity influences creativity (Taylor & Greve, 2006), how familiarity affects coordination and performance (Huckman et al., 2009), and how star scientists shape team productivity (Oettl, 2012). These studies have generally treated team composition as reflecting managerial choices driven by capability requirements, resource availability, or organizational routines. Our findings reveal that team composition also reflects strategic responses to human capital risks originating outside the firm, suggesting that observed team structures may be jointly determined by productive efficiency and resilience considerations.

Third, we extend organizational reliability theory from operational contexts to knowledge production settings by documenting how compositional and relational mechanisms serve as substitutes in providing insurance against disruption. Classic work on high-reliability organizations examined how organizations in hazardous operational environments, such as aircraft carriers, nuclear power plants, air traffic control systems, achieve remarkably low failure rates through redundant systems and "heedful interrelating" among participants (Weick & Roberts, 1993; LaPorte & Consolini, 1991). Our study suggests that analogous reliability principles apply to knowledge production, where the "failure" to be avoided is disruption of innovative activity rather than operational catastrophe. The substitution pattern we document between compositional and relational redundancy parallels the distinction in reliability engineering between component redundancy (multiple instances of critical elements) and system redundancy (alternative pathways to achieve functionality). The finding that these mechanisms substitute for one another suggests that firms face a portfolio optimization problem in allocating investments across alternative insurance mechanisms, with the optimal mix depending on the relative costs and availability of each.

Our findings offer actionable insights for R&D managers and executives responsible for innovation strategy. Most directly, the results suggest that team staffing decisions should account for mobility risk in addition to traditional considerations of capability matching and resource allocation. When key team members face elevated mobility threats, whether due to policy changes, competitive labor market conditions, or diminished firm-specific ties, managers may benefit from composing teams with greater knowledge overlap to buffer against potential disruption. This recommendation runs counter to conventional wisdom emphasizing the efficiency benefits of specialized, differentiated teams, but our framework clarifies when such efficiency-focused advice may be misguided. The substitution between compositional and relational redundancy further implies that investments in relationship-building activities, cross-training, collaborative projects, mentorship programs, may reduce the need for compositional redundancy, potentially preserving some specialization benefits while still achieving resilience. Organizations facing talent retention challenges might therefore audit their current levels of relational embeddedness before restructuring team compositions, as existing collaborative relationships may already provide substantial insurance.

Our study is not without limitations, pointing to opportunities for future research. First, our ethnicity-based identification of H-1B-affected inventors introduces measurement error, as not all inventors with Indian and Chinese surnames hold H-1B visas, and some may be U.S. citizens or permanent residents unaffected by the portability provision. While this measurement error biases against finding significant effects and our difference-in-differences design addresses time-invariant misclassification, future research with access to administrative visa records could provide more precise identification of affected workers and sharper estimates of firm responses. Second, our competitive intensity hypothesis received limited support across alternative operationalizations, suggesting that the relationship between competition and insurance investments may be more nuanced than our initial theorizing anticipated. One possibility is that competitive intensity operates through multiple countervailing mechanisms: while intense competition increases the costs of disruption (amplifying insurance value), it may also constrain firms' ability to sacrifice efficiency through redundancy (dampening insurance investments). Future theoretical and empirical work could decompose these mechanisms and identify conditions under which amplification versus constraint effects dominate.

Despite the limitations, our study introduces a complementary perspective to strategic human capital departure: firms can insure against the disruption that departures cause by structuring teams with compositional redundancy that renders any single member's departure less catastrophic. In this sense, the question facing knowledge-intensive firms may be shifting from "how do we keep key employees from leaving?" to "how do we ensure that knowledge production continues when they do?"

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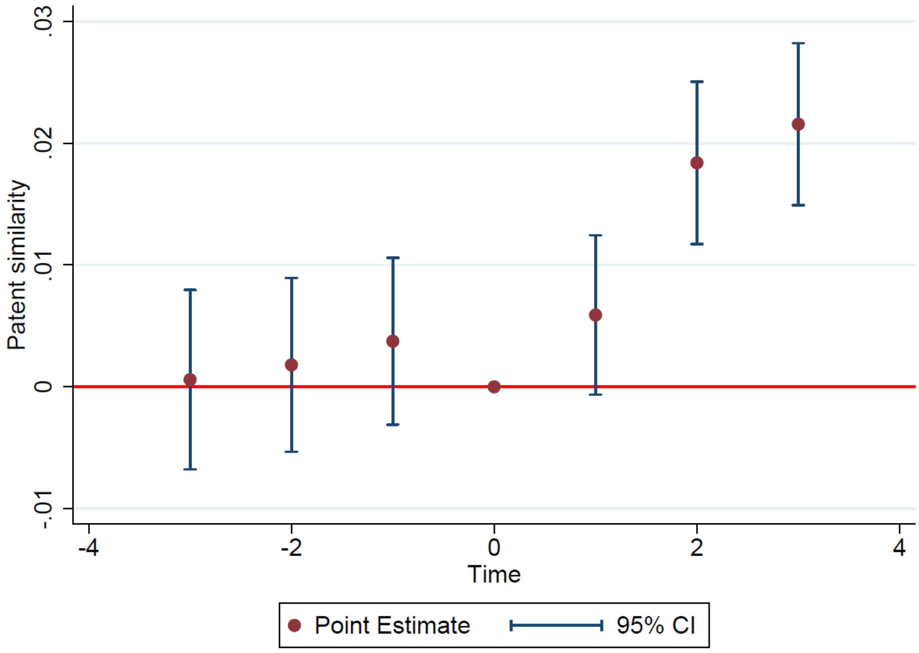
FIGURES

Figure 1. Events study coefficient plot (parallel trends; time 0 = 2001).



TABLES

Table 1. Placebo test for mean difference-in-differences, pre-shock period (N = 25554).

	Team knowledge similarity			
	Pre-period (1996 – 98)		Post-period (1999 – 2001)	
Patents with no Indian, Chinese inventors	Subsample mean: (N= 6879)	**0.109**	Subsample mean: (N= 9717)	**0.100**
Patents with Indian, Chinese inventors	Subsample mean: (N= 3122)	**0.108**	Subsample mean: (N=5836)	**0.098**
	Difference	**-0.001** (0.005)	*Difference*	**-0.002** (0.003)
			Difference-in-Differences:	**-0.001** (0.005)

Table 2. Placebo test for mean difference-in-differences, post-shock period (N = 34845).

	Team knowledge similarity			
	Pre-period (2000 – 02)		Post-period (2003 – 05)	
Patents with no Indian, Chinese inventors	Subsample mean: (N= 10734)	**0.139**	Subsample mean: (N= 9968)	**0.136**
Patents with Indian, Chinese inventors	Subsample mean: (N= 6624)	**0.142**	Subsample mean: (N=7519)	**0.132**
	Difference	**0.003**	*Difference*	**-0.003**
		(0.004)		(0.006)
			Difference-in-Differences:	**-0.007**
				(0.005)

Notes for Tables 1 and 2: Standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. Covariates include Technology domain overlap, Team technology diversity, Novice team, Team size, Firm size, R&D intensity, Number of patents, and Firm technology diversity.

Table 3. Placebo regressions of visa portability provision on team knowledge similarity in pre- and post-shock periods.

	Model 1 Placebo pre-shock	Model 2 Placebo post-shock
Affected team × Placebo pre-shock	-0.008	
	(0.044)	
Affected team × Placebo post-shock		-0.054
		(0.038)
Affected team	-0.003	0.053^{*}
	(0.049)	(0.030)
Placebo pre-shock	-0.143^{**}	
	(0.059)	
Placebo post-shock		-0.066
		(0.044)
Expertise overlap	1.914^{***}	1.790^{***}
	(0.069)	(0.050)
Team technological focus	0.473^{***}	0.259^{***}
	(0.110)	(0.099)
Novice team	-2.348^{***}	-2.011^{***}
	(0.123)	(0.129)
Team size	0.105^{***}	0.098^{***}
	(0.012)	(0.009)
Firm size	0.065	-0.031
	(0.058)	(0.048)
R&D intensity	0.053	0.013
	(0.116)	(0.017)
Number of patents	-0.016	-0.010
	(0.057)	(0.040)
Firm technological diversity	-0.036	0.061
	(0.076)	(0.103)
Constant	-2.124^{***}	-1.414^{***}
	(0.476)	(0.392)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	25554	34845
Number of Firms	141	147

Standard errors clustered by firm in parentheses. Firm and year fixed effects included.

Table 4. Descriptive statistics and correlations (N = 31,769)

		1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*
1	Team knowledge similarity	1															
2	Affected team	0.00	1														
3	Post	0.01	0.03	1													
4	Prior collaboration	0.10	0.30	0.07	1												
5	Competitor knowledge similarity	0.04	0.02	-0.13	0.02	1											
6	Competitor patents in 90th percentile	0.04	0.04	0.15	0.03	0.88	1										
7	Competitor firms in 90th percentile	0.03	0.01	0.12	0.01	0.88	0.88	1									
8	Technology domain overlap	0.50	-0.03	0.04	0.13	0.03	0.03	0.01	1								
9	Team technology diversity	0.04	-0.02	0.02	0.12	0.01	-0.02	0.02	-0.04	1							
10	Novice team	-0.28	-0.05	-0.02	-0.09	-0.05	-0.04	-0.03	-0.04	-0.08	1						
11	Team size	0.14	0.06	0.03	0.12	-0.03	-0.02	-0.04	-0.01	0.06	-0.10	1					
12	Firm size	-0.12	0.03	-0.05	-0.02	-0.10	-0.13	-0.11	0.01	-0.03	-0.04	-0.02	1				
13	R&D intensity	0.04	0.00	0.09	-0.01	-0.03	0.01	0.00	-0.02	-0.02	0.03	0.01	-0.40	1			
14	Number of patents	-0.10	0.03	0.02	0.05	-0.04	-0.10	-0.07	0.05	0.14	-0.12	-0.04	0.81	-0.22	1		
15	Firm technological diversity	0.08	0.02	-0.10	0.09	0.09	0.06	0.04	0.06	-0.03	-0.04	0.01	-0.49	0.14	-0.39	1	
16	Year	0.02	0.04	0.87	0.07	-0.15	0.17	0.13	0.05	0.02	-0.04	0.05	-0.01	0.08	0.02	-0.11	1
	Mean	0.18	0.38	0.57	1.12	0.05	3427.90	83.23	0.39	0.39	0.11	2.96	8.08	0.23	5.63	-1.92	2000.74
	Standard Deviation	0.18	0.49	0.50	4.09	0.02	2947.31	35.43	0.33	0.28	0.31	1.35	1.62	0.46	1.52	0.41	1.66

Table 5. Mean difference-in-difference in team knowledge similarity pre- and post-H1B visa portability provision.

	Team knowledge similarity			
	Pre-period		Post-period	
Patents with no Indian, Chinese inventors	Subsample mean: (N= 8792)	**0.118**	Subsample mean: (N= 10947)	**0.105**
Patents with Indian, Chinese inventors	Subsample mean: (N= 4998)	**0.111**	Subsample mean: (N=7032)	**0.113**
	Difference	**-0.007****	*Difference*	**0.008***
		(0.003)		(0.004)
			Difference-in-Differences:	**0.015*****
				(0.005)

Note: N = 31769. Standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. Covariates include Technology domain overlap, Team technology diversity, Novice team, Team size, Firm size, R&D intensity, Number of patents, and Firm technology diversity.

Table 6. Effects of visa portability provision on team knowledge similarity.

	Fractional Logit		OLS
	Model 1 Only controls	Model 2 Full model	Model 3 Full Model
Affected team × Post		**0.101***** **(0.037)**	**0.014***** **(0.005)**
Affected team		-0.036* (0.022)	-0.006** (0.003)
Post		-0.135** (0.065)	-0.022*** (0.008)
Technology domain overlap	1.862*** (0.068)	1.864*** (0.068)	0.282*** (0.013)
Team technology diversity	0.360*** (0.106)	0.359*** (0.105)	0.034** (0.013)
Novice team	-2.199*** (0.124)	-2.198*** (0.125)	-0.162*** (0.009)
Team size	0.111*** (0.011)	0.111*** (0.012)	0.015*** (0.001)
Firm size	-0.026 (0.042)	-0.030 (0.045)	-0.004 (0.007)
R&D intensity	0.029 (0.043)	0.028 (0.043)	0.004 (0.008)
Number of patents	0.044 (0.052)	0.046 (0.055)	0.004 (0.008)
Firm technological diversity	-0.023 (0.087)	-0.020 (0.089)	-0.006 (0.011)
Constant	-1.682*** (0.344)	-1.624*** (0.367)	0.033 (0.050)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
R-squared			0.381
Observations	31769	31769	31761
Number of Firms	150	150	142

Notes: Standard errors clustered by firm in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Firm and year fixed effects included.

Table 7. Moderating effects of prior collaboration on team knowledge similarity.

	Fractional Logit Model 2	OLS Model 1
Affected team × Post × Prior collaboration	-0.032***	-0.004***
	(0.007)	(0.001)
Affected Team × Post	0.185***	0.023***
	(0.055)	(0.007)
Affected Team	-0.109***	-0.014***
	(0.028)	(0.004)
Post	-0.141**	-0.022***
	(0.067)	(0.009)
Prior collaboration	-0.020*	-0.002
	(0.012)	(0.002)
Affected team × Prior collaboration	0.045***	0.006***
	(0.011)	(0.001)
Post × Prior collaboration	0.002	0.000
	(0.011)	(0.002)
Expertise overlap	1.861***	0.281***
	(0.066)	(0.013)
Team technological focus	0.356***	0.034**
	(0.102)	(0.013)
Novice team	-2.196***	-0.161***
	(0.125)	(0.009)
Team size	0.115***	0.015***
	(0.012)	(0.001)
Firm size	-0.030	-0.004
	(0.045)	(0.007)
R&D intensity	0.028	0.004
	(0.042)	(0.008)
Number of patents	0.045	0.004
	(0.050)	(0.007)
Firm technological diversity	-0.028	-0.007
	(0.087)	(0.011)
Constant	-1.640***	0.034
	(0.372)	(0.052)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
R-squared		0.382
Observations	31769	31761
Number of Firms	150	142

Notes: Fractional logit estimations. Standard errors clustered by firm in parentheses. Firm and year fixed effects included.

Table 8. Moderating effects of competition on team knowledge similarity.

	Model 1 Avg. proximity	Model 2 # competitors	Model 3 # patents
Affected team × Post × Competitor similarity	-2.088		
	(1.905)		
Affected team × Post × # Competitor patents > 90 percentile similarity		-0.000	
		(0.000)	
Affected team × Post × # Competitor firms with patents > 90 percentile similarity			-0.001
			(0.001)
Affected Team	-0.154^{**}	-0.089^{**}	-0.155^{**}
	(0.060)	(0.036)	(0.068)
Post	-0.207^{***}	-0.169^{***}	-0.229^{***}
	(0.065)	(0.064)	(0.066)
Affected Team × Post	0.209^{**}	0.132^{**}	0.208^{*}
	(0.099)	(0.063)	(0.117)
Competitor similarity	0.274		
	(1.583)		
Affected team × Competitor similarity	2.280^{**}		
	(1.153)		
Post × Competitor similarity	1.679		
	(1.383)		
# Competitor patents > 90 percentile similarity		-0.000	
		(0.000)	
Affected team × # Competitor patents > 90 percentile similarity		0.000^{*}	
		(0.000)	
Post × # Competitor patents > 90 percentile similarity		0.000	
		(0.000)	
# Competitor firms with patents > 90 percentile similarity			0.000
			(0.001)
Affected team × # Competitor firms with patents > 90 percentile similarity			0.001^{*}
			(0.001)
Post × # Competitor firms with patents > 90 percentile similarity			0.001
			(0.001)
Expertise overlap	1.865^{***}	1.866^{***}	1.868^{***}
	(0.069)	(0.069)	(0.069)
Team technological focus	0.356^{***}	0.359^{***}	0.355^{***}
	(0.100)	(0.103)	(0.099)
Novice team	-2.190^{***}	-2.190^{***}	-2.191^{***}
	(0.125)	(0.124)	(0.124)
Team size	0.111^{***}	0.111^{***}	0.111^{***}
	(0.012)	(0.012)	(0.012)
Firm size	-0.030	-0.031	-0.030
	(0.044)	(0.044)	(0.043)
R&D intensity	0.025	0.025	0.025
	(0.043)	(0.043)	(0.043)
Number of patents	0.049	0.049	0.050
	(0.055)	(0.055)	(0.054)
Firm technological diversity	-0.016	-0.016	-0.015
	(0.088)	(0.089)	(0.089)
Constant	-1.654^{***}	-1.620^{***}	-1.672^{***}
	(0.379)	(0.371)	(0.383)
Firm and Year fixed effects	Yes	Yes	Yes
Observations	31710	31710	31710
Number of Firms	148	148	148

Notes: Fractional logit estimations. Standard errors clustered by firm in parentheses. Firm and year fixed effects included.