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Essays on the Intersections of Knowledge, Organizations, and Labor Mobility

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Abstract

This thesis lies at the intersection of knowledge, organizational dynamics, and labor mobility, with a particular focus on the factors that shape knowledge creation and diffusion, as well as the influence of knowledge on entrepreneurial and innovative performance.

Chapter One (the job market paper) explores the effects of involuntary employee mobility on knowledge productivity. The findings show that when inventors move involuntarily from a source firm to a destination firm, their post-mobility productivity significantly declines. However, maintaining prior co-inventor relationships mitigates this negative impact. In contrast, moving to a firm with greater resources does not yield a statistically significant improvement in productivity outcomes.

Chapter Two shifts the unit of analysis from individuals to firms, investigating how uncommon knowledge combinations among founding teams affect entrepreneurial outcomes. The analysis demonstrates that startups with founder teams possessing more uncommon knowledge pairings are more likely to experience extreme outcomes, either notable market success or outright failure. While these uncommon combinations increase attractiveness to venture capitalists and facilitate early growth, they also lead startups to pursue multiple, less familiar market opportunities, thereby elevating the risk of failure.

Chapter Three transitions from startups to incumbent firms, examining knowledge diffusion within multi-clustered organizations. The results highlight a positive relationship between geographical dispersion and the quantity, diffusion, and exploitation of explorative patents. However, pre-existing co-patenting relationships between clusters signifi-

cantly constrain knowledge diffusion and exploitation.

This thesis contributes to the literature on strategic human capital, entrepreneurship, and innovation by underscoring the critical role of knowledge as a key form of human capital influencing firm performance. It extends the body of research on the portability of human capital across firms by differentiating the effects of involuntary mobility from those of other causes. Beyond employee-driven knowledge transfer, this work also enriches the understanding of founder team composition, intra-firm knowledge diffusion, and their influences on organizational performance.

Contents

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This has been a long journey, one that at times felt unending. Yet finally, I find myself at the finish line, a place of both relief and reflection.

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I would like to conclude this acknowledgment with a line from an ancient Chinese poem. It is not my favorite, but it resonates with my current emotions the most:

“ Turning my head, I see the dreary beaten track. 回首向来萧瑟处
Let me go back! 归去
Impervious to rain or shine, I’ll have my own will.” 也无风雨也无晴

Introduction

In today's rapidly evolving business landscape, firms increasingly compete not merely on tangible assets but on their ability to create, integrate, and deploy knowledge effectively. Of all possible resources that a firm might possess, its knowledge base has perhaps the greatest ability to serve as a source of sustainable differentiation and hence competitive advantage. This thesis investigates three critical dimensions of knowledge management that shape organizational outcomes: the mobility of knowledge workers, the composition of knowledge in entrepreneurial teams, and the spatial distribution of knowledge within organizations.

Knowledge, as conceptualized in strategic management literature, represents a firm's most valuable intangible asset—one that is difficult to imitate, socially complex, and causally ambiguous (Barney, 1991; Grant, 1996). Unlike physical assets that depreciate with use, knowledge assets often appreciate through application and recombination, generating increasing returns over time. However, the mechanisms through which knowledge translates into competitive advantage remain incompletely understood, particularly in dynamic environments characterized by technological disruption, workforce mobility, and geographical dispersion.

This thesis addresses this gap through three interconnected empirical studies that examine how knowledge flows, combinations, and distributions influence innovation and performance outcomes. Each chapter investigates a distinct yet related aspect of knowledge management, contributing to our understanding of how organizations can leverage their knowledge resources for strategic advantage in different contexts and under varying constraints.

The knowledge economy presents both unprecedented opportunities and formidable challenges for organizations seeking to maintain competitive advantage. Technological advancement has accelerated the pace of innovation while simultaneously reducing barriers to knowledge diffusion. Labor markets for skilled workers have become increasingly fluid, with talent moving across organizational boundaries more frequently than in previous decades. Meanwhile, digital communication technologies have enabled geographically dispersed work arrangements, fundamentally altering how organizations structure their operations and manage their knowledge assets.

These developments have profound implications for how firms acquire, develop, and retain knowledge. They raise important questions about the portability of human capital, the optimal composition of knowledge in teams, and the spatial organization of innovation activities. Understanding these dynamics is crucial not only for scholarly advancement but also for the practical management of knowledge assets in contemporary organizations.

This thesis is motivated by the recognition that knowledge management represents a critical yet incompletely understood dimension of competitive strategy. By examining how knowledge flows and transforms across individuals, teams, and organizational units, I aim to develop a more nuanced understanding of the mechanisms through which knowledge creates value in different contexts. The findings have important implications for talent management, entrepreneurial team formation, and organizational design in knowledge-intensive industries.

This thesis examines knowledge dynamics at the individual, team, and organizational levels, providing a multi-level perspective on knowledge management in contemporary organizations. The first chapter investigates the productivity outcomes of inventors following involuntary job transitions. While extensive research has examined voluntary mobility among knowledge workers, comparatively little attention has been paid to the consequences of involuntary transitions, despite their prevalence in innovation-intensive industries that regularly experience restructuring and layoffs. Drawing on linked data from LinkedIn profiles, USPTO patent records, and comprehensive mass layoff data in the United States, this study finds that involuntary mobility significantly decreases post-mobility productivity compared to both voluntary mobility and continued employment. However, the research also identifies an important mitigating factor: maintenance of social capital, particularly pre-existing collaborative networks, substantially reduces the negative effects of involuntary transitions. This chapter contributes to our understanding of human capital portability by highlighting the contingent nature of knowledge transfer across organizational boundaries. The findings suggest that knowledge embedded in collaborative relationships—what might be termed "social knowledge"—represents a particularly valuable and portable form of human capital that can provide resilience during career disruptions. These insights have important strategic implications for firms managing layoffs, talent retention, and knowledge continuity in innovation-intensive industries.

The second chapter shifts focus from individual knowledge workers to entrepreneurial founding teams, examining how the composition of knowledge within these teams influences venture outcomes. Moving beyond conventional measures of team diversity or complementarity, this study introduces and empirically validates the concept of "uncommon knowledge combinations"—unexpected pairings of expertise that deviate from typical skill configurations in the market. Using comprehensive data on startups and their founders, the analysis reveals that teams with higher levels of uncommon knowledge combinations experience more polarized outcomes—they are more likely to achieve exceptional success (successful exits) but also more likely to fail outright. This bifurcation occurs through dual mechanisms: while uncommon knowledge combinations enhance creativity and signal uniqueness to investors (increasing venture capital investment), they also lead teams to enter more complex and unfamiliar market combinations, heightening execution risks. This chapter extends our understanding of knowledge as a strategic resource by demonstrating how novel combinations of existing knowledge can create distinctive capabilities but also introduce significant uncertainties. The findings suggest that entrepreneurial teams face important trade-offs when assembling their knowledge portfolios, with implications for team composition, market-entry strategies, and resource allocation decisions.

The third chapter examines knowledge dynamics at the organizational level, investigating how geographical dispersion influences patterns of knowledge exploration and exploitation within firms. As organizations increasingly distribute their operations across multiple locations, questions arise about how spatial arrangements affect innovation processes and outcomes. Drawing on patent data from U.S. public companies between 1990 and 2015, this study finds that geographical dispersion increases both the quantity and diffusion of exploratory patents while also broadening the variance in patent quality. Furthermore, dispersed organizational structures enhance firms' ability to exploit knowledge across locations, though pre-existing co-patenting connections unexpectedly limit such diffusion, suggesting potential organizational rigidities. This chapter contributes to our understanding of how spatial distribution influences internal knowledge circulation and innovation efficiency. The findings highlight important trade-offs in designing organizational structures to optimize knowledge creation and utilization, with significant implications for firms seeking to balance local specialization with global integration of their innovation activities.

Collectively, the three chapters of this thesis make several important contributions to our understanding of knowledge as a strategic resource: First, they highlight the dynamic nature of knowledge assets, demonstrating how knowledge flows, transforms, and recombines as it moves across individuals, teams, and organizational units. This perspective extends beyond static conceptualizations of knowledge as a fixed resource to emphasize the processes through which knowledge creates value in different contexts.

Second, they illuminate the social embeddedness of knowledge, showing how knowledge is often inseparable from the relationships and collaborative networks in which it is created and applied. This insight challenges purely individualistic notions of human capital and highlights the importance of social structures in knowledge management.

Third, they demonstrate the dual-edged nature of knowledge novelty, revealing how unconventional knowledge combinations can simultaneously create distinctive advantages and introduce significant risks. This nuanced perspective helps explain heterogeneity in performance outcomes among seemingly similar knowledge-intensive organizations.

Finally, they illustrate the spatial dimension of knowledge management, showing how geographical arrangements influence patterns of knowledge creation, diffusion, and utilization within organizations. This spatial perspective complements traditional structural and relational views of knowledge dynamics. Beyond these theoretical contributions, the findings of this thesis have important practical implications for organizational strategy and management practice. They offer guidance for talent management in innovation-intensive industries, highlight considerations for entrepreneurial team formation and market-entry strategies, and provide insights for designing organizational structures that optimize knowledge flows across geographical boundaries.

This thesis employs diverse quantitative empirical methods to investigate knowledge dynamics across different contexts. Each chapter utilizes unique datasets that combine public and proprietary sources to examine specific aspects of knowledge management. Across these studies, I employ econometric techniques designed to address potential endogeneity concerns and establish causal relationships where possible. These include difference-in-differences designs, Heckman selection approaches, and matching methods that help isolate the effects of interest from confounding factors. By triangulating across multiple data sources and applying rigorous empirical methods, this thesis aims to provide robust insights into the complex dynamics of knowledge management in contemporary organizations.

As organizations navigate an increasingly knowledge-intensive competitive landscape, understanding how to effectively manage knowledge assets becomes paramount to sustainable advantage. This thesis investigates three critical dimensions of knowledge management—the mobility of knowledge workers, the composition of knowledge in teams, and the spatial distribution of knowledge within organizations—to develop a more comprehensive understanding of how knowledge creates value in different contexts. The findings highlight the complex, contingent, and often paradoxical nature of knowledge as a strategic resource. They demonstrate that knowledge assets are simultaneously valuable and vulnerable, embedded in social relationships yet transferable across boundaries, and capable of generating both extraordinary successes and significant failures. By illuminating these dynamics, this thesis aims to advance both scholarly understanding and management practice in the knowledge economy.

Chapter 1

Involuntary Mobility and Working Productivity: Evidence from the mass Layoffs in the United States

1.1 Introduction

Human assets often represent a critical competency and the primary driver of competitive advantage for organizations. This is particularly evident in high-skill, technology-driven industries, where employee expertise and capabilities significantly influence organizational performance (Campbell et al., 2012a; Coff, 1997; Hall, 1993). However, the ability of organizations to transform human capital into competitive advantage hinges on their capacity to attract and retain talent. The organizations will strengthen their competitive advantages by recruiting talent, but they will lose these advantages when key employees leave the organization. Employee mobility, therefore, can be a vital reason for the dynamics of the organizational performance (Ganco, 2013; Mawdsley and Somaya, 2016; Song et al., 2003; Tzabbar, 2009).

However, the extent to which that organizations benefit or disadvantage from mobility depends on such factors as the human assets the mobile employee carries, organizational capabilities that the source and destination organizations have, and drivers of the mobility (Campbell et al., 2012b; Corredoira and Rosenkopf, 2010; Somaya et al., 2008), giving rise to what has been termed the "portability paradox" in the literature (Campbell et al., 2014; Di Lorenzo and Almeida, 2017; Dokko et al., 2009; Fernández-Zubieta et al., 2016; Groysberg et al., 2008; Hoisl, 2007, 2009; Huang and Ertug, 2014; Raffiee and Byun, 2020). This paradox underscores the controversy surrounding how effectively mobile employees can transfer their previous performance across organizational boundaries. At its core, the paradox hinges on employees' ability to transfer both core and complementary assets, some of which are embedded in employees while others are jointly bound by employees and their firms (Campbell et al., 2012b; Teece, 1986).

Following this path, this paper investigates the paradox by emphasizing employees who move involuntarily. The emergence of the "portability paradox, wherein the transfer across organizations yields mixed outcomes, can be attributed to a fundamental assumption prevalent in the existing literature. This assumption posits that employees typically undertake mobility voluntarily, driven by factors such as better promotion prospects, higher wages, and more favorable geographical locations (Belal, 2023; Landau and Hammer, 1986; McLaughlin and Bils, 2001). In such scenarios, employees are better prepared for the transition, actively seeking firms that align with their skills and capabilities. Consequently, they can carry both assets that are embedded in employees and their relationships formed by interacting with others. In contrast, when individuals are forced to move, they have limited time and resources to improve the matching quality with the destination firm and facilitate a smooth transition to a new organizational setting. Facing the stress of leaving the source firm and finding another firm to work in, it may be harder for such employees to adjust and adapt to the new working environment. While assets embedded in employees may remain unaffected, firm-specific complementary assets are likely to suffer from reduced portability, which can result in a decline in performance.

The research aims to address the question about the effect of the employee's involuntary move on their productivity post-mobility. To identify individuals who move involuntarily, I focus specifically on individuals undergoing employment changes during mass layoffs within the United States (US). These mass layoffs are characterized by significant workforce reductions initiated by employers, often necessitating compliance with the Worker Adjustment and Retraining Notification Act (commonly known as the WARN Act) since its inception in 1988. Under the WARN Act, employers are mandated to provide advance notifications to affected employees and relevant state government authorities at least 60 days prior to the implementation of significant layoffs or office (plant) closures. The acts were later adjusted in different states, but the federal act has worked until now.

Literature defines the occurrence of a mass layoff when there is a significant reduction in employment levels, amounting to at least a 30 percent decrease; there is a permanent closure of organizational facilities or factories; or there is a displacement of more than 499 employees at a single site. (Bertheau et al., 2023; Cornfield, 1983; Schmieder et al., 2023). Moreover, mass layoffs are prevalent in the US, and their occurrence is not rare. For example, Reuters has reported that firms announced 55,597 and 72,821 layoffs in October 2024 and September 2024, respectively[1]. By leveraging this regulatory framework and using mass layoffs as a proxy for involuntary moves, this research aims to elucidate the consequences of involuntary mobility on subsequent productivity levels among affected individuals. This methodological rigor ensures that our analysis captures the unique dynamics associated with involuntary job transitions.

I investigate the productivity change after an involuntary leave in the context of US public companies in the Information and Communication Technology (ICT) industry between 2000 and 2015. Inventors in the ICT sector are particularly well suited for this research purpose because their performance has been documented in patenting records, and many mass layoffs have happened in the ICT industry. I construct a sample by linking laid-off inventors to their patents in the U.S. Patent & Trademark Office (USPTO) and employment recorded on LinkedIn. To find the counterfactual group of inventors who either never move across organizations or move voluntarily, I apply propensity score matching (PSM) and nearest neighborhood (NN) matching algorithms without replacement. I reach a balanced sample with 3,342 inventors, 1,671 in each group. Then, I use the research design of difference-in-differences (DiD) to conduct regressions. Results show a negative effect of being laid off on the inventor's number of applied patents after the layoff event. In other words, moving involuntarily decreases the performance of an inventor. Furthermore, I collect information on co-inventors and destination firms. Analysis shows that maintaining collaborations with pre-mobility co-inventors positively moderates the negative effect of involuntary mobility. However, moving to companies with high capabilities does not significantly influence the negative effect.

The paper contributes to the following strands of literature. First, it contributes to research on human assets by delving into the dynamics of performance portability across

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[1] `https://www.reuters.com/markets/us/us-planned-layoffs-drop-again-october-recruitment-firm-challenger-says-2024-10-31/`

organizational boundaries. Existing research has often delineated between human capital, which is mainly embedded in employees, and other complementary assets that are tied to firms. (Campbell et al., 2012a; Coff and Raffiee, 2015; Kryscynski et al., 2021; Raffiee and Coff, 2016). Based on the transferability and applicability of different assets across firms, mobility can influence the portability of such assets differently. This paper focuses specifically on involuntary mobility—characterized by sudden transitions with limited opportunities for deliberate job search—and demonstrates how such mobility often results in weaker matches between employees and new firms, hence diminishing the portability of prior performance. The analysis highlights that involuntary moves constrain the transfer of complementary assets, thereby complicating the transferability of social capital and reducing the quality of employee-firm fit. This insight underscores the interplay between human capital dynamics and the conditions under which performance can be sustained post-transition.

Second, the paper provides evidence of the outcome of mass layoffs. Using mass layoffs and census data, researchers have discussed a series of topics around mass layoffs. For example, the power of trade unions can influence the occurrence of mass layoffs (Medoff, 1979), the job superfluousness and the organizational structure can determine the individuals to be laid off (Cornfield, 1983), and generalists outperform specialists after being displaced (Byun and Raffiee, 2023). Beyond the determinants of mass layoffs, considerable attention has been devoted to understanding their consequences. Empirical evidence suggests a decrease in wages after being displaced, and the effect has been validated in different countries and can be as long-persistent as two decades (Couch and Placzek, 2010; Jacobson et al., 1993; Schmieder et al., 2023). Displaced workers may increase their consumption in the short term, but the consumption decreases sharply in the long run (Gerard and Naritomi, 2021; Pistaferri, 2015). This paper adds to this body of work by examining the specific impact of mass layoffs on innovation outputs, as captured by changes in patenting activity. By comparing patent counts before and after displacement, it reveals a negative impact on innovational outputs, highlighting the broader repercussions of layoffs on individuals' creative productivity. This finding underscores the need for strategies to alleviate the adverse effects of layoffs on innovation.

Third, this paper corresponds to the call for research on involuntary movement (Mawdsley and Somaya, 2016; Tzabbar and Cirillo, 2020a,b). While much of the existing literature on employee mobility has assumed implicitly that voluntary job transitions are driven by opportunities for career advancement, recent attention has turned towards understanding the dynamics of involuntary movements (Byun and Raffiee, 2023; Mawdsley and Somaya, 2016; Schmieder et al., 2023). By analyzing the experiences of individuals displaced through layoffs and their subsequent transitions, this paper deepens the understanding of the mechanisms and outcomes of involuntary mobility. In doing so, it contributes to a more nuanced framework for understanding the broader implications of workforce displacement on organizational and individual performance.

1.2 Conceptional Framework and Hypotheses

Human assets are an important input for organizations to create value. Organizations rely upon human assets to build, cultivate, and retain their competitive advantages, which can be weakened or enhanced by employee mobility. When employees move across organizations, the extent to which they will carry their assets is crucial in strategic human capital literature, which is central to the discussion of the "portability paradox". The portability of human assets varies based on their applicability, with more broadly applicable assets being more portable.

This paper argues that employees forced to leave their source firms face greater challenges in transferring and applying their assets to new firms compared to employees who voluntarily transit or remain with their firms. Given that involuntary movements may be a bad signal for employees in the labor market, it may be more difficult for employees

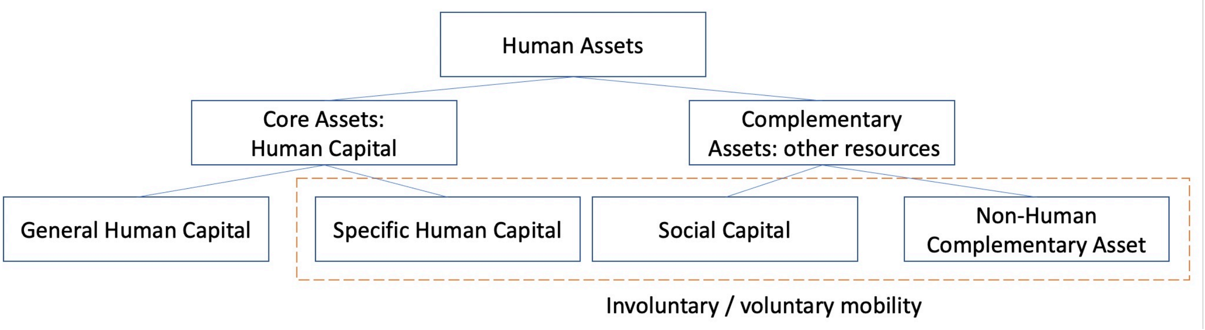

Figure 1.1: Human Assets

who move involuntarity to find another job. The fact of a sudden termination on the current job and potential longer unemployment duration may cause severe psychological and financial stress undertaken by such employees, which will influence their search on new jobs. Therefore, involuntary mobility can impair employee performance and diminish value creation at the destination firm.

Human assets consist of various assets, as shown in Figure 1.1. I distinguish human assets into two types: the core asset and complementary asset (Campbell et al., 2012b). The core asset refers to the human capital embodied in employees, while the complementary asset pertains to the additional human and organizational resources provided by the firm to facilitate value creation.

Human capital reflects individual capacities, such as knowledge, skills, abilities, or other characteristics (KSAOs) (Ployhart et al., 2014; Raffiee and Byun, 2020) that contribute to value creation. It can be further divided into general and specific human capital across various levels, including firm-specific, industry-specific, job-specific, and task-specific human capital. The primary distinction between general and specific human capital lies in their applicability. General human capital is widely applicable across firms, industries, occupations, and tasks, making it more portable for mobile employees. In contrast, specific human capital, developed through interaction with unique firm, industry, or job contexts, is less transferable and generally limited to similar environments.

This paper also explores two forms of complementary assets. One is social capital, which reflects the resources embedded in relationships utilizable to create value (Adler and Kwon, 2002; Raffiee and Byun, 2020). For instance, tacit knowledge embodied in other employees and connections with potential clients (Campbell et al., 2012b; Pennings et al., 1998). The other is the non-human complementary asset, which includes but is not limited to physical and financial capital provided by the firm, stock of knowledge in the firm, and contractual relationships with partners and clients (Campbell et al., 2012b). Employees accumulate such assets by building relationships and interacting with others related to the firm, thus making it more complicated to transfer the assets from the source firm to the destination firm and apply them to the destination firm.

Involuntary mobility primarily affects the portability of complementary assets and the specific human capital within core assets. This distinction arises from the varying applicability of asset types and highlights the nuanced challenges faced by involuntarily mobile employees in replicating their value in destination firms.

1.2.1 Human Assets, Job Matching, and Working Performance

Employee mobility serves as a mechanism for optimizing the allocation of human assets within the labor market, facilitating the match between employer and employee (Fredriksson et al., 2018; Gautier and Teulings, 2015; Jackson, 2013). The quality of matching between the employee and employer matters in the portability of the employee's previous performance and to what extent the destination firm will benefit from the mobility of the employee. Mobile employees can benefit from mobility by improving matches with the destination firm. They fit and integrate better with complementary assets in the destination firm, thus increasing post-mobility performance (Campbell et al., 2012b, 2021; Hess and Rothaermel, 2011). For instance, mobile inventors can access and profit from knowledge stocks in the new environment (Al-Laham et al., 2011; Cassiman et al., 2018; DeCarolis and Deeds, 1999; Tubiana et al., 2022). This access provides a fertile ground for innovation and knowledge exchange, driving productivity enhancements. This broader access enables inventors to tap into a more diverse pool of insights, perspectives, and expertise, fostering innovation synergies that transcend traditional organizational boundaries, thereby enhancing the productivity of individuals.

In addition to the complementary asset shaping the effects of employee mobility on working performance, employees should also be equipped with the absorptive capacity to combine the complementary asset (Al-Laham et al., 2011; Roper and Hewitt-Dundas, 2015; Stieglitz and Heine, 2007; Wu et al., 2014) in the destination firm (Hoisl, 2007). This capacity enables mobile employees to leverage their existing KSAOs, thereby enhancing their productivity in the destination firm. Indeed, mobile employees often exhibit above-average capacity and performance levels, which may partially explain their propensity to seek new opportunities. Central to this phenomenon is the concept of tacit knowledge, a form of human capital that is inherently tied to individual experiences and carried out by employees (Hoisl, 2007; Trajtenberg et al., 2006). Recruiting a key (or star) employee is one means to realize knowledge transfer and diffusion from the employee's source firm to the destination firm (Singh and Agrawal, 2011; Song et al., 2003). As a consequence, firms are incentivized to attract and retain productive employees from external sources. In turn, mobile employees are motivated by factors such as higher wages, better job prospects, and the opportunity to contribute their expertise to new ventures (Carnahan et al., 2012; McLaughlin and Bils, 2001).

Even though mobile employees may have tried to find the best-fitting firm during the process of searching, information asymmetry can cause a suboptimal match between the employee and the destination firm. (Fredriksson et al., 2018; Gautier et al., 2010). If the employee fails to improve matching quality to the new employer after mobility, they may face an immediate and temporary drop in performance. The mismatch can be unfolded into dimensions of the destination firm and the mobile employee. In case the employee moves to a less proficient firm, they may lack access to appropriate complementary assets, which can hinder employees from working effectively (Raffiee and Byun, 2020). For instance, Groysberg et al. (2008) analyzed security analyst performance and found evidence of an intermediate decline in performance when analysts moved to firms with lesser capabilities. Interestingly, this effect persisted even among star analysts, highlighting the significance of organizational context in shaping individual performance outcomes. Moreover, the generation of breakthrough knowledge often hinges on the recombination of distant and previously uncombined knowledge domains (Weitzman, 1998). If an employee's knowledge stock significantly overlaps with that of their new organization, they may find themselves unable to access novel or distant knowledge, consequently limiting their innovative output.

The capacity to cultivate one particular complementary asset, social capital, plays a pivotal role in facilitating the adaptation of mobile employees to new organizational environments (Tzabbar et al., 2022). The ability of mobile employees to establish and nurture new networks upon relocation emerges as a critical determinant of their post-mobility productivity (Baum et al., 2000). If an employee occupies a central position within these networks, characterized by numerous ties and interactions with other employees in the sourcing firm, their reliance on these collaborators for production may be substantial (Tzabbar et al., 2022). After moving, the employee may lose the benefits from previous networks. This loss becomes more pronounced if the individual fails to establish new networks in the new environment, further exacerbating the decline in productivity.

1.2.2 Involuntary Mobility and Decreased Performance

The lack of consensus regarding the portability of performance in the literature may come from the assumptions surrounding voluntary mobility (Iverson and Pullman, 2000; Mawdsley and Somaya, 2016). Many existing studies presume that individuals possess sufficient time and information to deliberate, search, and select new opportunities, thereby enabling them to optimize their employee-employer matches. However, a significant proportion of workforce transitions occur due to involuntary circumstances, such as mass layoffs, which challenge these assumptions (Bertheau et al., 2023; Schmieder et al., 2023; Pistaferri, 2015) and imply the involuntary mobility of employees. Consequently, involuntarily mobile employees may face heightened uncertainty and difficulty in securing roles that align with their skills, preferences, and career aspirations. Given these challenges, it is reasonable to anticipate that individuals who undergo involuntary mobility are more susceptible to experiencing a decline in productivity following job loss, compared to their counterparts who never move or move voluntarily, for the following reasons.

In addition, mobile employees, particularly those who have been involuntarily laid off, may exhibit reduced motivation and productivity due to various factors affecting their psychological well-being and financial stability. Regarding psychological issues, the experience of being laid-off may lower the employee's self-esteem (Brockner et al., 1993; Wiesenfeld et al., 2007) and generate doubts about their competence (Marks and De Meuse, 2005; Lim and Sng, 2006). The uncertainty about their ability may persist in their future work. As a result, laid-off employees are not as productive as they were in the past. Moreover, the financial repercussions of involuntary layoffs can be profound and enduring. Research indicates that employees displaced during mass layoffs experience large losses in earnings, which can last for almost two decades (Bertheau et al., 2023; Pistaferri, 2015; Schmieder et al., 2023). Such financial setbacks not only impact immediate financial security but also contribute to a reduced motivation to work as effectively as before.

Based on the above, mobile employees may not improve the quality of matching with the destination firm after the involuntary move. It is less likely for them to carry their human assets and apply them in the new firm while experiencing loss and stress psychologically and monetarily. Therefore, I propose the first hypothesis:

Hypothesis 1.1. *There exists a negative relationship between an employee's involuntary move and their performance post-mobility. Specifically, employees who have experienced involuntary mobility are more likely to exhibit a decline in productivity following the move.*

1.2.3 Social Capital

Social capital is one type of complementary asset, which stems from resources engendered from social relationships, thus being imperishable and interconnected among employees (Adler and Kwon, 2002; Moran, 2005). Compared to other types of assets, social capital is not as embedded in the firm as non-human complementary assets, nor as mobile as human capital moving with employees. Moreover, it can be divided into external social capital and internal capital based on sources of repeated interactions. External social capital refers to relationships that employees have developed outside the firm, while internal social capital refers to relationships developed within the bounds of the firm. Therefore, external social capital is less embedded in the firm than internal social capital. This paper focuses on mobility from the source firm to the destination firm and how the capital can be transferred, so both sources are relevant (Adler and Kwon, 2002; Raffiee and Byun, 2020).

When there is mobility between firms, existing relationships within the source firm may be disrupted, no matter the reason for the mobility, and employees who move involuntarily may suffer more under these circumstances. In scenarios where an employee is laid off, it is not very likely that their entire collaborative network would undergo a similar transition and continue their careers together in a new firm. Therefore, it matters how effectively mobile employees can carry their social capital from the previous firm to the new firm to create value.

The portability of social capital relies on the degrees of embeddedness of social capital in firms and employees. When it is less embedded in the firm and more embodied in the employee, it is more likely to transfer across firms. Therefore, employees who can maintain their social capital are better positioned to perform in their new roles, as they can carry over and apply social capital from the previous firm and leverage previous collaborations and networks to enhance their effectiveness in the new firm. The performance decline, which is typically associated with involuntary mobility, can be mitigated.

To summarize, employees who can transfer not only their human capital but also social capital will be influenced by the involuntary move less heavily. So, the decreasing productivity caused by involuntary mobility will be positively moderated for inventors who are better at maintaining their previous collaborations.

Hypothesis 1.2. *Carrying social capital in the source firm will positively moderate the negative effect of involuntary mobility on post-mobility performance. The more social capital an employee can maintain from their previous firm, the better their performance will be in the destination firm.*

1.2.4 Non-Human Complementary Assets in Firms

Firm value creation is a product of an interactive process between employees and their firms. Non-human complementary assets provided by firms can be essential by providing necessary resources that can return to other assets (Milgrom and Roberts, 1995). For instance, a robust knowledge stock (embodied in other employees in the firm or the intellectual properties owned by the firm) significantly impacts the generation of innovation. When moving to a firm with similar knowledge stock as the mobile employee owns, it may strengthen the advantage of the employee and make it easy for the new firm to integrate the asset brought by the mobile employee. It is also possible that the employer is hired by a new firm with a very different knowledge stock than his/hers. The firm can benefit from mobility because the hired employee can fill the void in the existing knowledge stock of the firm. Meanwhile, the mobile employee may benefit from distant knowledge, thus making breakthroughs for the firm (Raffiee and Byun, 2020). Hence, a more robust knowledge stock is not only an improvement of non-human complementary assets in a firm but also enhances the human capital of employees and their social capital via collaborations with other employees.

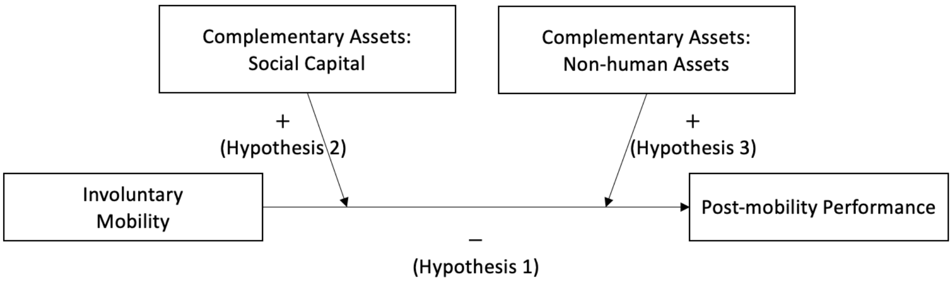

Figure 1.2: Theoretical Framework

However, it is more challenging for employees to transfer such an asset to the new firm, for it is not embodied in employees. While both firms and employees restrict the portability of social capital, the non-human complementary asset is purely bound by firms. Therefore, a high-quality match between the mobile employee and the firm is required. Employees who end up in a firm with more non-human complementary assets are less likely to be affected by involuntary mobility. Consequently, I propose the following hypothesis:

Hypothesis 1.3. *Moving to a firm with more non-complementary assets will positively moderate the negative effect of involuntary mobility on post-mobility performance. The more non-complementary assets provided by the destination firm, the better the mobile employee's performance will be.*

Theoretically, I predict that employees' involuntary mobility will significantly impact their working performance after mobility, and the negative effect can be mitigated if the mobile employee can maintain their previous social capital or access to non-human complementary assets provided by the destination firm. Figure **??** is a theoretical framework describing the hypotheses.

1.3 Context

To examine involuntary job mobility across organizations, this study leverages the context of mass layoffs within the US. Consistent with prior research, mass layoffs are defined as substantial workforce reductions characterized by a decrease of at least 30% in employment levels, the permanent closure of organizational facilities or factories, or the displacement of more than 499 employees at a single site. (Bertheau et al., 2023; Cornfield, 1983; Schmieder et al., 2023). In recent years, mass layoffs have become prevalent among different occupations in different firms and industries. For instance, the New York Times reported that Amazon started its largest-ever series of layoffs at the end of 2022, which has affected over 27,000 positions across various segments[2]. Similarly, Bloomberg reported that Google has also experienced its largest layoff of 12,000 employees, including engineering, assistants, and hardware teams, in January 2023 as a part of the company's plan to reduce expenses and shift focus on artificial intelligence[3]. By leveraging this regulatory framework and using mass layoffs as a proxy for involuntary moves, this research aims to elucidate the consequences of involuntary mobility on subsequent productivity levels among affected individuals.

In August 1988, the US Congress enacted the WARN Act to grant employees adequate notice to pursue alternative employment opportunities or engage in retraining before the termination of their positions. The legislation officially came into effect on February 4, 1989. It requires employers to give their employees or a union that represents those employees a written notice 60 calendar days before the occurrence of the event, and part-time workers are also included. Firms that violate the WARN Act face penalties including back pay and benefits to their employees and civil penalties, and the court system enforces the WARN Act[4]. Later, some states launched the Mini-WARN Act, aiming to offer stronger protections to laid-off employees. For instance, employers in New York and New Jersey need to provide notice to employees 90 days before the mass layoff date. In California, firms need to pay a civil penalty of 500 US dollars per day for

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[2] `https://www.nytimes.com/2022/11/14/technology/amazon-layoffs.html`

[3] `https://www.bloomberg.com/news/newsletters/2024-01-19/google-layoffs-are-now-business-as-usual-employee-says`

[4] More information and regulations on the topic can be found `https://www.dol.gov/general/topic/termination/plantclosings` and `https://www.dol.gov/sites/dolgov/files/ETA/Layoff/pdfs/WorkerWARN2003.pdf`

every violation. In terms of mass layoffs, the Mini-Warn Act has loosened the definition. Under federal law, a mass layoff is defined as one that impacts more than 500 employees. In Illinois, these protections extend to scenarios in which as few as 25 employees are terminated. Even though there are adjustments for the WARN Act across states, the federal law has worked until now.

The WARN Act notice given to employees must contain the following information: the notice should specify whether the layoff is permanent or temporary with the site information; the date of layoff and the date of the laid-off employee's separation, and the notice must be given to the employee 60 days before the first day of the separation period; a contact in the firm that laid-off employees can reach out to[5]. A real example of a layoff notice can be found in the Appendix (**??**). It shows that the event would occur on June 23, 2023, and the notice was sent at least 60 days before the event. I also know that approximately 152 employees would be affected by this permanent separation, according to the notice. At the end of the notice, there is a contact for further information.

The regulatory framework surrounding mass layoffs, while aimed at providing some degree of support and transition assistance to displaced workers, may inadvertently contribute to suboptimal job-firm matches and reduced productivity following involuntary mobility. The compressed timeline may limit the extent to which laid-off individuals can thoroughly assess potential employers and evaluate the compatibility of their skills, experiences, and preferences with the available job opportunities (Boswell et al., 2012; Mortensen, 1986), causing a heightened risk of mismatches between laid-off employees and their subsequent employers. Therefore, the laid-off employee may not be able to end up in the firm where they can apply their human assets the most, thus decreasing the output after involuntary mobility. This mismatch between employee assets and firm characteristics can have adverse effects on post-mobility outcomes, potentially diminishing productivity and innovation output.

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[5] If there exist bumping rights, they should also be included in the notice

1.4 Data and Methodology

1.4.1 Data and Sample

To test hypotheses, I built a sample with public companies in the US ICT industry and their employees who have patented it. Such employees, who have applied for at least one patent in the USPTO, are defined as inventors in this paper. The ICT industry and inventors are fit for my research questions for the following reasons. First, the ICT industry is a knowledge-intensive and high-skill industry, so the growth of firms relies on the performance of inventors or high-skill employees (Corredoira and Rosenkopf, 2010; Somaya et al., 2008). Second, I proxy the inventor's performance with the number of patents applied each year in the paper, so the performance of an inventor is clear and traceable based on their patenting records. Third, high-skilled employees are highly mobile, voluntarily or involuntarily. Therefore, the paper concentrates on public firms in the US ICT industry and their inventors.

I collected firm information from Compustat, a database covering public firms, based on the Standard Industrial Classification (SIC) code[6]. The descriptions of the codes can be found in Appendix Table A1. Then, I kept public ICT firms with at least two patents in each year in the period 1990-2015 and firms for which Compustat has reported the amount of R&D expenditures for each year, from the year they went public until the year they were acquired, dissolved, or taken private, and there are 180 firms identified. By matching firm names between Compustat and layoff notices that occurred from the year 2000 to the year 2016, I further identified 138 firms.

In the paper, the inventor's performance, or the number of patents applied each year by inventors and other patenting information was gathered from PatentsView. PatentsView is an open data platform that focuses on intellectual property (IP) data, and it allows

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[6] The SIC codes I use to identify ICT industry are 3570, 3571, 3572, 3576, 3577, 3578, 3661, 3663, 3669, 3674, 3678, 3679, 3812, 3825, 3826, 4210, 4813, 4841, 5961, 7370, 7372, 7373, 7374

inventors, researchers, policymakers, and the public to access all data from USPTO in its original form (Toole et al., 2021). It includes such patenting information as applications, their inventors, the locations of corresponding inventors, the number of claims included in the patent, and its technological categories.

Then, I merged inventors from USPTO with LinkedIn data on inventor names. LinkedIn has become a more and more prevalent data resource in research in recent years (Ng and Stuart, 2021; Zide et al., 2014), and has a relatively complete record of the account's working experience, where I could trace the mobility across firms. Therefore, I could gather data on the previous and postier firms, the time that the inventor left the sourcing firm and joined the destination firm (in a month-year format), job titles, tenures, and locations. It is considered more accurate than information derived from patents, in which case I could only observe the mobility of inventors who patented before and after the move, and it is more difficult to learn the exact time when the mobility occurred (Ge et al., 2016).

Moreover, I identified inventors who experienced involuntary mobility by checking whether they left their sourcing firms during mass layoffs. In general, firms give a notice to employees informing the layoff event, and the notice becomes effective in two to three months. The specification of laid-off inventors is based on three conditions:

(i) the inventor worked in the firm when it occurred a mass layoff;

(ii) before mobility, the inventor should be located in the same state where the layoff happened, taking into account that a firm may have branches in several states);

(iii) the inventor departed the firm between the notice month and the effective month of the layoff. I adopted a separation period of 60 days, which is stricter than 90 days, to make the results more conservative. Therefore, the effect can be larger in practice.

Take an example of the notice in Appendix A1. The treated inventors are those who were working in this firm on April 23, 2023, in California, and their profiles on LinkedIn show that they left the firm sometime between April 23, 2023, and June 23, 2023. 2,071 laid-off inventors can be identified after matching LinkedIn, USPTO, and layoff periods from the year 2000 to 2015 (both included). With matched inventors, there are three peak periods when most layoff events occurred: the first was around 2009, the second was from 2014 to 2015, and the third happened around 2002. These trends are consistent with the trend of mass layoffs including all occupations (see Figure 1.3). Among mass layoffs involving inventors, around one-third of laid-off inventors left their sourcing firms in 2015 and 2014, and almost 200 inventors were laid off in 2009 and 2006 (see Figure 1.4). These two periods consist of about half of the laid-off inventors. In terms of distribution across the US, California has the most laid-off inventors accounting for about half of the laid-off inventors.

I traced the counts of applied patents five years before and after the event to compare their performance, so I dropped those inventors who have worked for the sourcing firm for no longer than five years, thus leaving a sample of 1,671 inventors in 67 US public ICT firms.

1.4.2 Methodology

To examine the effect of an involuntary move on pre- and post-productivity, I labeled laid-off inventors as treated inventors and matched a control group of inventors to isolate the impact of a specific treatment or intervention, such as displacement in this paper. The potential control units are inventors who do not satisfy the three conditions on firm, state, and month simultaneously (Bertheau et al., 2023; Schmieder et al., 2023). It means they may transit to another firm voluntarily (not during mass layoffs) or remain in the same firm from the ex-post observations. Moreover, the control units have also worked for at least one US public ICT industry for five years, but their working periods are not limited between 2000 and 2015.

I used propensity score matching to construct the control group that provides the appropriate counterfactual trend in performance for the laid-off inventors in the design.

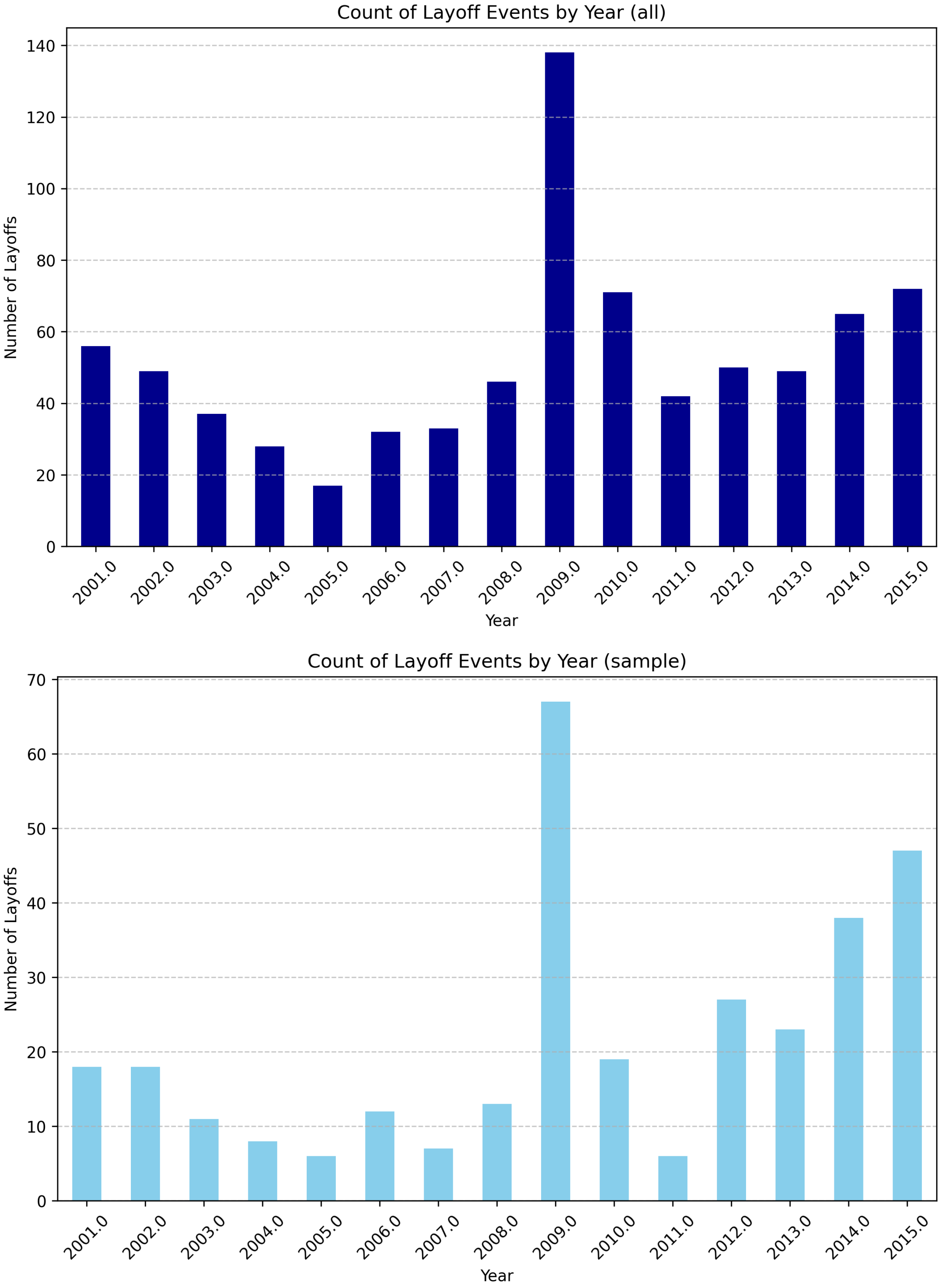

Figure 1.3: **Distribution of mass layoff events across years**

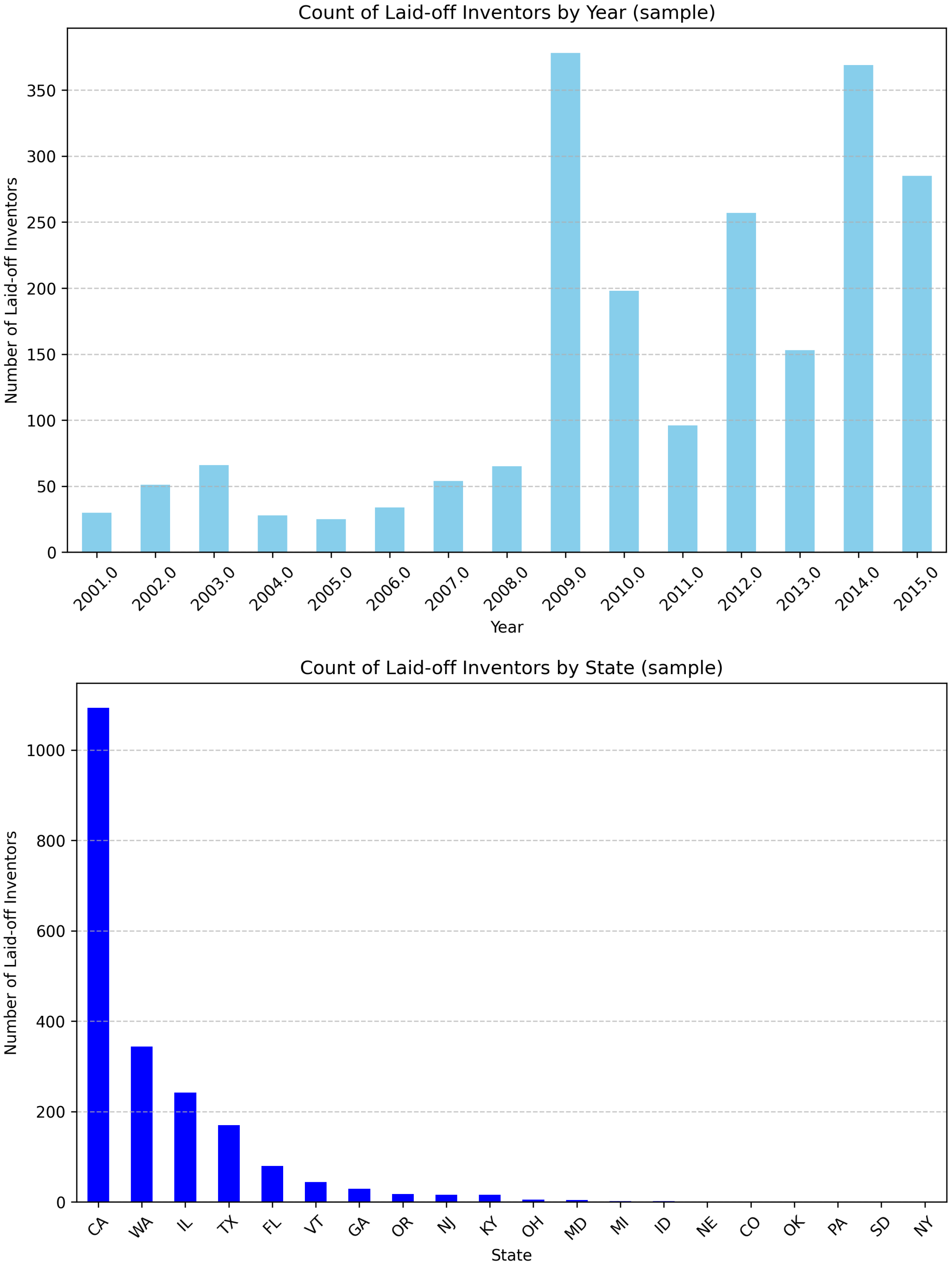

Figure 1.4: **Distribution of mass layoff events across years and states**

I estimate the propensity of being displaced using characteristics of inventors before the month m that an inventor was laid off, including the cumulative count of patents before m[7], the number of patents applied within five years before m, the number of patents applied two years and four years before m, respectively. I also match the technology scope deriving from the reverse of a Herfindahl-Hirschman Index (HHI) on the inventor's patenting dispersion in USPC classes in the five years before the focal month. In addition, I included the inventor's first year of patenting, as well as, job tenure (in months) in the sourcing firm, and whether they also served as a manager in that firm. Next, I proceeded by implementing a 1:1 nearest neighbor matching algorithm without replacement based on the inventor-month level, allocating one control inventor to each treated inventor.

Table 1.1 shows the characteristics of the treated group and the control group, and the PSM-NN matching algorithm yields the treated and control groups with balanced characteristics (A more detailed balance test on covariates by year can be found in Appendix Table A2). On average, inventors have applied for nine or ten patents until the focal month when the mass layoff occurred, which is month 78. In the recent five years before the focal month, they have applied for three or four patents, which is about $\frac{1}{3}$ of the accumulative number of applied patents. In the years two and four before the event, the average number of applied patents is around 0.7 and 0.8. Based on patenting classes, the dispersion of technologies is about 1.5. Inventors first patented between the years 1999 and 2000. Furthermore, inventors have spent around 11 years for the sourcing firm before the event, and about 36% inventors are also serving as managers.

Empirical Strategy

I study changes in employee productivity after a layoff event by conducting several event studies around the month of being laid off. Specifically, I use a difference-in-differences (DiD) research design in which I estimate changes in the number of patents applied by

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[7] I used January 2005 as the starting month, in other words, m=1 in January 2005

Covariates	Treat(Mean)	Control(Mean)	T-Statistic	P-Value
time (m)	78.20	78.21	-0.01	0.99
cumulative #pat	9.16	9.8	-0.79	0.43
#pat in past 5 years	3.49	3.78	-0.69	0.49
#pat in year -2	0.68	0.74	-0.64	0.52
#pat in year -4	0.71	0.79	-0.76	0.45
technology scope	1.52	1.49	0.44	0.66
first file year	1999.77	1999.56	0.81	0.42
tenure	167.02	167.17	-0.05	0.96
manager	0.36	0.37	-0.40	0.69

Notes: The p-values shown in the last column are from t-tests of mean values between groups.

Table 1.1: Balance tests of the matched sample

inventors in the 5 years before and after the layoff event, which is in comparison to a control group of inventors over the 11 years. The DiD specification is as follows:

$$Y_{it} = \beta_0 + \beta_1 D_t + \beta_2 T_i + \beta_3 (D_t \times T_i) + \beta_4 X + \epsilon_{it} \tag{1.1}$$

where Y_{it} is the outcome variable for unit i in period t. It indicates the number of patents applied by inventor i in year t, which is relative to the focal year of the layoff ($t = 0$). D_t is a dummy variable representing the post-treatment period ($D = 1$ if $t > 0$, 0 otherwise). T_i is a dummy variable indicating treatment status, which equals one for inventors in the treatment group and zero for the control. β_1 captures the post-treatment period effect over time for the control group, reflecting the time trend for inventors who were not laid off. β_2 captures the baseline group differences between the treatment and control groups, reflecting the difference in average patenting productivity between the treatment and control groups in the pre-treatment period. β_3 represents the DiD estimate, which quantifies the post-treatment change in the treatment group relative to the control group controlling the time trend and baseline differences, and is the focus of the study. X_{it} is a vector including other control variables that may also influence the patenting activities.

A further analysis of the moderating effects is specified with the Triple Differences estimation as follows:

$$\begin{aligned} Y_{it} = \beta_0 + \beta_1 D_t + \beta_2 T_i + \beta_3 M_i + \beta_4 (D_t \times T_i) + \beta_5 (D_t \times M_{it}) \\ + \beta_6 (T_i \times M_{it}) + \beta_7 (D_t \times T_i \times M_{it}) + \beta_8 X + \epsilon_{it} \end{aligned} \tag{1.2}$$

where M_{it} is the moderator for unit i in period t. I introduce three variables to examine the two moderating effects. *Maintain_coinventors* is a dummy variable to describe whether the focal inventor co-invents with their previous co-inventors after their mobility. It equals one when the collaboration continues in the post-treatment period, zero otherwise The previous co-inventors are those who have patented with the focal inventors in the five years before the event. Therefore, the variable always takes the value of one in the pre-treatment period for both treatment and control groups. Moreover, I include two variables to proxy the complementary assets of firms. One is *Public_firm*, a dummy variable that takes one when the inventor transits to a listed firm and zero when moving to a private firm. The other is *Firm_patented_before*, which is also a dummy variable to depict whether the firm has a patenting record or not before the event. It is one when the firm has patented before and zero when it has no patents before the event. While I do not have access to details of the non-human complementary asset each firm has, public firms and firms that have patents should be richer in resources (e.g. knowledge stock and equipment), thus proxying a larger amount of asset. With the definition, all sourcing firms in the sample are listed and patented. Firms that are public and have patents imply that they own more resources in finance, innovation, management, and so on. Therefore, they have a higher capacity, with which inventors are capable of innovating.

1.5 Results

1.5.1 Main Results

The change in the number of applied patents by inventors in the sample by year is visualized in Figure 1.5. Before the layoff, the average patenting productivities were highly similar in both groups ($F(1, 3300) = 0.04, Prob > F = 0.8515$) with an average yearly number of 0.7 or 0.8. However, performance in the treatment group drops to an average yearly number of 0.5 while performance in the control group is relatively stable at 0.7. It mitigates the concern that difference is potentially caused by the different abilities of inventors. In other words, laid-off inventors are not less capable than other inventors. Treated inventors produced less than those in the control group after experiencing mass layoffs, which means that it is the involuntary mobility that causes the productivity difference.

Event study Figure 1.6 shows the dynamic effect of involuntary mobility estimated using an event study specification. The coefficient estimates in the pre-reform period (when periods are negative) are essentially small in magnitude, implying that the assumption of the parallel trends is plausibly satisfied. In the post-reform period (when periods are positive), there is an immediate and persistent negative effect for at least four years, suggesting that involuntary mobility has decreased the inventor's performance, which confirms the prediction from the conceptual framework. In Appendix Figure A2, I restricted the sample to only treated inventors, and the trends hold.

Moderators Figure 1.7 presents the total number of applied patents under different conditions with the 95% confidence interval. Given that the values of all moderates are one in the pre-treatment period, Figure 1.7 only includes the post-treatment period. Maintaining previous co-inventors surges the number of applied patents in both groups as expected. However, moving to a public firm or a firm with patents before the mobility

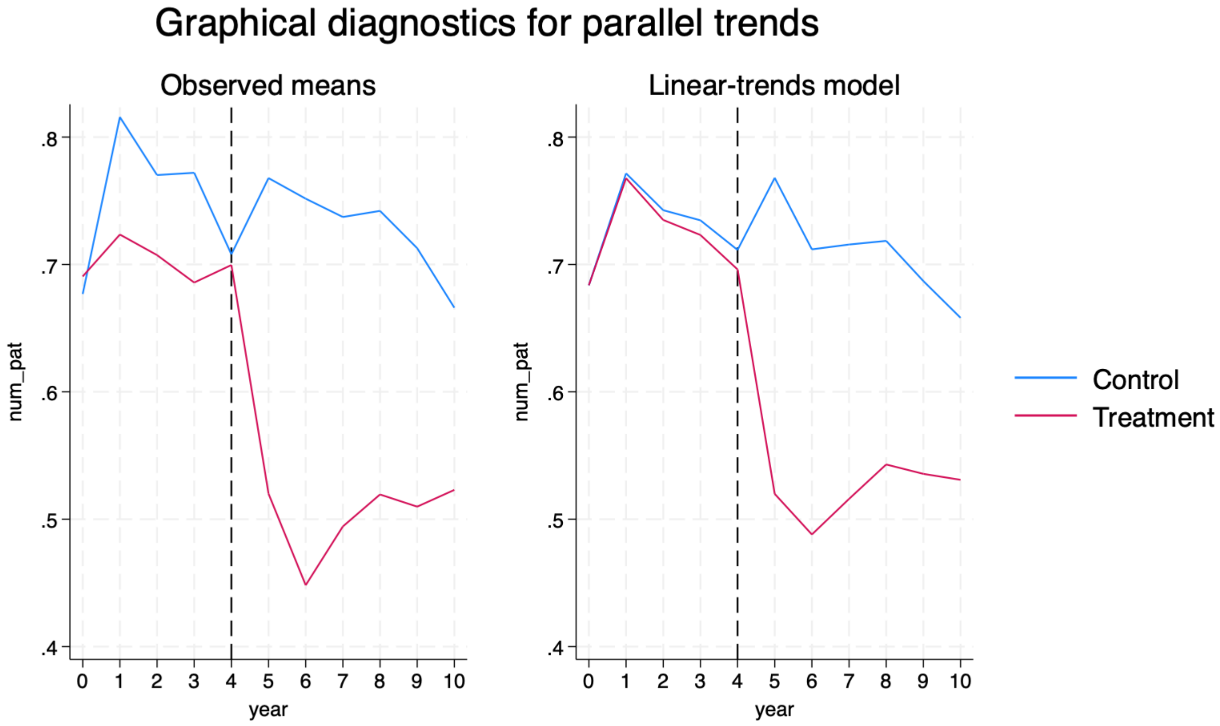

Figure 1.5: Graphical Diagnostics for Parallel Trends

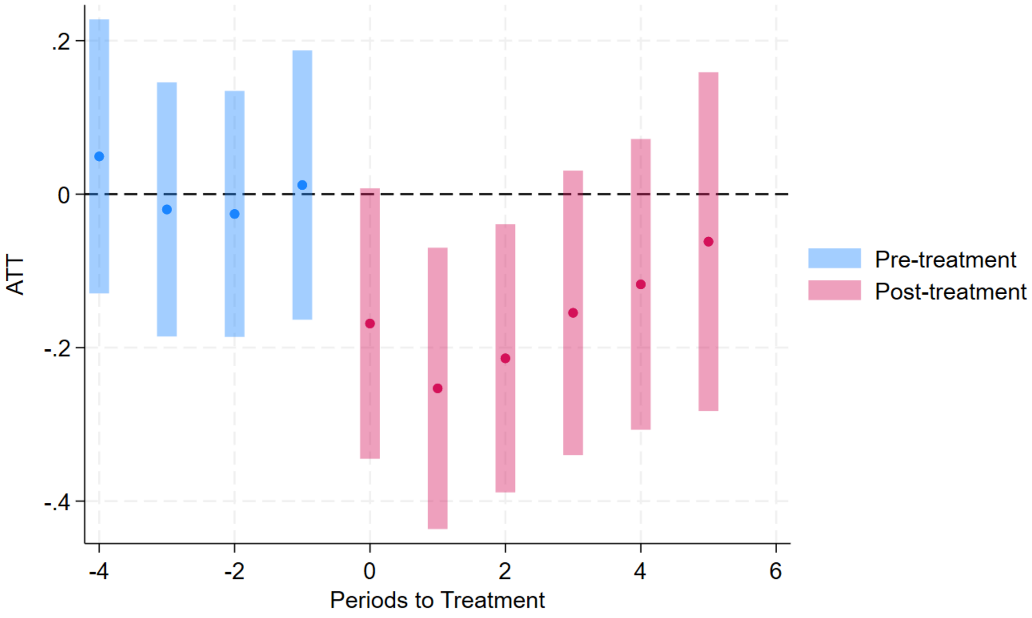

Figure 1.6: Dynamic Effect on #Patents Applied by Inventors (all in the sample)

seems not to make an impact on the number of patents applied by inventors.

Average effect Table 1.2 summarizes the dynamic treatment effect above into an average treatment effect. Column (1) reports the results using equation 1.1, controlling for only inventor and year fixed effects. The point estimate on *Treat* × *Post* is negative and statistically significant ($coef. = -0.177, s.e. = 0.054$), implying that relative to the control group, involuntary move makes laid-off inventors applied for 0.18 fewer patents. The average number of patents filed by an inventor was slightly lower than 0.7 five years ($t = -5$) prior to the event, so being laid-off means losing 26% productivity. Even in the year that inventors are most productive ($t = -4$ in the control group), 0.18 patents still indicate a loss of about 22 percent. Column (2) includes firm fixed effect controlling for the invariant variables over years within a firm. The coefficient of Treat × Post remains negative and significant ($coef. = -0.190, s.e. = 0.039$).

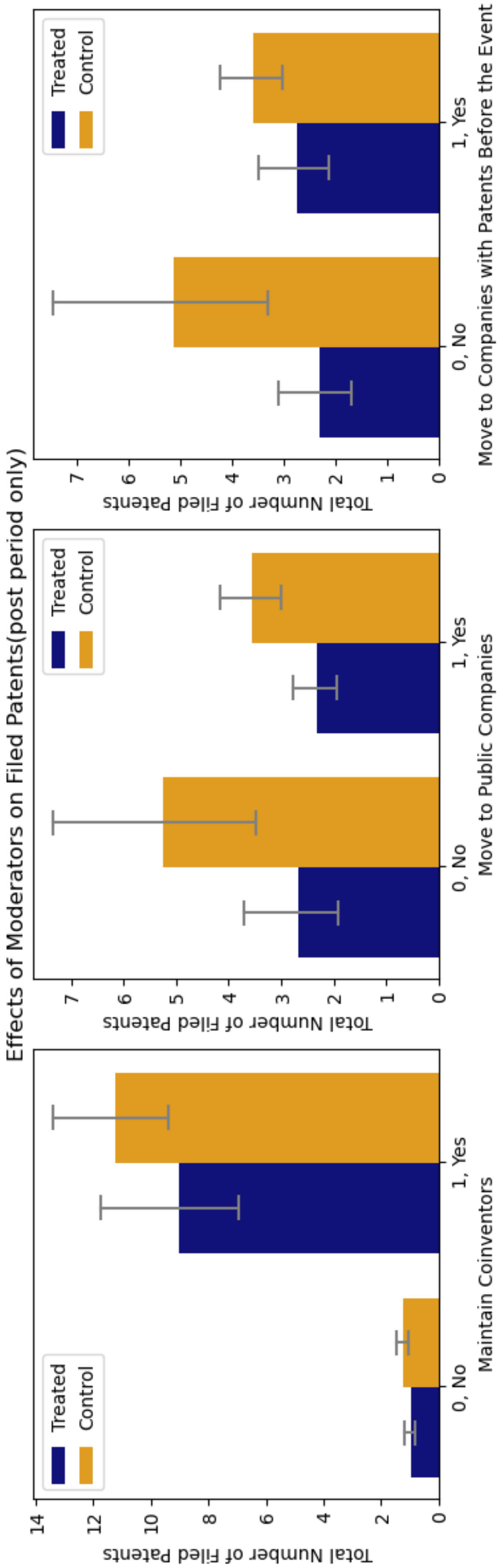

Figure 1.7: Effects of Moderators on Filed Patents (post-treatment period only)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Number of applied patents							
Treat × Post	-0.177***	-0.190***	-0.276***	-0.350***	-0.132	-0.120**	-0.132	-0.279
	(0.0542)	(0.0391)	(0.0496)	(0.0422)	(0.0913)	(0.0584)	(0.0842)	(0.188)
Treat × Post			1.059***	1.269***				
× Maintain_Coinventors			(0.178)	(0.178)				
Treat × Post × Public_Firm					-0.0174	-0.0604		
					(0.0921)	(0.0655)		
Treat × Public_Firm					0.0920**	1.308		
					(0.0446)	(0.818)		
Treat × Post							-0.00304	0.0907
× Firm_Patented_Before							(0.0964)	(0.191)
Treat × Firm_Patented_Before							0.112	-0.00390
							(0.0758)	(0.194)
Inventor FE	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y	N	Y
Observations	36,761	36,761	36,761	36,761	36,761	36,761	36,761	36,761
R-squared	0.579	0.663	0.582	0.667	0.579	0.663	0.579	0.663

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.2: Effect on # Patents

From column (3) to column (8) are results from equation 1.2. The point estimate on *Treat × Post × Maintain_Coinventors* in column (3) shows that keeping collaborations with previous co-inventors positively moderates the negative effect caused by involuntary mobility ($coef. = 1.059, s.e. = 0.178$). With the firm fixed effect included in column (4), the coefficient increases to 1.269 and is still significant. Both columns confirm the hypothesis that maintaining collaborators in the source firm will positively moderate the negative effect of involuntary mobility on post-mobility performance. Columns (5) and (6) use whether being public as an indicator of the firm's capacity. The coefficients of Treat × Post × Public_firm are not significant no matter firm fixed effect is included or not ($coef. = -0.017, s.e. = 0.092$ and $coef. = -0.060, s.e. = 0.066$, respectively). Therefore, moving to a public firm does not moderate the negative effect caused by involuntary mobility. In columns (7) and (8), I use whether patenting before as a proxy of the firm's capacity and the results are similar to those in columns (5) and (6). The point estimates are not significant with coefficients of -0.003 ($s.e. = 0.096$) and -0.003 ($s.e. = 0.096$), meaning that moving to a firm with patenting records does not help improve inventing productivity. Both measurements do not support the hypothesis that Moving to a public firm or a firm with patenting records will positively moderate the negative effect of involuntary mobility on post-mobility performance.

1.5.2 Robustness

Potential Measurement Errors I have proxied treated inventors who have experienced mass layoffs by comparing the month of leaving the source firm and the layoff month indicated by the notice. It is supposed to be more accurate than comparing at the year level in literature (Bertheau et al., 2023) but it does not mean that this is a perfect measurement. To further mitigate the measurement concern about being laid off, I eliminated inventors whose patents continued to be assigned to their source firms two years after their mobility. Research has shown that the average granting period for a patent is about

18 months (Squicciarini et al., 2013). Therefore, if an inventor's patents are still assigned to their previous employers three, four, or even five years after the mobility, I assume they leave voluntarily instead of involuntarily.

This restriction excluded 175 inventors in the treatment group and left $2,992$ inventor-month units in the sample. I did the same analysis as with the full sample, and the results are shown in the Appendix. Figure A3 and A4 exhibit the graphical diagnostics for parallel trends and the dynamic effect of mass layoffs with the event study specification. The results of the parallel-trends test suggest that the pretreatment period satisfies the parallel-trends assumption ($F(1, 2957) = 0.90, Prob > F = 0.3438$). In addition, Table A3 provides similar effects of involuntary on invention productivity. The average number of applied patents is about 0.18 ($coef. = -0.179, s.e. = 0.0513$), which is less for inventors who have experienced mass layoffs. Maintaining collaboration with previous co-inventors significantly mitigates the productivity decrease while moving to a destination firm that has patented and is public before does not significantly change the relationship.

Non-mobility Inventors Only The control group includes two types of inventors. One type is inventors that have never moved after the event month, and the other type is inventors that have moved in or after the event month. Given that mobility afterward may influence the post-mobility invention productivity in the control group, thus making the estimation of the main effect less accurate, I excluded the second type of inventors. Moreover, excluding mobile inventors in the control group can help disentangle the effect of departing the source firm and being forced to move.

Therefore, I dropped mobile inventors in the control group and their corresponding inventors in the treatment group, which left $2,736$ inventors in the sample. The same analysis has been applied to the sample, and the results are shown in the Appendix. Figure A5 and A6 exhibit the graphical diagnostics for parallel trends (it satisfies the parallel-trends assumption with $F(1, 2697) = 1.46, Prob > F = 0.2263$) and the dynamic effect of mass layoffs with the event study specification. Table A4 shows regression results, which are consistent with the main analysis. On average, the number of applied patents in the treatment group is significantly fewer than that in the control group ($coef. = -0.227, s.e. = 0.0543$). While collaborating with previous co-inventors significantly increases the number, moving to firms with more assets does not significantly influence the result.

1.6 Discussion

"Portability paradox" describes research in strategic human capital literature that when employees move across firms, the extent to which they can transfer their previous performance in the source firm to the destination firm. While literature implies that employees move voluntarily for better job opportunities and to fulfill their preferences, involuntary mobility is prevalent but understudied. The post-mobility performance of employees who have to move involuntarily may be worse than those who move voluntarily or never move because they may not end up in the best employee-firm fit, where such employees cannot maximize the core and complementary assets.

To empirically support the theoretical prediction, the paper examines the productivity change of employees after an involuntary move. By identifying inventors who were laid off in the US public ICT firm between the year 2000 and the year 2015, I built an inventor-patent-year sample with matched data from LinkedIn, USPTO, Compustat, and mass layoff notices in the US. After matching laid-off inventors with a group of control inventors using the PSM-NN procedure and DiD econometrics strategy, I found moving involuntarily decreases the productivity of inventors (Hypothesis 3.1). Further analysis with the triple-differences method shows that While carrying social capital accumulated in the previous firm can mitigate the negative effect (Hypothesis 3.2), moving to a public firm or firm with a patenting record does not help (Hypothesis 3.3).

This paper makes three key contributions to strategic management research. First, it advances understanding of human capital dynamics by examining the portability of performance across firms, particularly under involuntary mobility. It highlights how firm-specific and complementary assets are difficult to transfer, and how sudden transitions reduce the quality of employee-firm matching, emphasizing the critical role of social capital and fit. Second, it investigates the consequences of mass layoffs, drawing on extensive census data. The findings reveal persistent negative impacts on wages and consumption and a notable decline in innovation outputs, as evidenced by reduced patenting activity. These insights underscore the broader organizational and individual costs of mass displacement. Third, the paper responds to calls for a deeper exploration of involuntary mobility, addressing a gap in the literature that often centers on voluntary transitions. By analyzing the dynamics of layoffs and subsequent job transitions, it provides a nuanced perspective on the interplay between mobility, human capital, and organizational outcomes.

The findings shed light on practice as well. First, it confirms the necessity of making notice to employees before they are forced to leave their job positions. Mobile employees should utilize the period to seek a new job with a high-quality match, thus avoiding more performance loss. From the perspective of the receiving firm, it is vital to provide complementary resources for the employees. For employees, it is beneficial to maintain their social capital, which will mitigate the potential productivity loss in the new firm.

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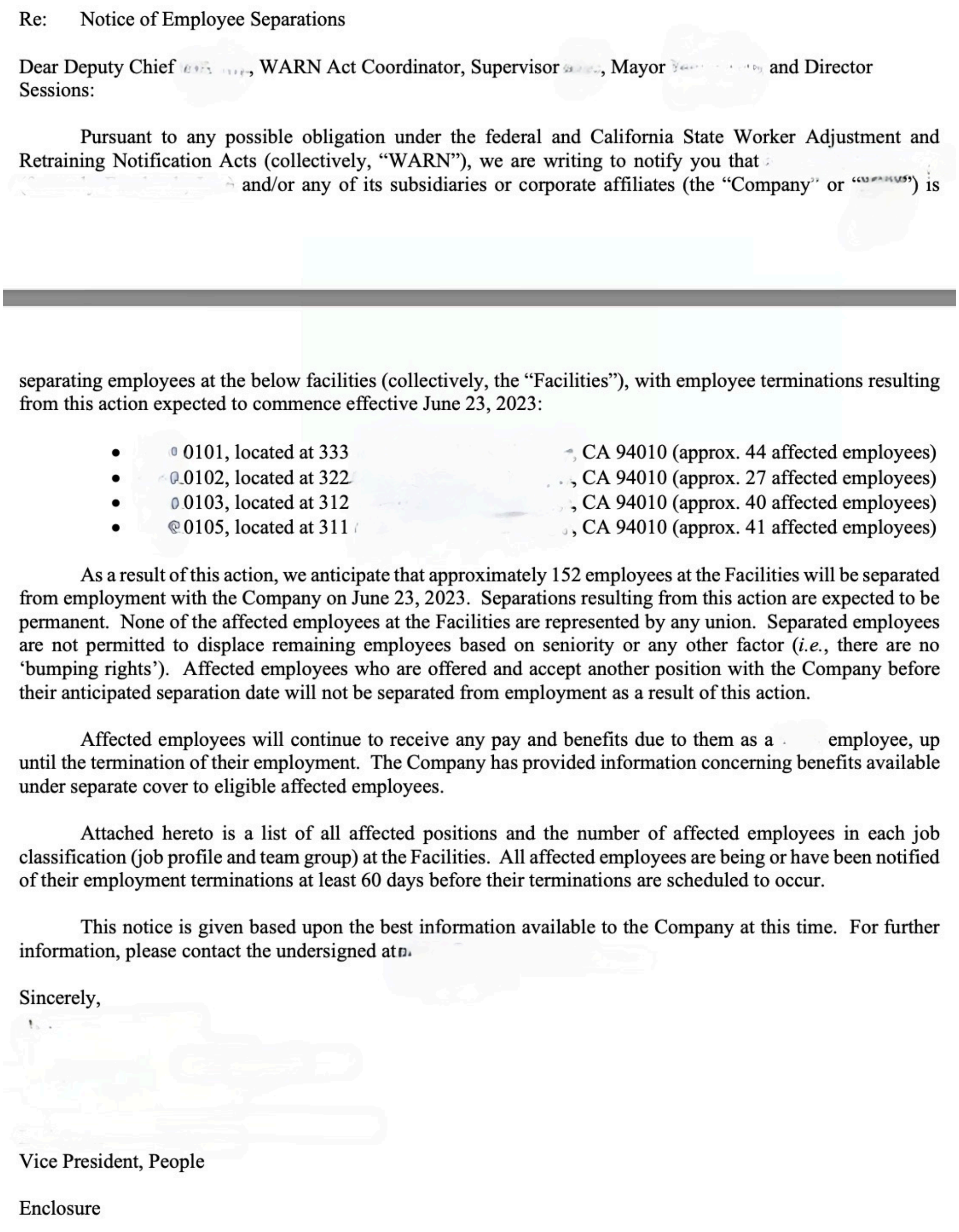
Appendices



Re: Notice of Employee Separations

Dear Deputy Chief [redacted], WARN Act Coordinator, Supervisor [redacted], Mayor [redacted] and Director Sessions:

Pursuant to any possible obligation under the federal and California State Worker Adjustment and Retraining Notification Acts (collectively, "WARN"), we are writing to notify you that [redacted] and/or any of its subsidiaries or corporate affiliates (the "Company" or "[redacted]") is

separating employees at the below facilities (collectively, the "Facilities"), with employee terminations resulting from this action expected to commence effective June 23, 2023:

- [redacted] 0101, located at 333 [redacted], CA 94010 (approx. 44 affected employees)
- [redacted] 0102, located at 322 [redacted], CA 94010 (approx. 27 affected employees)
- [redacted] 0103, located at 312 [redacted], CA 94010 (approx. 40 affected employees)
- [redacted] 0105, located at 311 [redacted], CA 94010 (approx. 41 affected employees)

As a result of this action, we anticipate that approximately 152 employees at the Facilities will be separated from employment with the Company on June 23, 2023. Separations resulting from this action are expected to be permanent. None of the affected employees at the Facilities are represented by any union. Separated employees are not permitted to displace remaining employees based on seniority or any other factor (*i.e.*, there are no 'bumping rights'). Affected employees who are offered and accept another position with the Company before their anticipated separation date will not be separated from employment as a result of this action.

Affected employees will continue to receive any pay and benefits due to them as a [redacted] employee, up until the termination of their employment. The Company has provided information concerning benefits available under separate cover to eligible affected employees.

Attached hereto is a list of all affected positions and the number of affected employees in each job classification (job profile and team group) at the Facilities. All affected employees are being or have been notified of their employment terminations at least 60 days before their terminations are scheduled to occur.

This notice is given based upon the best information available to the Company at this time. For further information, please contact the undersigned at [redacted].

Sincerely,

[redacted]

Vice President, People

Enclosure

Figure A1: An Example of the Notice

SIC Code	Description
3570	Computer and Office Equipment
3571	Electronic Computers
3572	Computer Storage Devices
3576	Computer Communications Equipment
3577	Computer Peripheral Equipment, Not Elsewhere Classified (NEC)
3578	Calculating and Accounting Machines, Except Computers
3661	Telephone and Telegraph Apparatus
3663	Radio, TV Broadcast, and Communication Equipment
3669	Communications Equipment, Not Elsewhere Classified (NEC)
3674	Semiconductors and Related Devices
3678	Electronic Connectors
3679	Electronic Components, Not Elsewhere Classified (NEC)
3812	Search, Detection, Navigation, and Guidance Systems, and Aerospace Systems
3825	Electrical Measurement and Testing Instruments
3826	Laboratory Analytical Instruments
4210	Trucking and Courier Services, Except Air
4813	Telephone Communications, Except Radiotelephone
4841	Cable and Other Pay TV Services
5961	Catalog and Mail-Order Houses
7370	Computer Programming and Data Processing
7372	Prepackaged Software
7373	Computer Integrated Systems Design
7374	Computer Processing and Data Preparation Services

Table A1: SIC codes used to define the US ICT industry

Years before	Covariates	Treat(Mean)	Control(Mean)	T-Statistic	P-Value
5	time (m)	78.20	78.21	-0.01	0.99
5	tenure	107.02	107.17	-0.05	0.96
5	cumulative #pat	5.53	6.35	-1.39	0.16
5	#pat in past 5 years	2.86	3.13	-0.73	0.46
5	#pat in year -2	0.53	0.58	-0.76	0.45
5	#pat in year -4	0.47	0.50	-0.57	0.57
5	manager	0.34	0.32	1.53	0.13
5	technology scope	1.65	1.58	0.98	0.33
5	first file year	1999.74	1999.29	1.61	0.11
4	time (m)	78.20	78.21	-0.01	0.99
4	tenure	119.02	119.17	-0.05	0.96
4	cumulative #pat	6.27	6.97	-1.07	0.28
4	#pat in past 5 years	3.05	3.28	-0.58	0.56
4	#pat in year -2	0.65	0.59	0.88	0.38
4	#pat in year -4	0.51	0.53	-0.34	0.73
4	manager	0.35	0.32	1.40	0.16
4	technology scope	1.71	1.64	1.05	0.30
4	first file year	1999.74	1999.38	1.30	0.19
3	time (m)	78.20	78.21	-0.01	0.99
3	tenure	131.02	131.17	-0.05	0.96
3	cumulative #pat	7.03	7.71	-0.94	0.35
3	#pat in past 5 years	3.23	3.51	-0.66	0.51
3	#pat in year -2	0.68	0.62	0.95	0.34
3	#pat in year -4	0.53	0.56	-0.37	0.71
3	manager	0.35	0.33	1.29	0.20
3	technology scope	1.76	1.67	1.27	0.20
3	first file year	1999.74	1999.49	0.89	0.37
2	time (m)	78.20	78.21	-0.01	0.99
2	tenure	143.02	143.17	-0.05	0.96
2	cumulative #pat	7.72	8.44	-0.90	0.37
2	#pat in past 5 years	3.39	3.63	-0.56	0.58
2	#pat in year -2	0.70	0.74	-0.54	0.59
2	#pat in year -4	0.65	0.57	1.07	0.29
2	manager	0.36	0.35	0.60	0.55
2	technology scope	1.73	1.66	1.08	0.28
2	first file year	1999.72	1999.48	0.89	0.37
1	time (m)	78.20	78.21	-0.01	0.99
1	tenure	155.02	155.17	-0.05	0.96
1	cumulative #pat	8.43	9.16	-0.87	0.38
1	#pat in past 5 years	3.49	3.72	-0.54	0.59
1	#pat in year -2	0.70	0.69	0.16	0.88
1	#pat in year -4	0.67	0.61	1.00	0.32
1	manager	0.36	0.36	0.20	0.84
1	technology scope	1.67	1.60	1.11	0.27
1	first file year	1999.76	1999.58	0.64	0.52

Table A2: Balance tests of the matched by year

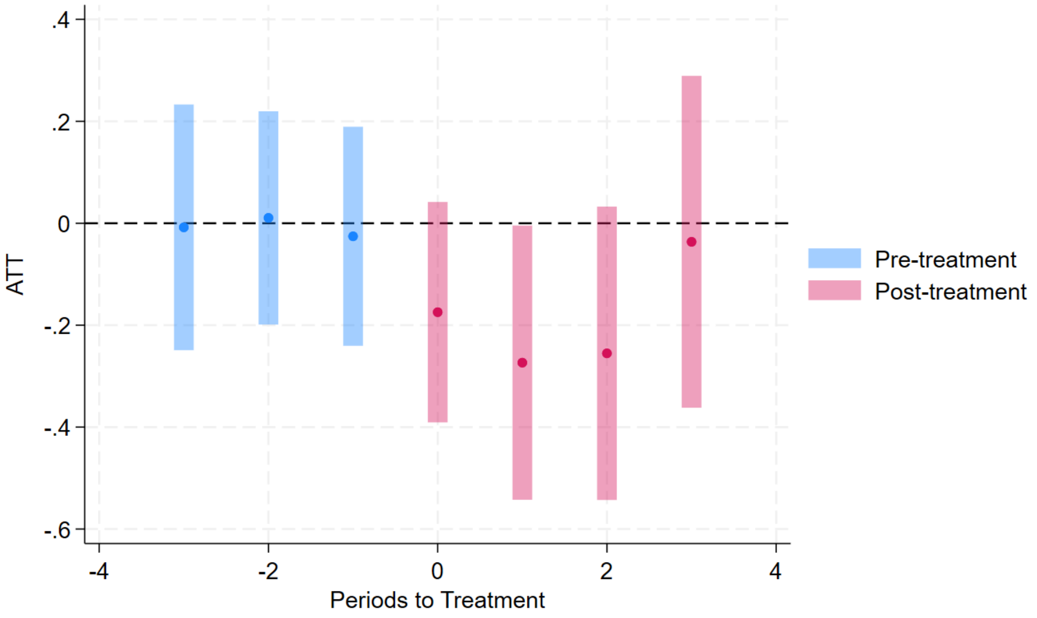


Figure A2: Dynamic Effect on #Patents Applied by Inventors
(only treated inventors in the sample)

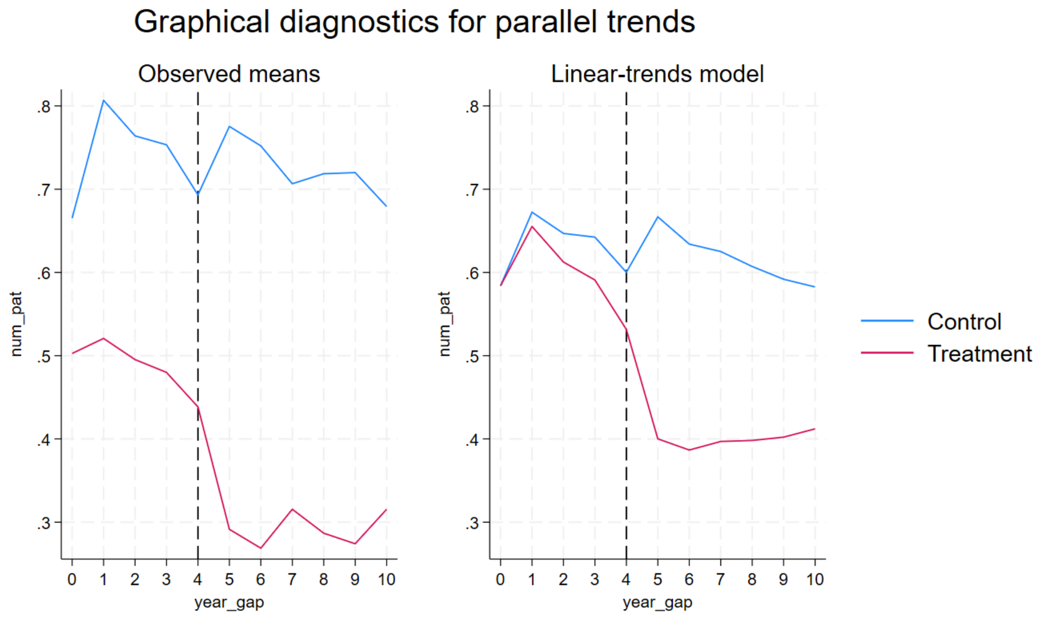


Figure A3: Graphical Diagnostics for Parallel Trends
(after eliminating the potentially misidentified laid-off inventors)

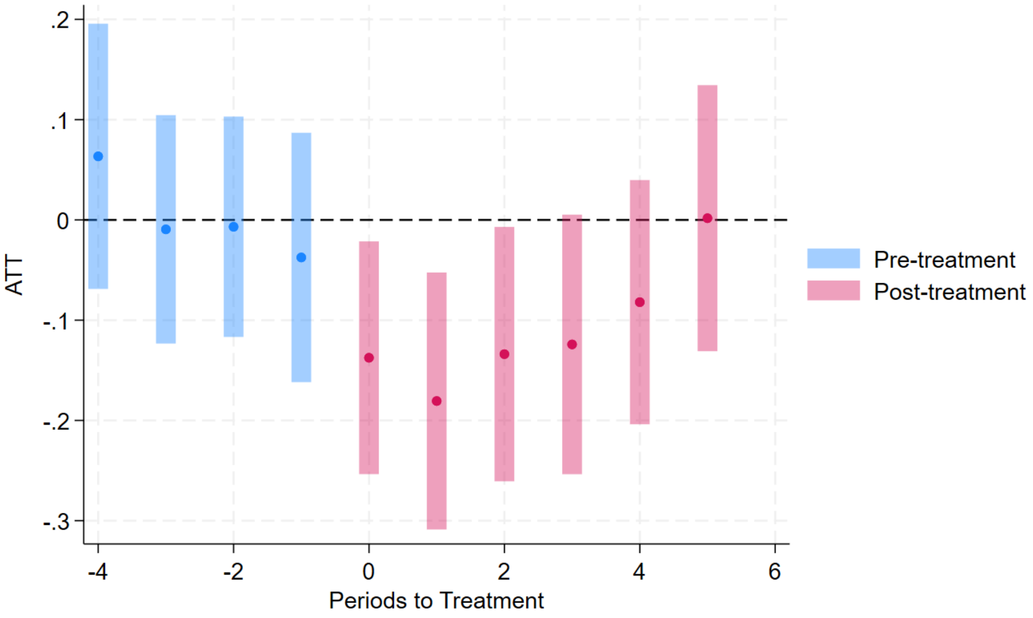


Figure A4: Dynamic Effect on #Patents Applied by Inventors
(after eliminating the potentially misidentified laid-off inventors)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Number of applied patents							
Treat × Post	-0.179***	-0.221**	-0.237***	-0.270***	-0.135**	-0.334	-0.105	-0.415
	(0.0513)	(0.0952)	(0.0512)	(0.0976)	(0.0615)	(0.613)	(0.0790)	(0.285)
Treat × Post			1.078***	1.400***				
× Maintain_Coinventors			(0.146)	(0.155)				
Treat × Post × Public_Firm					0.00644	0.119		
					(0.0786)	(0.619)		
Treat × Public_Firm					0.0736			
					(0.0477)			
Treat × Post							-0.0403	0.185
× Firm_Patented_Before							(0.0871)	(0.286)
Treat × Firm_Patented_Before							0.0916	-0.270**
							(0.0728)	(0.115)
Inventor FE	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y	N	Y
Observations	32,911	30,849	32,911	30,849	32,911	30,849	32,911	30,849
R-squared	0.557	0.669	0.560	0.671	0.558	0.669	0.557	0.669

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3: The Effect on #Patents
(after eliminating the potentially misidentified laid-off inventors)

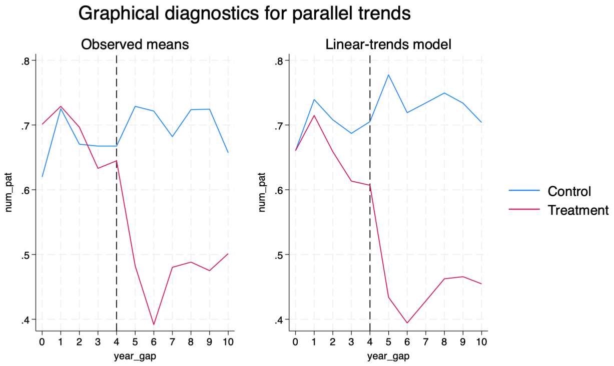


Figure A5: Graphical Diagnostics for Parallel Trends
(after eliminating mobile inventors in the control group)

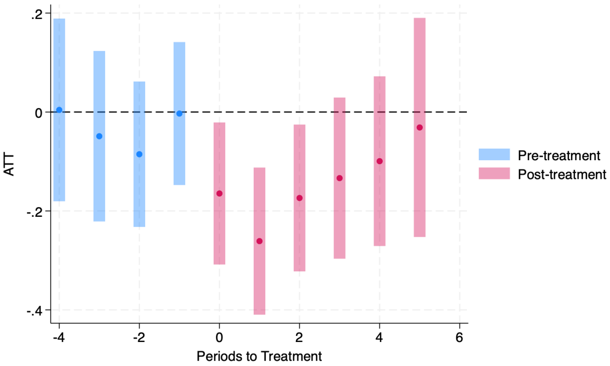


Figure A6: Dynamic Effect on #Patents Applied by Inventors
(after eliminating mobile inventors in the control group)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Number of applied patents							
Post × Treat	-0.227***	-0.224***	-0.324***	-0.386***	-0.185*	-0.148	-0.199**	-0.187
	(0.0543)	(0.0397)	(0.0476)	(0.0461)	(0.0955)	(0.106)	(0.0913)	(0.237)
Post × Treat × Maintain_Coinventors			1.044***	1.267***				
			(0.208)	(0.209)				
Post × Treat × Public_Firm					-0.0269	-0.0756		
					(0.103)	(0.110)		
Treat × Public_Firm					0.0669			
					(0.0451)			
Post × Treat × Firm_Patented_Before							0.0150	-0.0360
							(0.111)	(0.236)
Treat × Firm_Patented_Before							0.0967	-0.290
							(0.0821)	(0.222)
Inventor FE	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y	N	Y
Observations	30,094	30,094	30,094	30,094	30,094	30,094	30,094	30,094
R-squared	0.495	0.570	0.498	0.574	0.495	0.570	0.495	0.570

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A4: The Effect on #Patents
(after eliminating mobile inventors in the control group)

Chapter 2

Uncommon Combinations of Skills and Extreme Entrepreneurial Outcomes

2.1 Introduction

Organizations leverage strategic resources to improve their performance, with human capital being one of the most critical assets for achieving competitive advantage (Barney, 1991; Crook et al., 2008; Grant, 1996b). Human capital refers to the knowledge, ability, and skills that are embedded in individuals that cannot be separated from their owners (Coff and Kryscynski, 2011; Huselid et al., 1997; Lundvall and Johnson, 1994). In the context of startups—firms in the early stages of their development—human capital embedded in founders is particularly vital, as entrepreneurs often lack access to other key strategic resources.

A robust body of research underscores the significance of skill diversity, heterogeneity, complementarity, and combination in enhancing problem-solving and team performance (Anderson, 2017; Kaplan and Vakili, 2015; Lazear, 2004; Pan, 2017). Such studies suggest that the value of skills in a startup is not solely decided by individual capabilities, but also by how these skills interact with one another. Some skills are complementary or synergistic, amplifying each other's effectiveness and yielding a combination that is more valuable than the sum of their separate contributions. On the other hand, certain skill pairings offer no added value when combined, relative to their standalone utility (Anderson, 2017; Dibiaggio et al., 2014; Dimitriadis and Koning, 2022; Stephany and Teutloff, 2024). Therefore, it is not merely the possession of knowledge and skills that creates competitive advantages for startups, but rather effective combinations and integrations of resources in unique and value-creating ways. The uncommon skills combinations, whose appearance is much lower than the expected appearance of the two skills, enable firms to build and sustain a long-term competitive advantage (Barney, 1991; Grant, 1996a).

The uncommonness focuses on how rare and unexpected different skills are combined, which extends research on skill diversity, heterogeneity, and complementarity by capturing the rarity of skill combinations among the startup population. Skill diversity and heterogeneity stress the breadth and variance across skills within a startup team, but not their unexpected combinations. While some unique skills lead to high diversity and heterogeneity, the expected co-occurrence of such skills may also be low, which makes the combinations not uncommon. Moreover, highly complementary skills frequently co-occur, and their uncommonness depends on whether these skills are expected to work collectively or not. Therefore, the research on uncommon knowledge combinations extends the current understanding of the team composition and its impact on firm performance.

While uncommonness may help form competitive advantages, there are also dark sides to uncommon skill combinations, especially when skills are from different entrepreneurs in the founder team. Different skills imprint different apprehensions and perceptions on founders, so the cognitive discrepancy among founders in the startup becomes large citepkaplan2008thinking. It may yield a heavier cost of communication and knowledge exchange in the startup (Edwards, 2011). Moreover, uncommon knowledge combinations may help startups generate unique products or services, which do not necessarily have to be accepted by customers, for such products or services are not always consistent with their cognition or expectation. Overall, uncommonness may also imply uncertainty and harm the performance of startups.

For instance, Patrick Collison and John Collison founded their startup, Stripe, a payment processing platform for the Internet, and it has grown to a unicorn in 2023. In the LinkedIn profiles of the brothers Collison, we noticed that Patrick Collison is an expert in programming languages, while John Collison reported such business-related skills as strategy and product management. Even though programming and management skills are common skills, the combination of programming and management skills is extremely rare Anderson (2017). The uncommonness of such skill combinations may be the reason for the boost in Stripe's high valuation. However, another fintech startup, Bench Accounting, whose founders also reported similar skills (e.g., programming languages and product management), posted a notice of closure on its website in December 2024 stating that the platform would be inaccessible.

Therefore, this paper investigates the effect of uncommon skill combinations on entrepreneurial outcomes, which can be successful and unsuccessful. To quantify the degree of uncommonness of skill combinations, we utilized data from LinkedIn, a professional networking platform. Following the methodology of Uzzi et al. (2013), we analyzed the extent to which each skill pair's occurrence in startup teams deviates from its expected frequency, and standardized the deviation into a score. Hence, each combination has a corresponding score to quantify its deviation, in other words, the uncommonness. We gathered startup data from CrunchBase, a widely recognized database that provides information on startups and venture capital transactions (Breschi et al., 2019; Gompers et al., 2020; Hellmann and Thiele, 2015). Then, we examined how uncommon skill pairs influence entrepreneurial outcomes, specifically focusing on successful exits (via IPO or acquisition) and failures (inability to sustain operations).

Our findings reveal that startups with highly uncommon skill combinations are more likely to experience extreme outcomes—either success or failure. Startups with such combinations tend to have a higher probability of securing VC investments, which enhances their chances of success. However, these skill combinations also increase the likelihood of entering diverse and novelly-combined markets, raising the risk of failure.

This research makes several theoretical contributions. First, it adds to the literature on resource-based view and knowledge-based view, and the relationship between strategic resources and organizational performance (Crook et al., 2008). Our findings suggest that entrepreneurs should focus not only on acquiring valuable resources but also on how these resources should be combined differently. This insight bridges the gap between studies on team diversity and the strategic balance of resources (Corrocher and Lenzi, 2022; D'Acunto et al., 2020; Deephouse, 1999; Østergaard et al., 2011).

The paper also contributes to the study of skills in organizations. The paper explicitly discusses the role of skills and their impact on performance, investments from venture capitalists, and market entry choices. It complements current research on skill diversity, specialization, and re-combination by comparing skill combinations within and across organizations. Empirically, the research extends beyond prior studies, which often use educational background or work experience as proxies for skills, or generalize knowledge to managerial knowledge and professional knowledge (Hartog and Oosterbeek, 2007; Hoenig and Henkel, 2015; Le, 1999). By using self-reported skills from entrepreneurs and clustering them into broader categories, we provide a more nuanced analysis of the impact of specific skill combinations. This approach maintains the integrity of skill characteristics while offering clear differentiation between them. As one of the first studies to investigate the effects of specific skill combinations on entrepreneurial performance, this paper opens new avenues for future research on human capital in startups.

2.2 Theoretical Background

By surveying 885 venture capitalists from 681 venture capital firms (VCs), Gompers et al. (2020) found that 95% of VCs consider the management team a critical factor in investment decisions, with 47% identifying it as the most important factor. For startups, the knowledge embedded within the management team can be one of the most powerful sources of sustainable differentiation and long-term competitive advantage (Gupta and Govindarajan, 2000).

Since knowledge in organizations works collectively and collaboratively, this paper investigates the effects of knowledge combinations in startup teams on entrepreneurial performance. The degree of commonness depends on the frequency at which such a combination has occurred previously and is standardized by the expected occurrence. An uncommon combination refers to a combination whose occurrence is lower than expected (Mukherjee et al., 2016; Uzzi et al., 2013).

The degree of uncommonness in knowledge combinations within a startup team is conceptually distinct from existing constructs such as knowledge diversity, heterogeneity, and complementarity for the following reasons. First, knowledge diversity emphasizes the breadth of knowledge types within a team (**??**), but this does not necessarily imply uncommon combinations. For example, one startup team might possess programming (P), user interface design (UID), and management (M) skills, while another has only P and M. Although the first team is more diverse in terms of knowledge breadth, both teams may exhibit a similar level of uncommonness if the core combinations (e.g., P and M) are observed at a similar level in startup contexts (**?**). Second, heterogeneity refers to the variance across knowledge domains (**??**), yet this, too, does not guarantee uncommonness. For instance, scripting languages and materials science are very heterogeneous, but their combination may not be considered uncommon if such domains are rarely expected to interact meaningfully within a startup. Third, complementarity captures the synergistic value of combining knowledge types—that is, when the joint value exceeds the sum of individual contributions (**??**). However, complementarity does not account for expectedness. For example, logo design (LD) and illustration work (IW) are highly complementary in fields like graphic or product design, but their frequent co-occurrence makes such a combination expected rather than uncommon. Therefore, this paper contributes to the literature on team knowledge by focusing on the uncommonness of knowledge combinations, which is defined not by breadth, variance, or synergy, but by the randomity and unexpectedness of certain knowledge pairings within a startup team.

The degree of uncommonness formed by knowledge combinations in a startup team is different from the existing knowledge diversity, heterogeneity, and complementarity for the following reasons. First, knowledge diversity in a startup team emphasizes the breadth of knowledge (Aggarwal and Woolley, 2019; Imhof and Kräkel, 2023), and it may not relate to the uncommonness of knowledge combinations. For example, a startup team has three diverse skills: programming (P), user interface design (UID), and management (M), while another startup has only P and M skills. The startups with three skills have more diverse knowledge than those with two, but the uncommonness level of both startups may be highly similar, which may be decided by the combination of P and M (Anderson, 2017). Second, heterogeneity stresses the variance within or across knowledge (Imhof and Kräkel, 2023; Kaplan and Vakili, 2015). There can be two types of knowledge, but combined with a random frequency. For instance, scripting languages and materials science are heterogeneous across knowledge types, but they may not be an uncommon combination for startups, as they are not expected to be working collectively. Third, complementarity describes the extent to which the joint value of two knowledge types is higher than the sum of individual values, and the more often the two knowledge types appear together, the higher value they have together (Pan, 2017; Sinha and Cusumano, 1991). However, this does not consider the expected co-occurrence of knowledge types. For example, logo design (LD) and illustration work (IW) are highly complementary skills, especially for jobs in graphic design, brand, or product design. Nevertheless, LD and IW are also highly expected in such jobs, thus being less uncommon. Therefore, this paper complements current research on knowledge in teams by focusing on the uncommonness of knowledge combinations.

A high degree of uncommonness in skill combinations presents a dual risk for startups. On one side, it can offer a competitive edge, enabling startups to differentiate themselves from competitors and reduce direct competition, leading to better performance and higher chances of a successful exit (Deephouse, 1999; Guzman and Li, 2023). On the other side, uncommon combinations also introduce greater uncertainty, as they are less familiar and less frequently used, increasing the likelihood of failure. We propose potential mechanisms that drive the extreme outcomes of startups with uncommon skill combinations. Uncommon skill combinations may be attractive for venture capitalists, who appreciate the possibility of disruptive products, markets, and industries brought by uncertainties (Pontikes, 2012). With the support of VCs, startups with uncommon combinations will receive more resources and constant monitoring, which is helpful for success. Moreover, uncommon combinations of knowledge may lead startups to enter diverse markets, whose combinations are also more uncommon. Similarly, uncommonness refers to markets that other organizations have not frequently entered simultaneously, which may imply limited demand from customers, thus causing the failure of startups.

2.2.1 Knowledge Combinations and Entrepreneurial Performance

The unique value of knowledge as a strategic resource is well-established in both scholarly and practical discourse and is often seen as a key source of sustainable competitive advantage. Studies on team diversity and the "Jack-of-all-Trades" (JoT) in organizations highlight the importance of varied skills and knowledge within founder teams. While these studies share similarities with research on uncommon combinations, they also differ. Team diversity (e.g., differences in gender, education, and knowledge) is associated with more innovation and faster growth (Corrocher and Lenzi, 2022; Østergaard et al., 2011; D'Acunto et al., 2020). Likewise, JoT entrepreneurs, who possess broad and balanced skill sets, are more likely to succeed in starting and growing their ventures (Lazear, 2004, 2005; Silva, 2007). However, having a wide range of skills does not necessarily translate into uncommon combinations of skills. In an extreme case where a startup team has two skills that no other entrepreneurs have, the combination is highly uncommon. Still, the diversity is low, relative to another team with five skills, and for each skill, half of the entrepreneurs in the world own it.

A high level of uncommonness in combining knowledge in the startup team implies that some particular knowledge endowed by the founding team may be unexpected. The expected knowledge can be a strategic resource for startups because it is exclusively embedded in the entrepreneurs. Therefore, it will be challenging for other startups whose entrepreneurs have not mastered such knowledge to appropriate or imitate. Moreover, unique knowledge may extend knowledge boundaries when searching for information. It allows startups to search beyond the organization or familiar knowledge domains to find a more creative solution. As the organization develops, unique knowledge helps build dynamic capacity that makes the organization adapt to changing environments. Hence, startups with high uncommonness in knowledge combinations have advantages in knowledge searching, creation, and accumulation.

Uncommon combinations of knowledge, in other words, infrequent combinations of knowledge, may stem from combining previously non-connected knowledge. Some knowledge exists across organizations, but not all entrepreneurs can connect their prior non-combined knowledge to create new knowledge and make innovations. In this process, extraordinary combinations may arise and form novel perspectives and exploratory innovations (March, 1991; Phene et al., 2006; Trajtenberg et al., 1997). Since Weitzman (1998)'s seminal paper models combination in the endogenous growth production function, the idea-based growth states re-combinations of existing knowledge as an important source for innovation and driver of economic growth (Strumsky and Lobo, 2015; Verhoeven et al., 2016). Entrepreneurs may apply such uncommon combinations of knowledge to create new technologies and products and eventually realize their advantages in the market competition. Overall, uncommon combinations of knowledge in organizations may come from the unique knowledge the organization owns and the re-combination of existing knowledge. In addition, such combinations can be a strategic resource for organizations to create and accumulate knowledge and form the capacity to retain their competitive advantages, thus succeeding in the market.

While uncommon knowledge combinations offer potential benefits, they also come with drawbacks. While implying unique knowledge, the difference in knowledge endowed in different entrepreneurs may yield a heavier cost of communication and knowledge exchange in the startup (Edwards, 2011). This may happen because different knowledge imprints different apprehensions and perceptions on founders, so the cognitive discrepancy among entrepreneurs in the team becomes larger (Kaplan and Tripsas, 2008). It takes time for founders to understand and communicate with each other, which may affect the problem-solving process.

Except for the communication barriers set by high uncommonness, knowledge difference influences familiarity with knowledge components among founders in the startup team (lo Storto, 2006). Since Fleming (2001) has analyzed how the invention's usefulness is influenced by the inventor's familiarity with components of inventions, we argue that the knowledge familiarity in the startup team influences the usefulness of products and services that the startup provides as well. Hence, knowledge combinations in startups may foster startups to produce unique products or services that are not consistent with the customer's cognition or expectations. Such products may mislead startups, making them fail to position themselves in the most appropriate markets. Under the circumstances, startups cannot survive in the market and will fail. Facing higher costs within the founding team and misalignment with customers and the market, startups with higher uncommonness in knowledge combinations may be more likely to exit the market unsuccessfully.

Hypothesis 2.1. *Startups that have a higher degree of uncommonness in their skill combinations are more likely to have extreme performance outcomes, either exiting the market successfully or failing.*

2.2.2 Potential Mechanisms

We propose that the success of uncommon-combination startups benefits from their attraction to VC firms, and a large body of literature has discussed the critical role in helping startups to grow and scale. There are several reasons why such startups might be particularly appealing to VCs.

First, VCs are often "market-makers" who are drawn to opportunities that have the potential to disrupt existing markets or create entirely new ones (Pontikes, 2012; Kaplan and Vakili, 2015). Startups with high levels of uncommonness may introduce innovative products and technologies that disrupt, or even reconstruct markets, thus offering high returns on VC investments.

Second, in the early stages of venture development, VCs rely on human capital as a key indicator to mitigate the severe information asymmetry between startups and investors. Some VCs value human capital more than the entrepreneurs themselves do, considering it a strong predictor of success (Black et al., 2010). As such, startups with uncommon knowledge combinations are more likely to secure VC funding.

However, if high degrees of uncommonness imply high levels of uncertainty, we should observe it in VC investment patterns. When facing Finally, VCs typically stage their investments over multiple funding rounds, closely monitoring the progress of startups. This staged investment approach (reducing the initial investment and staging into multiple funding rounds) allows VCs to reduce initial risk, observe whether the startup meets its milestones, and withdraw support if necessary (Kaplan and Strömberg, 2004; Tian, 2011). This method enables VCs to provide continuous support while avoiding excessive risk. Accordingly, we expect to observe a similar pattern in the investment of startups with uncommon knowledge combinations.

Hypothesis 2.2. *Startups with a higher degree of uncommonness are more likely to receive funding from VCs, receive lower initial funding amounts, and undergo more funding rounds.*

2.2.3 A Potential Mechanism for Failure: Markets

The market and industry context significantly influence the survival prospects of startups. Startups operate within specific industries that provide the economic and competitive environment in which they develop. For instance, startups entering sunrise industries with promising growth potential are likely to perform better than those in sunset industries with dwindling resources. As startups grow, they become increasingly imprinted by the industries they operate in, which shapes their development paths. The path-dependent nature builds the trajectories of startups and affects their survival.

Entrepreneurs enter industries based on their pre-entry capacities. The initial endowment of startups with uncommon combinations of knowledge may lead organizations to more industries (the source of uncommonness is unique skills), uncommon combinations of industries (the source is combining non-connected knowledge), or both. We have argued that uncommon combinations of knowledge can be formed by unique knowledge in the organization or the re-combination of existing knowledge. Similarly, entering novel combinations of industries means that organizations either enter or create a new industry or simultaneously compete in industries that other organizations generally do not. This may happen because the products they have generated are new to customers. It is also possible that the products satisfy demands from diverse groups of customers, but cannot be compared with products targeting one specific group. No matter whether such startups enter small niches or provide products to multiple markets, they may only achieve limited or controlled growth (McDougall and Robinson Jr, 1990). Eventually, they fail in the market competition.

In sum, the potential mechanism behind the failure is that startups with the high uncommonness of knowledge combinations enter inappropriate industries and compete in inappropriate markets. That is to say, startups are more likely to enter multiple markets, and the combination of markets is also uncommon, which can cause the startup to fail.

Hypothesis 2.3. *Startups with a higher degree of uncommonness in their knowledge combinations are more likely to enter multiple or uncommon industry combinations, increasing their probability of failure.*

2.3 Data and Methodology

2.3.1 Data and Sample

We collected data from CrunchBase and LinkedIn to examine the effect of skill combinations on entrepreneurial performance and how VC fundraising and industries influence the effect. CrunchBase, a database held by TechCrunch, is commonly used in the literature to retrieve VC funding information and characteristics of new ventures (Breschi et al., 2019; Cumming et al., 2019; Hellmann and Thiele, 2015; Homburg et al., 2014; Yu, 2020; Zhou et al., 2016). In this paper, we got information on entrepreneurial success and failure, socio-demographic characteristics of startups and their founder teams, and VC deals from the database. From the year 2002 to 2021 (both included), there were 176,403 ventures and 252,262 founders on CrunchBase worldwide.

We obtained information on the skills of entrepreneurs from LinkedIn. LinkedIn is an employment-oriented online service and provides a professional social network for users. Entrepreneurs can advertise themselves and their ventures on LinkedIn to update and promote their business. In recent years, LinkedIn has become a more and more prevalent data resource in research (Ng and Stuart, 2021; Zide et al., 2014). With LinkedIn API, we also gathered information about the educational background and working experience from the platform.

We then merged data from CrunchBase and LinkedIn to construct our sample. To guarantee the completeness and accuracy of data, we kept startups that all founders had a LinkedIn profile. 89,105 startups founded by 113,340 entrepreneurs were left. Next, we dropped startups containing one skill, for there are no skill combinations existent in such startups. The number of startups where all founders have a LinkedIn profile and own over one skill was 73,800, founded by 90,495 entrepreneurs.

We further cleaned skill data by unification and categorization. One limitation of the skills on LinkedIn is that they are self-claimed by users, so one skill may be expressed differently. For instance, “m & a”, “M & A”, and “mergers and acquisition” should be regarded as the same skill. Another concern is that differences in some skills are so trivial (e.g., “c” and “c++”) that they can be merged into one larger category. To address such questions, we refer to skills provided by Burning Glass Technologies (BG) and skill clusters by OECD. OECD skill clusters summarize BG skills into a larger category. For example, the skill “go to market strategy” goes to the taxonomy “Marketing Strategy”. We used “BG skills - OECD clusters” as the training sample, and predicted skill clusters of LinkedIn skills with a series of machine learning methods (BERT, fastText, GloVe, Neural Networks, and Word2Vec) and corpus (Google News corpus, fastText corpus, and Glove corpus). Multiple methods and corpus can cross-validate the accuracy of cluster prediction. For those skills that we could not cluster with machine learning methods, we clustered them manually. Eventually, we classified 52,626 skills reported on LinkedIn to 579 skill clusters.

Last, we dropped startups whose founders did not reveal their educational background and working experience on LinkedIn. Education and past working experience are the main sources for entrepreneurs to gain their skills, so they are necessary for our analysis. In addition, they can validate the skills reported by entrepreneurs. Finally, our sample contains 39,822 startups.

2.3.2 Variables

Independent Variable We use *z scores* to measure the extent to which observed co-occurrences of skill combinations differentiate from the expected random co-occurrences of skill combinations. Formally, let $I = \{1, 2, ...N\}$ be a pool of startups, each endowed with a skill set $A_i = \{s_1, s_2, ...s_k\}$, and $A = \{A_1, A_2, ...A_N\}$ denotes the set of all skill sets (We assumed that one skill couldn’t be counted twice if the skill was claimed by over one founder in a startup). Let n_i be the number of skill sets (in other words, startups) containing skill s_i, n_j be the number of skill sets containing skill s_j, and n_{ij} be the number of skill sets containing both s_i and s_j (Anderson, 2017; Uzzi et al., 2013).

The expected number of startups that have both s_i and s_j, which follows the hypergeometric distribution, is (Uzzi et al., 2013):

$$\mu_{ij} = \frac{n_i n_j}{N}$$

and variance is:

$$\sigma_{ij}^2 = \mu_{ij}(1 - \frac{n_i}{N})(\frac{N - n_j}{N - 1})$$

Then, we standardized the co-occurrence difference to get a z-score for the skill combination $i - j$:

$$z_{ij} = \frac{n_{ij} - \mu_{ij}}{\sigma_{ij}}$$

Z scores above zero indicate skill combinations that co-occurred within a startup more often in the sample than expected by chance, indicating relatively common combinations. Z scores below zero indicate combinations that co-occurred less often in the sample than expected by chance, indicating relatively uncommon pairs. Table 2.1 summarizes the combinations of skills, the number of startups that have them, and their corresponding z-scores in the sample. Panel A shows the most uncommon combinations, and most of the combinations are composed of a business-related skill and a scripting or programming language. It indicates that the startup team should master diverse skills that cover both the development of technologies and the promotion of products, which is consistent with the research findings on team diversity in knowledge and JoT entrepreneurs. Panel B presents combinations with a z-score around zero, which indicates combinations in a randomized skill network. Such skills can be complementary to each other, but not highly common or uncommon to combine. For example, scripting languages and materials science are highly complementary in industries where automation, simulation, data analysis, or process optimization are needed. However, this is not an uncommon combination with a z-score of around zero. Panel C exhibits the most common combinations of skills, which comprise skills that are highly relevant to each other. In other words, if entrepreneurs have mastered one skill, it is relatively easy for them to learn the other.

skill combinations	n_ij	z scores
Panel A: the most uncommon combinations		
Business Strategy & Scripting Languages	7046	-52.33
General Marketing & Programming Languages	4391	-49.43
Business Strategy & Web Development	10735	-46.39
Business Strategy & Programming Languages	5332	-44.69
Business Strategy & SQL Databases and Programming	4606	-40.17
Panel B: random combinations		
Scripting Languages & Materials Science	6	0.00
Programming Principles & Lending Assessment	7	0.00
Parallel Computing & Clean Energy	4	0.00
PHP Web & Fintech	3	0.00
Journalism & Surveillance	1	0.00
Panel C: the most common combinations		
Web Development & Scripting Languages	13086	151.97
Molecular Biology & Cellular Biology	847	156.13
Scripting Languages & SQL Databases and Programming	8864	159.37
Natural Gas & Oil Refining	91	160.01
Molecular Biology & Biologics Industry Knowledge	1481	197.57

Table 2.1: Examples of Skill Combinations and Z Scores

One startup usually owns multiple skill combinations, thus having multiple z-scores. To characterize a startup's tendency to master uncommon combinations of skills, we examined the startup's 10th-percentile z score as the uncommonness level of the startup. The distributions of the z scores in the 10th percentile of all the startups in our sample are shown in Figure 2.1. To make the empirical results more intuitive to read, we multiplied the z score by -1 to get *uncommonness*. Hence, a larger value means more uncommon.

Dependent Variables This paper examines two types of entrepreneurial outcomes: success and failure. *Success* is a dummy variable and equals one when startups either get

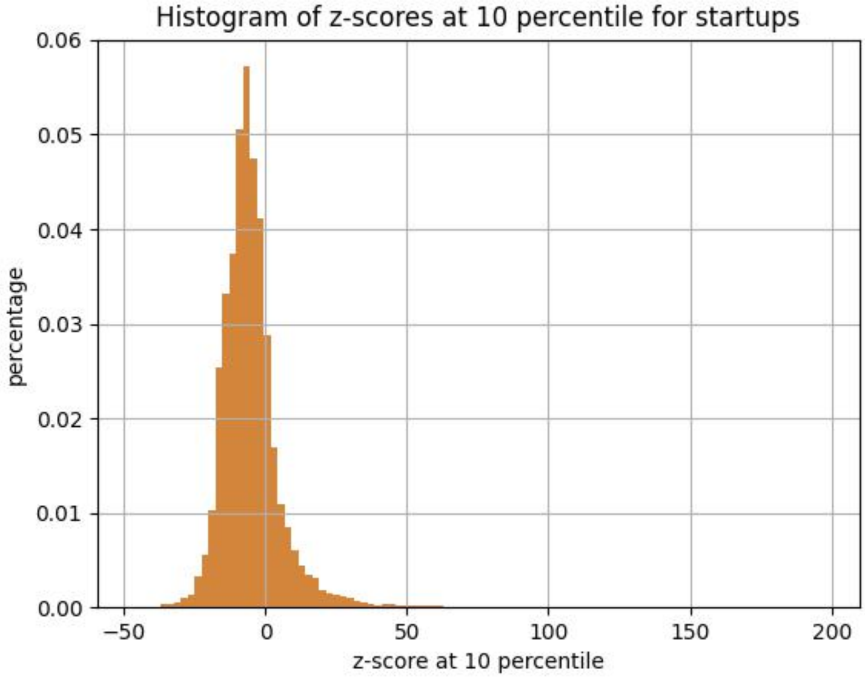


Figure 2.1: Distributions of z-scores at 10th percentile

acquired by other companies or go public, and zero otherwise. *Failure* is also a dummy and coded as one if the status of the startup on CrunchBase is failed or their official website is inactive, and otherwise zero.

We propose that VCs' resources and monitoring are the potential reasons for a startup's success, so we constructed *Funded* as a dummy variable that takes one when VCs have funded the startup, and 0 if not. If uncertainty is a concern of VCs, we should observe the staged strategy. Therefore, for those startups that have received funding, variable *ln_amount* records the logarithm of the investment amounts in the first VC funding round, and variable *num_rounds* records the number of funding rounds invested by VCs.

Startups with high uncommonness are more likely to enter multiple markets, and the uncommonness of market combinations is also higher, which can be the reasons of failure. Therefore, *num_industries* describes the number of industries that each startup has been in. With the same methodology, we first computed the real and expected co-occurrence frequencies of industry combinations in the sample, and the corresponding z scores of the combinations. Then, we took the 10th percentile z score in a startup to measure the uncommonness of industry combinations (variable *uncommon_industry*).

Control variables We control other startup-related variables emphasized in the literature that also influence entrepreneurial performance. The educational background of founders in a startup is critical for performance (Bates, 1990; Colombo and Grilli, 2005; Jo and Lee, 1996), so we controlled the highest *degree* in a startup and the corresponding *field* (Hartog and Oosterbeek, 2007; Le, 1999). Moreover, we used the average number of skills per founder *meanskill* as a proxy of the startup's absorptive capacity, which affects entrepreneurial performance as well. (Gray, 2006; Qian and Jung, 2017). Research also points out the importance of the founder's work experience (Beckman et al., 2007; Gompers et al., 2010; Hsu and Ziedonis, 2013), so we included working years before the new venture as the *experience* in the regressions. Many papers argue that the gender of entrepreneurs influences the probability of founders to get VC funding, thus impacting performance (Orser et al., 2006; Verheul and Thurik, 2001), so we encoded *female* as one if there is at least one female founder in the founder team and zero if all founders are males. *num_founders* in the founder team is another factor that influences performance, so we also included it.

In addition, we included investor-related variables when examining VCs' impacts. Distance between startups and investors influences the investor's support. To measure geographical proximity, we obtained the distance between cities where startups and VCs are located with Google Geocoding API and OpenCage Geocoding API, then chose the shortest distance in all funding rounds, plus one, and took the logarithm form to build the variable *ln_distance*. We also controlled the investment experience of VCs by counting the number of funding rounds that VCs have participated in Crunchbase before each funding round in our sample. The variable *ln_invest_rounds* is the logarithm of the funding rounds of VCs. The variable *ln_invest_industries* is the logarithm of the number

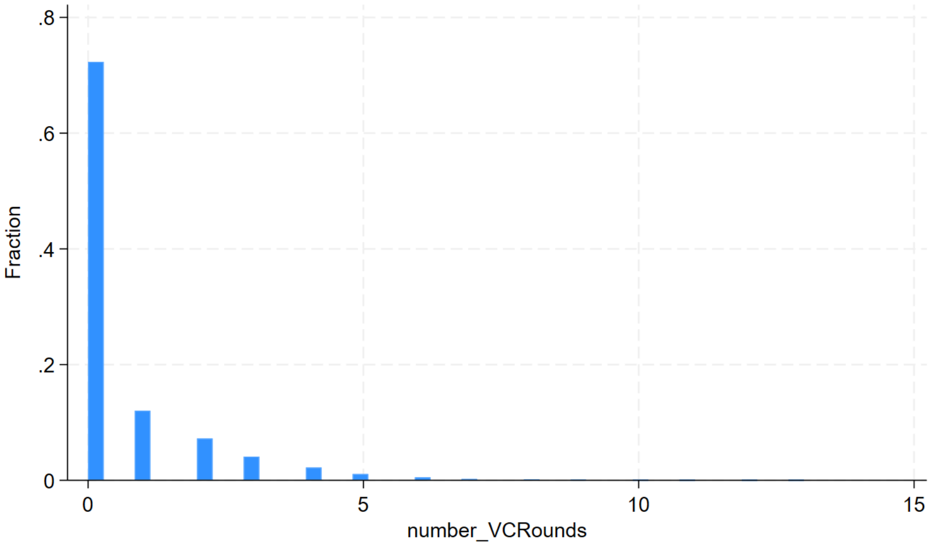


Figure 2.2: Number of VC Funding Rounds

of industries that VCs have invested in before each funding round. In addition, *num_VCs* counts the number of VCs in each funding round. *VC_city* takes the value of one if the startup locates in a VC-clustered city and zero otherwise (Beckman et al., 2007; Hartog and Oosterbeek, 2007; Tian, 2011). Table 2.2 summarizes the definitions of all variables.

2.3.3 Model and Identification Specifications

We applied a linear probability model (LPM) for our main regression, which examines the effect of uncommonness on performance outcomes. Similarly, we used LPM when testing the effect on the probability of being funded by VCs. We also included probit and logit regressions as a robustness check. Given the property of being non-negative in the numbers of funding rounds (Figure 2.2) and industries (Figure 2.3), we applied Poisson regressions when the dependent variables are *num_rounds* and *num_industries*. For robustness, we did zero-inflated Poisson regressions (ZIP). Moreover, we adopted the ordinary linear squared model when examining the effect on the amount of VC investments and uncommonness of industry combinations, for they are continuous variables.

Endogeneity problems may exist in our analysis, and one cause may be reverse causal-

Variables	Description
uncommonness	The z-score at the 10th percentile in skill pairs in the startup and multiply it with -1
success	Dummy variable, whether the startup has successfully exited the market. success = 1: the startup gets acquired or goes public
failure	Dummy variable, whether the startup has failed or not. failure = 1: the startup goes bankrupt or is not operating
funded	Dummy variable, whether the startup gets funding from VCs or not. funded = 1: the startup is funded by VCs
ln_amount	Logarithm of funding amount received by the startup in their first VC funding round
num_rounds	The number of funding rounds involving VCs
uncommon_industry	The z-score at the 10 percentile in industry pairs in the startup and multiply it with -1
meanskill	The average number of skills that each founder has in the founding team
experience	The average working years that each founder in the founding team has had before starting the business
female	Dummy variable, whether there are female founders in the founding team. female = 1: there are female founders
num_founders	Number of founders in the founding team
ln_distance	The natural logarithm of the sum of one plus the distance between the startup and its VCs in this funding round
ln_invest_rounds	The natural logarithm of the total number of funding rounds that VCs have invested before this funding round
ln_invest_industries	The natural logarithm of the total number of industries that VCs have invested in before this funding round
num_VCs	The number of VCs involved in the funding round
VC_city	Dummy variable, whether the startup is located in a VC-clustered city. vc_city = 1: the startup is in the top 10 VC-clustered cities in our sample
degree*	A series of dummy variables indicating the highest degrees of founders in the founding team, so one startup may have over one degree
field*	A series of dummy variables indicating the major of the highest degrees of founders in the founding team, so one startup may have different majors
founded	The startup's founding year
country	The startup's country

Table 2.2: Definitions of Variables

ity. While we argue that uncommonness in knowledge combinations will generate specific performance, entrepreneurs may learn new knowledge and skills from their prior entrepreneurial experience. Some skills can be exclusively learned from entrepreneurship,

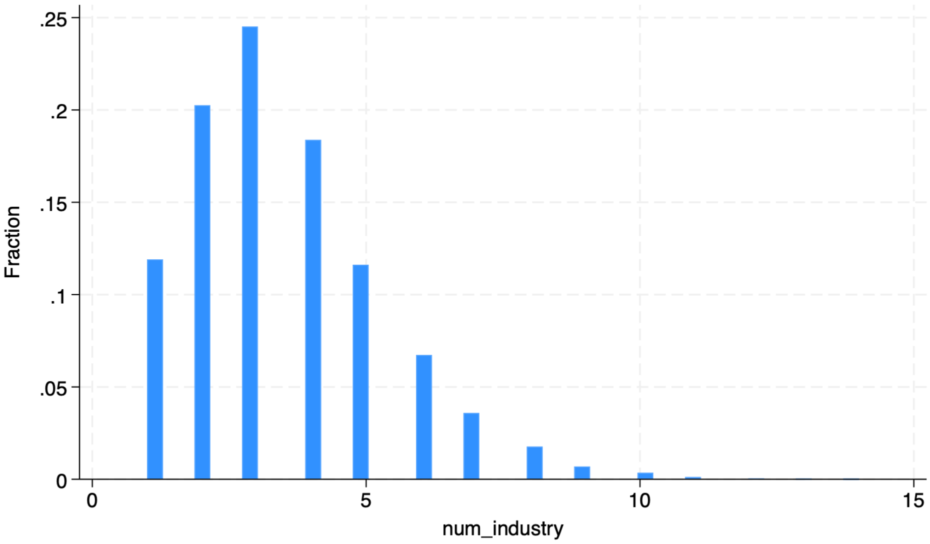


Figure 2.3: Number of Industries

and such unique skills can be a source of uncommon combinations of skills. To alleviate the concern, we excluded serial entrepreneurs and their ventures from our sample and re-ran the analysis.

When analyzing the investment behavior of VCs', in particular, the amount of the first-round funding, there may exist selection bias. An underlying assumption of the hypothesis is that all startups would like to receive funding from VCs and they will receive funding after putting in efforts to seek VC funding. However, not every startup needs VC funding because some may not need extra money and some may get funding from other channels, for example, bank loans, and some may not get financing even though they have tried. For startups, how much funding they get is not completely dependent on their willingness to seek financing. Therefore, there exists a self-selection problem for startups, and we only observed the effect of uncommonness on funding amount conditional on the fact that startups have been selected for funding by VCs. We used the Heckman selection model to alleviate the selection into VC funding problem in our paper. In the first step of the Heckman model, we built a variable num_CVCs to describe the number of corporate venture capitals (CVCs) in the city where each startup is located, up to the year it was founded.

The number of CVCs should positively affect the probability for startups to receive VC funding for the following two reasons. First, VC firms are generally clustered in several cities (New York, San Francisco, Boston, London, Beijing, Shanghai, and Tokyo in our sample), and a large number of CVCs are also located in these cities. Therefore, a large number of CVCs implies a large number of VCs. Entrepreneurs who select such cities to start their ventures are more likely to connect with VCs, and should positively associate with the probability of getting funding. Second, acquisition is a channel for startups to exit the market successfully, and for VCs to realize their investment success and high returns (Gompers and Lerner, 2000; Sorensen, 2004). Residing in cities that are clustered by CVCs may increase the interactions between startups and CVCs, thus increasing the probability of investment success of VCs. We expect that startups in such cities also would like to contact VCs and seek funding from them.

2.4 Results

2.4.1 Descriptive Statistics

Table 2.3 shows the number of observations, means, standard deviations (SD), and correlation matrix of our model variables. 10.2% of startups in our sample either get acquired or go public, while about 18.2% of startups fail. VC firms have invested in 27.7% startups in the sample, with an investment amount of about 1.21 million US dollars in the first VC round, on average. The average number of funding rounds is one. Startups enter three to four markets, with an uncommonness level of 0.1. The uncommonness of skill pairs in startups is four, indicating a lower frequency of knowledge combinations in founder teams than expected by combining skills randomly. For controls, the average number of skills per founder in a startup is eight, and there are about two founders in a startup team. Moreover, 16.5% of startups in the sample have at least one female founder. On average, founders have worked for 10.1 years before starting their new ventures. As for the characteristics of VC firms, they are experienced, with a history of 54 funding rounds across 30 industries. The syndication is small, and there are one to two firms in each VC funding round. In addition, about 31.5% of startups choose their locations in VC-clustered cities, and the average distance between the startup and its VCs is 69.1 miles.

2.4.2 Entrepreneurial Performance

Table 2.4 presents the main results on entrepreneurial performance. Model 1 includes all startups in the sample, and the estimated coefficient for uncommonness on success is 0.0001. The estimated coefficient means that when uncommonness (z-score) increases by one, the probability of exiting the market successfully has increased by 0.01 percentage points. However, the coefficient is not statistically significant. It becomes marginally significant when we restrict the sample to startups that have not failed in column 2. Given that there are three statuses of startups in the sample: successful, ongoing, and failed, it will not be possible for startups to succeed if it has exited the market unsuccessfully. The estimated coefficient is 0.0003, meaning a positive relationship that a one-standard deviation (SD, here 12.46) in uncommonness changes 1.2 percent of the SD in success.

Columns 3 and 4 show the results of uncommon skill combinations on the probability of failure. Similar to columns 1 and 2, column 3 includes all startups in the sample, and column 4 only includes startups that have not succeeded yet. The results show a significantly positive relationship between the uncommonness and the probability of failure of startups with the estimated coefficients 0.0006 and 0.0007, respectively. Column 3 indicates that one unit change in uncommonness brings a 0.06 percentage point change in the probability of failure. For not-yet-successful startups in column 4, one unit change in uncommonness brings a 0.07 percentage point change in failure. Measured in standard deviations, a one-standard-deviation change in uncommonness changes failure probability by 1.9 percent (column 3) and 2.3 percent (column 4). Such results support Hypothesis 1, which proposes that startups with a higher degree of uncommonness in skill combinations are more likely to have extreme performance outcomes.

VARIABLES	N	mean	s.d.	1	2	3	4	5	6	7	8
1. success	39,822	0.102	0.303	1							
2. failure	39,822	0.182	0.386	-0.16	1						
3. funded	39,822	0.277	0.447	0.15	-0.08	1					
4. ln_amount	10,587	14.01	1.801	0.14	-0.11	.	1				
5. num_rounds	39,822	0.603	1.252	0.14	-0.08	0.78	0.1	1			
6. num_industries	39,492	3.491	1.808	0.02	-0.01	0.11	-0.02	0.1	1		
7. uncommon_industry	34,788	0.127	34.95	-0.01	0.01	0.05	-0.12	0.04	0.38	1	
8. uncommonness	39,822	4.014	12.46	0.03	0.04	0.08	-0.08	0.08	0.07	0.08	1
9. meanskill	39,822	8.310	2.877	-0.04	0	-0.06	-0.03	-0.07	0	0.02	0.16
10. experience	39,822	10.09	7.006	0	-0.06	0.02	0.18	0.01	-0.01	-0.03	-0.05
11. female	39,822	0.165	0.371	-0.04	0.01	0.02	-0.11	0.01	-0.02	0	0.01
12. num_founders	39,822	1.585	0.785	0.08	0.03	0.24	-0.03	0.25	0.11	0.07	0.31
13. ln_distance	10,615	4.250	3.528	-0.02	0	.	-0.01	-0.03	0.01	-0.01	-0.03
14. ln_investment_rounds	10,352	3.996	1.948	0.01	0	.	0.08	0.06	0.01	0.02	0.01
15. ln_investment_industries	10,246	3.377	0.921	-0.01	0	.	0.09	0.05	0.04	0.06	0.04
16. num_VCs	11,021	1.568	1.073	0.06	-0.01	.	0.26	0.09	0.01	-0.02	0.02
17. VC_city	11,021	0.315	0.465	0.02	0.02	.	-0.01	0.08	0.05	0.06	0.05
18. num_CVCs	39,822	3.793	6.948	-0.03	-0.02	0.09	-0.03	0.08	0.05	0.03	0.04

VARIABLES	9	10	11	12	13	14	15	16	17	18
9. meanskill	1									
10. experience	0.05	1								
11. female	-0.04	-0.01	1							
12. num_founders	-0.24	-0.08	0.11	1						
13. ln_distance	0.01	0.01	0.01	-0.03	1					
14. ln_investment_rounds	-0.01	0	0.04	0.07	0.01	1				
15. ln_investment_industries	-0.03	-0.02	0.03	0.11	-0.11	0.85	1			
16. num_VCs	-0.03	0.02	0	0.08	-0.24	0.38	0.56	1		
17. VC_city	-0.01	-0.07	0.06	0.08	-0.14	0.14	0.16	0.11	1	
18. num_CVCs	0	0.02	0.08	0.06	-0.13	0.16	0.18	0.13	0.77	1

Table 2.3: Descriptive Statistics and Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	success		failure		non-serial: success		non-serial: failure	
	all	non-failed	all	unsuccessful	all	non-failed	all	unsuccessful
uncommonness	0.0001	0.0003*	0.0006***	0.0007***	0.0001	0.0002	0.0006***	0.0007***
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
num_founders	0.0333***	0.0394***	-0.0045	0.0053	0.0269***	0.0324***	0.0022	0.0099**
	(0.0026)	(0.0031)	(0.0031)	(0.0035)	(0.0029)	(0.0034)	(0.0035)	(0.0039)
meanskill	-0.0019***	-0.0021***	0.0015**	0.0009	-0.0015***	-0.0017**	0.0018**	0.0015*
	(0.0005)	(0.0006)	(0.0007)	(0.0008)	(0.0006)	(0.0007)	(0.0008)	(0.0008)
female	-0.0298***	-0.0348***	0.0054	-0.0021	-0.0251***	-0.0291***	0.0033	-0.0028
	(0.0037)	(0.0045)	(0.0053)	(0.0056)	(0.0038)	(0.0046)	(0.0056)	(0.0059)
experience	0.0012***	0.0011***	-0.0021***	-0.0020***	0.0009***	0.0008***	-0.0021***	-0.0021***
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
Education controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry fixed effect	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y	Y	Y	Y	Y
Country fixed effect	Y	Y	Y	Y	Y	Y	Y	Y
Observations	39822	32559	39822	35757	32081	26675	32081	29208
Adjusted R^2	0.066	0.089	0.075	0.092	0.059	0.077	0.070	0.084

Table 2.4: LPM models predicting the probability of success and failure

From column 5 to column 8, we excluded startups whose founders are serial entrepreneurs. This is to mitigate the concern of reverse causality, stressing that prior entrepreneurial experience may equip entrepreneurs with less common skill combinations. The results remain highly similar with the main analysis in the first four columns supporting the positive relationship between uncommonness and extreme outcomes, and the effect on failure is more robust than that on success.

2.4.3 Mechanisms

Hypothesis 2 and 3 investigate potential mechanisms underlying the performance of startups with high uncommonness: resources and monitoring provided by VC firms are critical for success while entering diverse and uncommon combinations of markets deteriorates the future of startups. A one-unit increase in the degree of uncommonness increases the probability of getting VC funding by 0.08 percentage points (see Table 2.5 column 1), and a one-standard-deviation change in uncommonness leads to a 0.02 one-standard-deviation change in the funding probability. Because of the non-negative property of the variable *num_VCrounds*, we used the Poisson regression in column 2 in Table 2.5. The coefficient is 0.0057, suggesting that a one-unit increase in uncommonness gives one more VC funding round to startups. Moreover, the amount of the first VC investment decreases as the uncommonness increases, and Table 2.6 Panel A presents the details. Column 1 exhibits that a one-unit increase in uncommonness level increases the VC investment by 0.0047 unit, that is, $5,687$ US dollars on average. To mitigate the selection concern, we used the Heckman Selection Model with the selection variable *num_CVC*. Columns 2 and 3 show the main results from step two in the Heckman selection model, and columns 4 and 5 are results from the first step. On average, the VC investment dropped $8,954$ US dollars without controlling for VC characteristics (column 2) and $6,897$ (column 3) US dollars after controlling for VCs. In the selection process, the number of CVCs is a statistically significant indicator of startups seeking support from VC firms.

	(1) all: funded	(2) all: num_ VCrounds	(3) all: num_ industries	(4) all: uncommon_ industry	(5) non-serial: funded	(6) non-serial: num_ VCrounds	(7) non-serial: num_ industries	(8) non-serial: uncommon_ industry
uncommonness	0.0008***	0.0057***	0.0003***	0.0651***	0.0007***	0.0055***	0.0003***	0.0631***
	(0.0002)	(0.0010)	(0.0001)	(0.0145)	(0.0002)	(0.0012)	(0.0001)	(0.0162)
num_founders	0.1188***	0.4363***	0.0092***	0.3431	0.1172***	0.4154***	0.0095***	0.5335**
	(0.0037)	(0.0133)	(0.0016)	(0.2323)	(0.0043)	(0.0154)	(0.0019)	(0.2658)
meanskill	-0.0032***	-0.0239***	-0.0001	0.0140	-0.0027***	-0.0225***	-0.0002	0.0323
	(0.0008)	(0.0043)	(0.0004)	(0.0575)	(0.0008)	(0.0049)	(0.0004)	(0.0647)
female	-0.0116*	-0.0880***	-0.0008	-0.4435	-0.0127**	-0.0941***	-0.0016	-0.3725
	(0.0061)	(0.0265)	(0.0026)	(0.4208)	(0.0064)	(0.0297)	(0.0029)	(0.4623)
experience	0.0007**	0.0010	-0.0004**	-0.0509**	-0.0000	-0.0014	-0.0004**	-0.0561**
	(0.0003)	(0.0015)	(0.0002)	(0.0242)	(0.0003)	(0.0017)	(0.0002)	(0.0268)
Education controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry fixed effect	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y	Y	Y	Y	Y
Country fixed effect	Y	Y	Y	Y	Y	Y	Y	Y
Observations	39822	39822	39492	34788	32081	32081	31759	27758
Adjusted R^2	0.119			0.363	0.129			0.368

Table 2.5: Potential mechanisms for performance: funded, VC rounds, and markets

We then restricted the sample to startups that do not contain serial entrepreneurs and the results are consistent with the full sample of startups. We found that the increase in uncommonness significantly increases the probability of getting funded from VC firms (see column 5 Table 2.5) and the number of invested rounds provided by VCs (see column 6 Table 2.5). Meanwhile, the amount of the first-round VC investment decreases (see Table 2.6 Panel B), and the role of *num_CVC* holds. Overall, the analysis of VC investments confirms our hypothesis 2. High uncommonness of knowledge combinations in startups is attractive for VC firms, who provide supports, resources, and monitoring to startups and help them to succeed in the market.

Column 3 in the Table 2.5 presents that a one-unit increase in uncommonness increases the number of industries that the startup entries by 0.03 percentage points, and a standard-deviation change in uncommonness leads to a 0.002 standard-deviation change in the number of industries. This verifies our hypothesis that high uncommonness in knowledge combinations encourages startups to enter more diverse markets. Moreover, the coefficient (0.0651) in column 4 Table 2.5 shows a significantly positive effect on the uncommonness in industry combinations. One more score of uncommonness in knowledge combinations brings the uncommonness in industry combinations by 6.51 percentage point changes. In other words, one standard-deviation difference in the uncommonness in knowledge combinations makes a difference of 0.0232 standard deviation in the uncommonness level of industry combinations. This is aligned with our hypothesis 3 that startups with a higher degree of uncommonness in their knowledge combinations are more likely to enter less common-combined industries. The last two columns in Table 2.5 show results after startups with serial entrepreneurs were excluded. The coefficients are 0.0003 and 0.0631 respectively, which are highly similar to those from the full sample. Therefore, hypothesis 3 is supported, and entering inappropriate markets are harmful for startups.

Table 2.6: Potential mechanisms for performance: amount of 1st VC round

Panel A	(1)	(2)	(3)	(4)	(5)
			all: ln_amount		
	OLS	Heckman: main		Heckman: select	
uncommonness	-0.0047***	-0.0074***	-0.0057***	0.0033***	0.0035***
	(0.0015)	(0.0017)	(0.0017)	(0.0007)	(0.0007)
num_CVC				0.0132***	0.0141***
				(0.0012)	(0.0012)
num_founders	0.1111***	-0.1168*	-0.0408	0.3485***	0.3524***
	(0.0227)	(0.0633)	(0.0784)	(0.0113)	(0.0116)
meanskill	-0.0300***	-0.0205***	-0.0206***	-0.0114***	-0.0116***
	(0.0068)	(0.0074)	(0.0075)	(0.0028)	(0.0029)
female	-0.4075***	-0.3787***	-0.3972***	-0.0491**	-0.0515**
	(0.0445)	(0.0459)	(0.0452)	(0.0198)	(0.0204)
experience	0.0392***	0.0370***	0.0388***	0.0043***	0.0035***
	(0.0026)	(0.0027)	(0.0027)	(0.0011)	(0.0011)
ln_distance			0.0111**		
			(0.0049)		
ln_invest_rounds			0.0269		
			(0.0169)		
ln_invest_industries			-0.0554		
			(0.0400)		
num_VCs			0.4200***		
			(0.0185)		
VC_city			-0.0197		
			(0.0570)		

/mills lambda				-0.9700***	-0.4740
				(0.2476)	(0.3122)
Education controls	Y	Y	Y	Y	Y
Industry fixed effect	Y	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y	Y
Country fixed effect	Y	Y	Y	Y	Y
Observations	10587	39822	38777	39822	38874
Adjusted R^2	0.198				

Panel B	(1)	(2)	(3)	(4)	(5)
			non-serial: ln_amount		
	OLS	Heckman: main		Heckman: select	
uncommonness	-0.0062***	-0.0092***	-0.0068***	0.0031***	0.0032***
	(0.0017)	(0.0019)	(0.0019)	(0.0007)	(0.0008)
num_CVC				0.0140***	0.0149***
				(0.0014)	(0.0014)
num_founders	0.1091***	-0.1657**	-0.0811	0.3471***	0.3523***
	(0.0266)	(0.0722)	(0.0894)	(0.0131)	(0.0135)
meanskill	-0.0228***	-0.0123	-0.0123	-0.0105***	-0.0104***
	(0.0076)	(0.0084)	(0.0084)	(0.0032)	(0.0033)
female	-0.3976***	-0.3563***	-0.3803***	-0.0583***	-0.0614***
	(0.0504)	(0.0527)	(0.0518)	(0.0220)	(0.0227)
experience	0.0379***	0.0370***	0.0390***	0.0023*	0.0017
	(0.0029)	(0.0030)	(0.0029)	(0.0012)	(0.0013)
ln_distance			0.0131**		
			(0.0057)		
ln_invest_rounds			0.0281		

			(0.0194)		
ln_invest_industries			-0.0859*		
			(0.0454)		
num_VCs			0.4722***		
			(0.0225)		
VC_city			0.0043		
			(0.0678)		
/mills lambda				-1.1636***	-0.6442*
				(0.2783)	(0.3528)
Education controls	Y	Y	Y	Y	Y
Industry fixed effect	Y	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y	Y
Country fixed effect	Y	Y	Y	Y	Y
Observations	8107	32081	31251	32081	31251
Adjusted R^2	0.198				

2.4.4 Robustness

We adopted alternative regressions to validate the robustness of our results. We used the same control variables and fixed effects as in the main analysis, and the results are shown in Appendix Table A1. More uncommonness in knowledge combinations in startup teams result in a higher probability of extreme results, which is more significant after we exclude those startups that have exited the market successfully or unsuccessfully. Also, less common startups are more likely to get VC investments, more rounds, and enter more diverse markets. The robustness check aligns with the main analysis, thus supporting all hypotheses.

2.5 Discussion

This paper investigates the influence of uncommonness in knowledge combinations on startup performance, revealing that a higher degree of uncommonness in skill combinations tends to produce extreme performance outcomes. Specifically, startups with high uncommonness in knowledge combinations are more likely to either exit the market successfully or fail. Two potential mechanisms are identified: (1) startups with uncommon combinations of knowledge are more attractive to venture capitalists (VCs), whose support can enhance their chances of success, and (2) the tendency of these startups to enter multiple, less-explored markets simultaneously increases their risk of failure due to the uncertainty and lack of demand in such markets.

2.5.1 Theoretical Implications

This research contributes to several theoretical domains. First, it advances RBV by providing insights into how strategic resources—specifically, the combination of human capital—affect entrepreneurial performance. RBV emphasizes that an organization's resources can lead to competitive advantages, but this paper goes further by demonstrating that the way these resources are combined matters. Entrepreneurs should focus not only on the resources themselves but also on how to combine them differently from competitors. This contributes to research on team diversity and its relationship to performance (Corrocher and Lenzi, 2022; D'Acunto et al., 2020; Østergaard et al., 2011), adding a new dimension to the effects of uncommon combinations.

Secondly, this paper makes significant contributions to studies on the role of knowledge by examining its impact on entrepreneurial outcomes, including performance, venture capital investment, and market entry. The paper highlights the importance of knowledge recombination and demonstrates that uncommon combinations of knowledge influence performance. This contrasts with previous studies that generalized knowledge proxies

(Hartog and Oosterbeek, 2007; Hoenig and Henkel, 2015; Le, 1999), making this one of the first studies to investigate the effects of specific skills on entrepreneurial outcomes.

2.5.2 Practical Implications

Table 2.1 summarizes the degree of uncommonness of skill combinations in our sample. When building the knowledge stock for startup teams, entrepreneurs should consider their knowledge and how their knowledge can interact with others. Except for heterogeneity and complementarity between knowledge, it is also beneficial to consider whether the combination is common among the startup population. High uncommonness may make the startup outstanding, but also relate to the high uncertainty.

For venture capitalists, the study suggests that paying close attention to startups with uncommon skill combinations can yield higher returns. These startups often exhibit the potential for disruptive innovation, a characteristic attractive to VCs. However, VCs should also be mindful of the risks involved. By monitoring these startups closely and staging investments, VCs can manage the inherent uncertainties, shortening the investment cycle when a venture shows signs of failure, thereby reducing losses.

2.5.3 Limitations and Future Research

Despite the contributions, this paper has limitations that future research can address. First, the paper does not account for direct outputs from knowledge combinations, such as prototypes or products, which often guide VC investment decisions. Future research could enhance the analysis by incorporating product information, allowing for a more direct assessment of the outcomes produced by different knowledge combinations.

Secondly, the use of LinkedIn data to track skills introduces potential inaccuracies, as profiles can be updated or edited retroactively. As a result, the skills founders report on their profiles might not have been present when they launched their startups. To mitigate this limitation, future research should seek more reliable data sources or develop methods to verify the temporal accuracy of reported skills.

In sum, while this study provides valuable insights into the effects of uncommon knowledge combinations on entrepreneurial performance, future work is necessary to build on these findings, particularly by exploring the direct outputs of knowledge combinations and addressing the potential data issues related to skill reporting.

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DV	sample	regressions	coefficients
success	all	probit	0.0008
		logit	0.0018
	non-failed	probit	0.0015*
		logit	0.0032*
fail	all	probit	0.0027***
		logit	0.0048***
	unsuccessful	probit	0.0030***
		logit	0.0053***
funded	all	probit	0.0033***
		logit	0.0058***
num_VCrounds		ZIP	0.0044***
num_industries			0.0003***

Table A1: Results for robustness tests

Appendices

Chapter 3

Knowledge in Multi-Clustered Firms: Exploration, Internal Exploitation, and Integration

3.1 Introduction

Geographically dispersed teams have become more common recently, benefiting from the advances in telecommunication and information technologies. This shift has captured the attention of both researchers and practitioners, with growing interest in understanding how such teams operate across various organizational contexts. Studies have concentrated on the role of leadership (Hill and Bartol, 2016; Joshi et al., 2009), effectiveness (Cramton and Webber, 2005; Polzer et al., 2006; Tzabbar and Baburaj, 2019), knowledge creation (Gibson and Gibbs, 2006; Reuer and Lahiri, 2014; Tzabbar et al., 2013), knowledge quality (Lahiri, 2010) and knowledge sharing (da Silva et al., 2022) within such organizations.

While much of the existing literature suggests that geographically dispersed teams enable increased inventive activities by providing inventors with access to a broader knowledge base, the focus has largely been on knowledge diffusion to external competitors in the local market. However, there is limited research on how innovation is diffused and integrated within firms across clusters, particularly in terms of factors that foster knowledge circulation and enhance the efficiency of a firm's research and development (R&D) investments.

For literature that focuses on intra-firm knowledge transfer and integration, scholars pay much attention to muti-national enterprises and investigate such factors as the organizational structure, internal stickiness, knowledge similarity, absorptive capacity, and position in the network that influence knowledge inflow and outflow dynamics (Foss and Pedersen, 2004; Gupta and Govindarajan, 2000; Szulanski, 1996; Tsai, 2001). One factor that has not been fully discussed is the degree of geographical dispersion among clusters within the organization, and this is an inherent feature of a multi-clustered organization.

Overall, research provides evidence on the effect of geographical dispersion on explorative knowledge, while it is unclear whether and how geographical dispersion influences intra-firm knowledge transfer. This paper seeks to address these gaps by investigating how geographical dispersion impacts the production, quality, and dissemination of explorative patents within firms, with particular attention to the moderating role of connections among different innovation clusters.

Utilizing patent data from PatentsView and OECD REGPAT Database, along with firm information from Compustat, we construct an unbalanced panel dataset comprising publicly traded U.S. companies and inventors filing patents in all clusters. Our dataset encompasses 30,509 observations spanning 3,451 firms from the year 1990 to 2015. We examine the number and distribution of explorative patents of each company and whether other clusters have exploited such patents other than the one that invented them. Suppose that there are three clusters i, j, and k in a company. Cluster i has a patent that includes a new technological class c in the year t, so this is an explorative patent. In some year after t, this patent is cited by a patent in the cluster j, which is defined as exploitation of the explorative patent. It is also possible that inventors in other clusters do not cite the patent explicitly, but learn relevant knowledge from inventors in cluster i and apply it to their following inventions. We assume that this is the case when technology class c has never been involved in patents in k before the year t, but inventors in k patent in c after the year t.

Our findings reveal that increased geographical dispersion positively correlates with the number of explorative patents. While the average quality of these patents remains unaffected, their variance exhibits an upward trend with greater dispersion. By investigating citations and other means of diffusion of these patents by inventors in different clusters within a firm, we observe a positive association between dispersion and the diffusion of explorative patents. Moreover, both the average quality and its variance for patents are positively linked to the extent of dispersion. Surprisingly, prior co-patenting connections negatively impact knowledge exploitation and diffusion, contrary to our initial hypothesis.

This study contributes to the literature on knowledge exploration within geographically dispersed teams, extending insights into the effects of dispersion on innovation

(Alcácer and Zhao, 2012; Gibson and Gibbs, 2006; Tzabbar and Vestal, 2015) and innovation quality (Lahiri, 2010; Lanjouw and Schankerman, 2004). Additionally, it enriches our understanding of knowledge exploitation and diffusion in multi-clustered teams, emphasizing the internal integration of knowledge. Unlike existing research, which often focuses on knowledge spillover to competitors in the same market (Alcácer and Zhao, 2012; Jaffe et al., 2000; Lahiri, 2010; Thompson and Fox-Kean, 2005), our work highlights the benefits that inventors in different locations can derive from activities elsewhere within the firm, ultimately enhancing the efficiency of innovative endeavors.

3.2 Theory and Hypotheses

We investigate the explorative behavior in geographically dispersed teams and whether and how explorations are transferred and used by other clusters within the organization. Following the extant literature, we define geographically dispersed teams by "the criteria of traditional work teams — boundedness, stability of membership, commonality, and interdependence of task, and authority to manage their internal processes — as well as the fact that geographic distances separate at least some members, leading them to use information technologies to communicate" (Cummings, 2004; O'Leary and Cummings, 2007; Piccoli and Ives, 2003). Geographically dispersed teams include spatial and temporal dispersion among team members (Joshi et al., 2009; O'Leary and Cummings, 2007). The spatial and temporal dimension refers to the geographic distance and time difference among teams, respectively (O'Leary and Cummings, 2007). Teams with a higher level of spatial dispersion are not necessarily distant in the temporal dimension. Only teams that are east-to-west dispersed are also dispersed on temporal dispersion; teams that are dispersed from the north to the south may not be dispersed on temporal dispersion. Given that spatial and temporal dispersion are not always consistent, we consider both levels.

3.2.1 Explorative Outputs in Geographically Dispersed Teams

Recombining existing knowledge and combining previously non-connected knowledge are potential mechanisms to make breakthroughs (Fleming, 2001; Weitzman, 1998). Knowledge can be tacit, codified or not, or routine-based (Cummings, 2004; Kogut and Zander, 1993; Nelson and Winter, 1982; Zander and Kogut, 1995). The advantage of geographically dispersed teams in innovation activities is that it may increase the firm's access to new sources of knowledge and the ability to understand and adapt to diverse knowledge.

Compared to teams that collocate in the same cluster, geographically dispersed teams are located in different clusters or countries, thus having the opportunity to interact with different local knowledge embedded in such clusters and receive specialized local knowledge from external knowledge sharing. (Lahiri, 2010; Vestal and Danneels, 2022). External knowledge sharing refers to "the exchange of information, know-how, and feedback with customers, organizational experts, and others outside of the group" (Cummings, 2004). If knowledge received in each cluster is sufficiently different from another's, firms may establish extra research facilities to tailor existing technological knowledge to meet the demands of local markets (Kuemmerle, 1999; Leiponen and Helfat, 2011). For example, Von Hippel (1998) points out that the direct users of a product or service, who benefit from solutions and have sticky local information, help solve problems that firms face. Such knowledge and demand from users are tacit and locally specialized (Fabrizio and Thomas, 2012). Compared to collocated teams, geographically dispersed teams that provide products and services to local markets can obtain more external knowledge sharing from users and others outside the firm, thus accumulating more local knowledge from feedback in different clusters. Therefore, inventors in geographically dispersed teams can gain access to diverse and previously unavailable knowledge, leading to the creation of explorative inventions, and firms will benefit from knowledge spillovers from the diverse and location-specific technological knowledge.

Therefore, higher access to new and diverse knowledge yields a positive relationship between the extent of geographical dispersion and innovation novelty, and we propose the first hypothesis below:

Hypothesis 3.1a. *The relationship between the geographic dispersion of a firm's innovative activity and a firm's innovative novelty is positive. The innovation novelty increases as the degree of the geographic dispersion of the firm members increases.*

Yet, ceteris paribus, geographic dispersion may explain a higher variance in the expected quality of these explorative inventions. Teams in different clusters offer firms the opportunity to tap into more specialized local knowledge, so the likelihood of inventors exploring new and locally nonexistent knowledge elements increases as the geographic dispersion increases. Accordingly, firms can select knowledge elements from a larger pool of knowledge elements, which may lead to two results in terms of the quality of explorations by the firms: The first potential is that the quality of innovative activities may increase. When a firm increases the diversity of the pool of knowledge elements it can use, it can increase the number of trials, and the probability of exploring new knowledge elements increases. Therefore, there is a higher chance for firms to create more innovative inventions, and the average quality becomes higher.

However, because of information asymmetry that firms may face when seeking knowledge from external sources, the likelihood of selecting quality knowledge pieces may also decrease. Suppose that distributions of quality of innovative activities are the same in all pools of knowledge, and extremely good or impactful knowledge elements are relatively rare (e.g., normal distribution), firms may have problems in discerning the quality of knowledge elements as the range of choices increases. When selecting from a larger pool of possible trials, the likelihood of selecting bad knowledge elements should increase, with everything else constant. In other words, the variance of novel innovation outputs should increase. We, for the above reasons, propose the following hypothesis:

Hypothesis 3.1b. *Geographic dispersion increases the average quality of a firm's novel inventions, yet it also increases the standard deviation of such quality.*

3.2.2 Exploitation of Newly Explored Knowledge

After explorative innovations are created, they may be kept in the original cluster or diffused to the other clusters of the firm. Inventors in other clusters may get access to exploit such explorative innovations, and geographical dispersion of teams may facilitate the exploitation for the following reasons: firstly, inventors in teams need to integrate and re-combine distant knowledge elements to make breakthrough inventions (Harvey, 2014; Singh and Fleming, 2010; Vestal and Danneels, 2022). Geographically dispersed teams have more exposure to different environments and require more communication with inventors from other clusters. Inventors in such teams have more opportunities to share external and internal knowledge, compared with those who collocate in the same cluster. As a result, the ability of inventors to circulate and integrate knowledge from other clusters is enhanced, and the chance to improve inventions is higher.

Secondly, the amount and quality of a firm's innovative novelty are positively related to the degree of geographical dispersion. Geographically dispersed firms are more likely to accumulate explorative innovations because inventors in such firms have access to diverse and local technological knowledge and adapt to local markets to make "user-based" innovations. They can choose among a larger number of novel inventions to exploit, and the average quality of novel inventions is higher. Therefore, more explorative innovation can be exploited in more geographically dispersed firms.

For reasons similar to those discussed in the last section, we also expect higher average quality and larger variance of the innovative activities that firm members exploit. The pool of knowledge elements increases as the geographical dispersion increases, so choosing more impactful elements becomes more difficult, and the probability of picking up the extremely good or bad elements is lower. Therefore, the variance of quality is larger.

However, the average quality should be higher when the diversity of the pool increases, as the degree of geographical dispersion increases. Hence, we have the following hypotheses: **Hypothesis 3.2a.** *The relationship between geographic dispersion and a firm's exploitation of its novel inventions is positive. The exploitation increases as the degree of the geographic dispersion of the firm members increases.* **Hypothesis 3.2b.** *Geographic dispersion increases the average quality of a firm's exploitation of its novel inventions, yet it also increases the standard deviation of such quality.*

3.2.3 Integration of Firm Social Capital

While geographically dispersed teams provide a larger pool of new knowledge elements, they may also generate information overload and cause high costs, which makes the exploitation of newly explored inventions less likely. Firstly, the likelihood of inventors in different teams having face-to-face interactions decreases as the geographic dispersion increases. Spatial dispersion separates inventors from each other. As a result, spontaneous communication among inventors reduces, and the cost of communication grows (Cramton, 2001; Forman, 2005). Secondly, geographical dispersion, especially temporal dispersion, raises the level of difficulty in instant interaction, thus decreasing the likelihood of inventors in different clusters of face-to-face interaction and reducing the probability of solving real-time problems (Magni et al., 2013; O'Leary and Cummings, 2007). Thirdly, the geographical dispersion may bring intra- and inter-team coordination complexity. As dispersion increases, it becomes more challenging for the inventors in different clusters to achieve a common belief and awareness. So, the intra- and inter-conflicts increase as well, and the coordination costs to integrate inventors expand (Boh et al., 2007; Hinds and Mortensen, 2005; Kabanoff, 1991; Yoo and Alavi, 2001). The potential increase in costs reveals the difficulty for highly geographically dispersed firms to circulate and integrate newly explored knowledge.

We argue that firm-specific social capital can mitigate the high costs by favoring information circulation and integration and assisting inventors to interpret and evaluate distinct knowledge. Firm-specific social capital can be accumulated by the collaborations among inventors in different clusters, and dense inter-cluster ties formed by prior collaborations should permit geographically dispersed teams to benefit from newly explored knowledge generated by other clusters (Vestal and Danneels, 2022). On the one hand, such social capital can build wide bridges among inventors in dispersed clusters, and the bridges can serve as channels for the open exchange of tacit and specialized knowledge among clusters (Centola and Macy, 2007; Ren et al., 2015; Hansen, 1999). The flow of information and expertise among distinct geographical teams is fostered because inventors can better understand and interpret knowledge through prior collaborations. Therefore, costs caused by the lack of spontaneous and synchronized communication among inventors with different knowledge should be lower.

On the other hand, social capital formed by dense collaborations fosters inventors in different clusters to develop the belonging and a cohesive identity as a whole group. Inventors share a superordinate social identity, where members across different locations perceive themselves as integral parts of the overarching team. This collective sense, in one aspect, encourages inventors to be open to inventors and knowledge from other clusters, as they belong to the same firm and share the same identity; in another aspect, this shared identity becomes instrumental in overcoming the physical distance among team members (Hinds and Mortensen, 2005), so dispersed team members experience with a sense of identification with their counterparts even in different locations. Consequently, team members can better evaluate knowledge originating from diverse locations, fostering motivation to invest efforts in understanding the newly explored knowledge brought from their respective members from other clusters. Hence, the potential conflicts existing in highly dispersed teams decrease, benefiting from the arising common awareness of identity, thus decreasing the coordination costs among team members.

Firm-specific social capital formed by dense collaboration mitigates the potential costs caused by high dispersion and makes the positive relationship more solid. Therefore, we propose Hypothesis 3 as follows:

Hypothesis 3.3 *The positive relationship between geographic dispersion and the firm's exploitation of its novel inventions is positively moderated by the firm-specific social capital of the firm's members. A high level of social capital increases the positive effect of dispersion.*

3.3 Data and Methodology

3.3.1 Data and Sample

To empirically examine the positive relationships between geographically dispersed teams, their explorations of inventions, exploitations of such inventions, and the moderating effect that the firm-specific social capital has on the relationships, we collected data on public companies in the United States. Additionally, these companies should conduct innovative outputs in multiple clusters from the year 1990 to the year 2015.

In the paper, we proxied innovative outputs with the applications of patents and gathered patenting information from PatentsView. PatentsView is an open data platform that focuses on intellectual property data, and it allows inventors, researchers, policymakers, and the public to access all data from the U.S. Patent & Trademark Office (USPTO) in its original form (Toole et al., 2021). From the patenting data, we learned the patent applications by each firm in each year, their inventors, and the locations of corresponding inventors. Other patenting information, such as the number of claims and technological categories (CPC), can also be derived from it. We then identified the quality of patents by measuring the number of forward citations that a patent has after five years of its application. The OECD REGPAT Database provides a worldwide dataset of patents whose applications filed to the European Patent Office's Worldwide Statistical Patent Database and under the Patent Co-operation Treaty at the international phase (Maraut et al., 2008;

Squicciarini et al., 2013), so we supplemented the patenting information with the OECD REGPAT Database.

We got firm information from Compustat through Wharton Research Data Services, which provides comprehensive market and corporate financial data globally. We derived data on the firm's industry and annual research and development (R&D) inputs from the database. Finally, we got an unbalanced company-year panel sample with $30,509$ observations covering $3,451$ firms during the year 1990 and year 2015. Empirically, we assume countries other than the United States has one cluster for research and inventions. In the United States, companies may conduct research activities in multiple states, so we used states as clusters.

3.3.2 Variables

Dependent variables. We first test the effect of geographical dispersion on the exploration of knowledge. The extent of exploration is compared with the previous innovation invented by inventors, so we count the number of patents applied by inventors in year t at all clusters within company c (variable *No. explorative patents*). Explorative patents are those that contain new patent subclasses, and a new patent subclass is the one that has not previously appeared in patents applied from the cluster where the applicant is in before year t in company c (Cirillo et al., 2014). In addition, we build another variable *No. explorative patents (log)* by adding one to *No. explorative patents* and then take the logarithm of the value.

The average quality of patents is described by the number of forward citations they have received within five years after the application of patenting. The variable *average citations explorative patents have (log)* is built by adding one to the number of citations and taking the log form. For the variance of the quality (variable *std citations explorative patents have (log)*), we take the standard deviation of the number of citations, plus one, and take the log.

To test our hypothesis about exploitations of explorative patents in other clusters, we count the number of explorative patents cited by inventors in all clusters within the firm every year (variable *No. cited explorative patents*), and the number of patents that inventors have produced by citing such explorative patents (variable *No. citing patents*). Then, we also construct variables *No. cited explorative patents (log)* and *No. citing patents (log)* by logarithmizing the number of cited and citing patents respectively. The average quality (variable *average citations citing patents have (log)*) and variance of quality (variable *std citations citing patents have (log)*) of the citing patents are measured with the same method as measuring the explorative patents.

Given that knowledge is tacit and may be uncodified, knowledge may be diffused among inventors in different clusters but not reflected by citations. For instance, inventors may attend the same conferences or meetings, or even have casual chats to exchange their information and specialized local knowledge, which fosters knowledge diffusion as well. To capture this potential and unobservable knowledge diffusion, we count the number of explorative patents in cluster i before year t whose subclasses are contained in the other clusters (e.g., j) in year t within company c, and such subclasses have never appeared in cluster j before year t, and then aggregate all the clusters in year t to form the variable *No. learned explorative patents*. For those patents in cluster i in year t that contain new subclasses from cluster j, we count the numbers and aggregate them in all clusters in year t and form the variable *No. learning patents*. Then, we built variables *No. learned explorative patents (log)* and *No. learning patents (log)* by adding one to the numbers and taking the log form. Similarly, with the previous method, we measure the average quality (variable *average citations learning patents have (log)*) and the variance of the quality of the learning patents (variable *std citations learning patents have (log)*) by calculating the number of forward citations in five years and its standard deviation.

Independent variables. We consider two dimensions of geographically dispersed teams, spatial dispersion and temporal dispersion. Following O'Leary and Cummings

(2007), we compute the spatial distance index and time zone difference index in year t within company c with the following formulas respectively:

$$\frac{\sum_{i-j}^{k}\left(\text{Kilos}_{i-j}\cdot n_i\cdot n_j\right)}{\frac{N^2-N}{2}}$$

$$\frac{\sum_{i-j}^{k}\left(\text{TimeZones}_{i-j}\cdot n_i\cdot n_j\right)}{\frac{N^2-N}{2}}$$

where $Kilos\_i-j$ is the kilometers between cluster i and cluster j, and $TimeZones\_i-j$ is the time zone difference between cluster i and cluster j. k is the total number of clusters in the firm. n_i is the number of inventors in cluster i, and n_j is the number of inventors in cluster j. N is the total number of inventors in the firm, all clusters included.

Moderators. We measure the firm-specific social capital based on the patenting collaborations that occurred between every two clusters within firm c five years prior to the year t. We transform the Freeman Segregation Index, which captures the extent to which the defined groups of vertices tend to have more edges with vertices from the same group than with other groups. Formally, the index gauges the observed count of ties between groups against the expected count of ties between groups under random tie-creation conditions (Bojanowski and Corten, 2014; Freeman, 1978). We evaluate the social capital (variable *connection*) with the following formulas:

$$\text{Connection}=\frac{pN(N-1)}{\left(\left(\sum_{i=1}^{k}n_i\right)^2-\sum_{i=1}^{k}n_i^2\right)}$$

where

$$p=\frac{\sum_{i,j:i\neq j}m_{ij1}}{m_{++1}}$$

m_ij1 is the number of dyads (collaborations on patents) from cluster i to cluster j, m_++1 is the expected count of ties between clusters in collaborations that would be created randomly. The other parameters have the same meanings as in the prior formulas.

Control variables. We control the R&D inputs of each firm annually, which is the logarithmically transformed value of total R&D expenditures undertaken by company c in the prior five years before year t, and the value is incremented by one before applying the logarithm (variable *RnD (log)*). We also control the property of social networks formed by co-patenting within the firm, particularly, the number of inventors in the largest component of the network. We construct the variable *inventors (log)* by logarithmically transforming the value of the number of inventors in the largest connected component within company c in year t, based on patents applied in the past five years.

In addition, we control the technological distance between clusters (variable *tech_distance*), which will influence knowledge creation. Following previous literature (Hall et al., 2001; Tzabbar, 2009; Vestal and Danneels, 2022), we first identify patents applied in the past five years by all firms in our sample in each cluster and specify the technological classes of each patent (CPC section in the USPTO database). By calculating the percentages of each technological class that patents occupy in each cluster, we get a 9-dimensional vector for each cluster in the sample. Then, for each firm, we use the vectors of all clusters to compute the angular distance between them with the following formulas:

$$\theta = \cos^{-1}\left(\frac{\mathbf{i}\cdot\mathbf{j}}{||\mathbf{i}||\cdot||\mathbf{j}||}\right)$$

where

$$||\mathbf{i}|| = \sqrt{\mathbf{i}\cdot\mathbf{i}} = \sqrt{\sum_{x=1}^{y}(i_x)^2},$$

$$\mathbf{i}\cdot\mathbf{j} = \sum_{x=1}^{y}(i_x\cdot j_x) = i_1j_1 + i_2j_2 + \cdots + i_nj_n$$

i and j are clusters, and x and y are technological classes. If there are over 2 clusters in a firm, I measure the distance of every two clusters and take the average value of all distances.

3.4 Empirical Evidence and Analysis

3.4.1 Descriptive Statistics

The descriptive statistics and correlation matrix about variables are summarized in Appendix Table A1 and Table A2. On average, inventors in a firm apply for five explorative patents every year, with 14 forward citations after five years of application and the standard deviation of citations among clusters is almost nine. About two explorative patents are cited by another two patents in other clusters in the later years within the same company. The number of learned and learning patents, which describe the potential and unobserved diffusion of knowledge, is much higher. The average number of learned patents applied by inventors in all clusters is 26, while the average number of learning patents is four. The former is 13 times as large as that of explorative patents, and the latter is twice the number of citing patents. Moreover, the average number of citations citing patents have received in five years is around 18 with a standard deviation of 12. For learning patents, they get about 15 citations with a standard deviation of almost 9.

The means of the two measurements of geographical dispersion are about 716.4 and 0.478, respectively. In other words, the spatial distance among clusters in a firm is 716.4 kilometers while the time zone difference among clusters in a firm is around 29 minutes. Moreover, the inter-cluster connection level in a firm is 0.492. For control variables, the average technological distance among clusters is 0.322, where the range of the distance is from 0 to 1.57. The aggregated number of R&D investments five years before the year of application is about 582 million US dollars. In addition, there are nearly 582 inventors in the largest component of the social network formed by inventors who have applied for patents in the past five years in a firm.

3.4.2 Results

The first hypothesis predicts a positive relationship between the degree of geographical dispersion in a firm and its innovation outputs in terms of explorative patents. Given that our sample is unbalanced panel data and the potential endogenous problem that the locations of clusters are not determined randomly and it should be a consequence of firm strategies, we include the firm fixed effect and the year (the filing years of patents) fixed effect. The results are shown in Table 3.1. Column 1 displays the result of the Ordinary Least Squares (OLS) regression, meaning that a 100% change in the weighted distance in kilometers has a 0.6 percent change in the number of explorative patents in a firm, and the coefficient is significant ($\beta = 0.006, p < .05$). Firms may not invent every year, so the number of explorative patents is nonnegative. Therefore, we also conduct the Poisson regressions with firm- and year-fixed effects, whose results are consistent with the OLS regression (column 2, $\beta = 0.035, p < .01$) and hypothesis 3.1a. Column 3 and column 4 exhibit the effect of temporal dispersion. Results in column 3 are derived from an OLS regression and show that a unit change in the weighted time zone difference has a 3.5 percent change in the number of explorative patents in a firm ($\beta = 0.062, p < .01$). The Poisson regression also shows similar results in column 4 ($\beta = 0.168, p < .01$). Consequently, a higher degree of geographical dispersion in a firm can bring more innovation outputs, thus supporting H3.1a.

From column 5 to column 8, we examine the effect of geographical dispersion on the quality of explorative patents. Columns 5 and 6 present the effect of spatial dispersion with the OLS regressions, but the effect on the average number of citations is negative and not significant (column 5, $\beta = 0.005, p > .1$), which is contrary to the hypothesis. In column 6, we find that the spatial dispersion is positively related to the variance of the average number of citations ($\beta = 0.013, p < .05$). Columns 7 and 8 reveal the effect of temporal dispersion with the OLS regressions and the results are similar to the spatial dispersion. The coefficient of time zone difference on the average number of citations is slightly negative and not significant (column 7, $\beta = 0.003, p > .1$), but the coefficient on the variance of the number of citations is positive and significant (column 8, $\beta = 0.084, p < .01$). This means that a larger time zone difference among clusters increases the variance of quality. Such results partly support hypothesis 3.1b. The average quality of explorative patents is not significantly influenced by the geographical dispersion among teams in a firm, but the variance of the quality of explorative patents significantly increases as the dispersion level increases.

	No. explorative patents (log)	No. explorative patents	No. explorative patents (log)	No. explorative patents	average citations explorative patents have (log)	std citations explorative patents have (log)	average citations explorative patents have (log)	std citations explorative patents have (log)
sdi (log)	0.006**	0.035***			-0.005	0.013**		
	-0.003	-0.008			-0.005	-0.006		
tzi			0.062***	0.168***			-0.003	0.084***
			-0.015	-0.037			-0.026	-0.032
tech_distance	0.785***	1.513***	0.785***	1.525***	0.192***	0.679***	0.190***	0.683***
	-0.021	-0.058	-0.021	-0.058	-0.044	-0.05	-0.044	-0.05
RnD (log)	0.013***	0.017***	0.013***	0.017***	0.040***	0.047**	0.043***	0.050**
	-0.002	-0.005	-0.002	-0.005	-0.015	-0.02	-0.015	-0.02
inventors (log)	0.034***	0.038*	0.038***	0.045**	0.001	0.008**	0	0.008**
	-0.012	-0.021	-0.012	-0.021	-0.003	-0.004	-0.003	-0.004
R2	0.735		0.736		0.473	0.486	0.473	0.486
Adjusted R2	0.702	0.719	0.702	0.719	0.398	0.412	0.398	0.413
N	24,058	23,480	24,058	23,48	16,788	16,784	16,788	16,784
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y

Robust standard errors: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1: The number of explorative patents and their quality

In hypothesis 3.2a, we discuss the positive effect that geographical dispersion may have on the exploitation of the explorative patents produced in other clusters in the firm. Table 3.2 shows the effect of dispersion on the numbers of cited explorative patents and citing patents. In other words, how many patents cite explorative patents by inventors in other clusters in a firm? Columns 1, 3, 5, and 7 use OLS regressions with firm and year-fixed effects, and columns 2, 4, 6, and column 8 apply Poisson regressions with firm- and year-fixed effects. Column 1 illustrates that a 100% change in the weighted distance in kilometers has a 1.3 percent change in the number of cited explorative patents, and the coefficient is significant ($\beta = 0.013, p < .01$), and column 2 shows a consistent result ($\beta = 0.296, p < .01$). When measuring the geographical dispersion with temporal dispersion, the results are similar to the spatial distance. Column 3 reveals that one more hour in the time zone difference makes 11.1% more explorative patents be cited ($\beta = 0.111, p < .01$), and column 4 gives a consistent result ($\beta = 0.433, p < .01$).

We then test the number of (citing) patents that cite such explorative patents and results are exhibited from column 5 to column 8. A 100% change in the weighted distance in kilometers has a 1.5 percent change in the number of citing patents (column 5, $\beta = 0.015, p < .01$), while a unit change in the weighted time zone difference has an 11.9 percent change in the number of citing patents (column 7, $\beta = 0.119, p < .01$). The results with Poisson regressions align with the OLS regressions (column 6, $\beta = 0.342, p < .01$; column 8, $\beta = 0.551, p < .01$), and all coefficients are significant. Accordingly, results in Table 2 support H3.2a, which suggests that highly dispersed firms foster the diffusion of explorative patents.

	No. cited explorative patents (log)	**No. cited explorative patents**	**No. cited explorative patents (log)**	**No. cited explorative patents**	**No. citing patents (log)**	**No. citing patents**	**No. citing patents (log)**	**No. citing patents**
sdi (log)	0.013***	0.296***			0.015***	0.342***		
	-0.002	-0.025			-0.002	-0.033		
tzi			0.111***	0.433***			0.119***	0.551***
			-0.011	-0.053			-0.011	-0.062
tech_distance	0.173***	1.367***	0.175***	1.452***	0.181***	1.511***	0.183***	1.621***
	-0.013	-0.099	-0.013	-0.097	-0.013	-0.127	-0.013	-0.123
inventors (log)	0.154***	0.334***	0.159***	0.311***	0.166***	0.405***	0.171***	0.380***
	-0.01	-0.026	-0.01	-0.026	-0.011	-0.034	-0.011	-0.034
RnD (log)	0.010***	0.039***	0.010***	0.042***	0.011***	0.039***	0.011***	0.042***
	-0.002	-0.007	-0.002	-0.007	-0.002	-0.009	-0.002	-0.009
R2	0.756		0.756		0.755		0.755	
Adjusted R2	0.725	0.752	0.725	0.75	0.724	0.774	0.724	0.772
N	24,058	15,116	24,058	15,116	24,058	15,116	24,058	15,116
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y

Robust standard errors: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2: The numbers of cited and citing patents

Our hypothesis 3.2b predicts that geographical dispersion also influences the quality of citing patents. Results in Table 3.3 confirm the hypothesis, and all regressions in four columns are OLS regressions. A 100% change in the weighted distance in kilometers has a four percent change in the number of citations that citing patents have received (column 1, $\beta = 0.040, p < .05$), while a unit change in the weighted time zone difference has a 9.7 percent change in the number of citations (column 3, $\beta = 0.097, p < .1$). Therefore, the average quality of citing patents increases as the degree of dispersion increases. Moreover, both measurements of dispersion have similar effects on the variance of the number of citations, and the results are positive and significant (column 2, $\beta = 0.075, p < .01$; column 4, $\beta = 0.153, p < .05$). For the quality, we find positive relationships between graphical dispersion and both the average quality and the variance of quality.

	average citations citing patents have (log)	**std citations citing patents have (log)**	**average citations citing patents have (log)**	**std citations citing patents have (log)**
sdi (log)	0.040**	0.075***		
	-0.017	-0.02		
tzi			0.097*	0.153**
			-0.057	-0.075
tech_distance	0.092	0.642***	0.095	0.649***
	-0.101	-0.132	-0.101	-0.132
inventors (log)	0.071***	0.162***	0.070***	0.159***
	-0.026	-0.034	-0.026	-0.034
RnD (log)	0.012**	0.032***	0.012**	0.033***
	-0.005	-0.007	-0.005	-0.007
R2	0.538	0.522	0.538	0.522
Adjusted R2	0.478	0.461	0.478	0.46
N	7,354	7,349	7,354	7,349
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y

Robust standard errors: * p < 0.1, ** p < 0.05, *** p < 0.01

Table 3.3: The quality of citing patents

Tables 3.4 and 3.5 provide evidence of the potentially implicit diffusion of knowledge, which captures the (learning) patents that contain new knowledge elements in the local cluster, but such elements contained in (learned) patents have appeared in other clusters before the focal year. Table 3.4 describes the effect of dispersion on the number of learned and learning patents. We use OLS and Poisson regressions with firm and year-fixed effects, and the results are similar to those in Table 3.2. More geographically dispersed teams have more learned and learning patents from other clusters, thus supporting H3.2a as well.

Table 3.5 shows results that examine H3.2b, which states a positive relationship between dispersion and the quality of learning. Unfortunately, the coefficients are not significant in all regressions, and the effect of spatial dispersion on the average number of citations is negative, which is opposite to the hypothesis. Therefore, H3.2b is not fully supported under the circumstance of implicit knowledge diffusion.

	No. learned explo-rative patents (log)	**No. learned explo-rative patents**	**No. learned explo-rative patents (log)**	**No. learned explo-rative patents**	**No. learning patents (log)**	**No. learning patents**	**No. learning patents (log)**	**No. learning patents**
sdi (log)	0.017***	0.198***			0.009***	0.099***		
	-0.003	-0.016			-0.002	-0.012		
tzi			0.163***	0.268***			0.085***	0.244***
			-0.021	-0.041			-0.014	-0.043
tech_distance	1.237***	1.825***	1.239***	1.864***	0.745***	2.096***	0.746***	2.125***
	-0.031	-0.08	-0.031	-0.079	-0.018	-0.075	-0.018	-0.074
inventors (log)	0.076***	0.150***	0.086***	0.140***	0.020*	0.043**	0.025**	0.043**
	-0.017	-0.017	-0.017	-0.018	-0.012	-0.021	-0.012	-0.021
RnD (log)	0.023***	0.051***	0.023***	0.053***	0.014***	0.023***	0.014***	0.023***
	-0.003	-0.006	-0.003	-0.006	-0.002	-0.005	-0.002	-0.005
R2	0.793		0.793		0.766		0.766	
Adjusted R2	0.767	0.918	0.767	0.917	0.737	0.748	0.737	0.748
N	24,058	21,292	24,058	21,292	24,058	21,292	24,058	21,292
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y

Robust standard errors: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.4: The numbers of learned and learning patents

	average citations learning patents have (log)	**std citations learning patents have (log)**	**average citations learning patents have (log)**	**std citations learning patents have (log)**
sdi (log)	-0.01	0.009		
	-0.009	-0.009		
tzi			0.01	0.065
			-0.035	-0.041
tech_distance	0.168**	0.418***	0.166**	0.419***
	-0.073	-0.077	-0.073	-0.077
inventors (log)	0.042**	0.046**	0.047***	0.050**
	-0.018	-0.022	-0.018	-0.023
RnD (log)	-0.001	0.007	-0.001	0.007
	-0.003	-0.005	-0.003	-0.005
R2	0.456	0.484	0.456	0.484
Adjusted R2	0.381	0.413	0.381	0.413
N	12,649	12,648	12,649	12,648
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y

Robust standard errors: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.5: The quality of learning patents

Then, we test the moderating effect brought by the social capital accumulating by the prior collaborations among inventors on exploitations of explorative patents. Hypothesis 3.3 expects a positive relationship between the degree of dispersion and patent exploitations. Table 3.6 reveals the results on the number of cited explorative patents with OLS and Poisson regressions. Although the coefficients of dispersion remain significantly positive, the coefficients of the interaction term are significantly negative. The positive relationship between dispersion and the number of cited patents is negatively moderated by the connection built among inventors. It indicates that the denser collaborations that inventors have before, the fewer patents that inventors in a cluster cite patents in another cluster. This finding is opposite from H3.3.

Then, we examine the moderating effect of connections among inventors on the number of citing patents, and the results are exhibited in Table 3.7. The coefficients of the interaction term of dispersion and connection are negative and significant, which is not consistent with the hypothesis.

Furthermore, we investigate the effect of the moderator, connection, on the number of learned and learning patents. Table 3.8 depicts the effect on the number of learned patents, and the results are negative and significant. It implies a lower level of implicit knowledge diffusion when the connection among clusters is higher, in other words, inventors in different clusters collaborate more frequently. Such results are consistent with the effect on the number of cited patents but oppose the hypothesis. The effect on the number of learning patents is highly similar (see 3.9). The coefficients of the interaction term are negative and significant, meaning that dense inter-cluster collaborations prohibit knowledge diffusion. Overall, H3.3 is not supported, and the connection has a negative effect on the positive relationship between dispersion and exploitation.

	No. cited explorative patents (log)	No. cited explorative patents (log)	No. cited explorative patents	No. cited explorative patents	No. cited explorative patents (log)	No. cited explorative patents (log)	No. cited explorative patents	No. cited explorative patents
sdi (log)	0.026***	0.033***	0.322***	0.394***				
	-0.003	-0.004	-0.032	-0.048				
connection	-0.035**	0.045	-0.423***	0.662	-0.027*	0.001	-0.462***	-0.258*
	-0.015	-0.029	-0.106	-0.444	-0.015	-0.017	-0.101	-0.144
$sdi(log) \times connection$		-0.015***		-0.170**				
		-0.005		-0.066				
tzi					0.120***	0.156***	0.372***	0.509***
					-0.012	-0.02	-0.054	-0.086
$tzi \times connection$						-0.075***		-0.366**
						-0.026		-0.171
tech_distance	0.182***	0.182***	1.323***	1.335***	0.184***	0.185***	1.352***	1.361***
	-0.015	-0.015	-0.099	-0.099	-0.015	-0.015	-0.099	-0.098
inventors (log)	0.162***	0.163***	0.349***	0.352***	0.166***	0.168***	0.330***	0.332***
	-0.011	-0.011	-0.026	-0.026	-0.011	-0.011	-0.026	-0.026
RnD (log)	0.010***	0.010***	0.038***	0.038***	0.010***	0.010***	0.041***	0.040***
	-0.002	-0.002	-0.007	-0.007	-0.002	-0.002	-0.007	-0.007
R2	0.754	0.754			0.754	0.754		
Adjusted R2	0.724	0.724	0.75	0.75	0.724	0.724	0.748	0.749
N	21,365	21,365	14,499	14,499	21,365	21,365	14,499	14,499
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y

Robust standard errors: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6: Moderation on the number of cited patents

	No. citing patents (log)	**No. citing patents (log)**	**No. citing patents**	**No. citing patents**	**No. citing patents (log)**	**No. citing patents (log)**	**No. citing patents**	**No. citing patents**
sdi (log)	0.028***	0.037***	0.354***	0.526***				
	-0.003	-0.004	-0.041	-0.053				
connection	-0.038**	0.066**	-0.627***	1.702***	-0.030**	0.012	-0.661***	-0.239*
	-0.015	-0.031	-0.122	-0.359	-0.015	-0.017	-0.117	-0.145
$sdi(log) \times connection$		-0.019***		-0.365***				
		-0.006		-0.058				
tzi					0.126***	0.181***	0.476***	0.753***
					-0.013	-0.02	-0.062	-0.095
$tzi \times connection$						-0.114***		-0.753***
						-0.027		-0.184
tech_distance	0.189***	0.190***	1.475***	1.494***	0.192***	0.192***	1.498***	1.509***
	-0.015	-0.015	-0.128	-0.126	-0.015	-0.015	-0.124	-0.124
inventors (log)	0.176***	0.177***	0.423***	0.434***	0.180***	0.183***	0.405***	0.411***
	-0.012	-0.012	-0.034	-0.034	-0.012	-0.012	-0.034	-0.034
RnD (log)	0.011***	0.011***	0.039***	0.038***	0.011***	0.011***	0.041***	0.041***
	-0.002	-0.002	-0.008	-0.008	-0.002	-0.002	-0.008	-0.009
R2	0.754	0.754			0.754	0.754		
Adjusted R2	0.723	0.723	0.772	0.772	0.724	0.724	0.77	0.771
N	21,365	21,365	14,499	14,499	21,365	21,365	14,499	14,499
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y

Robust standard errors: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7: Moderation on the number of citing patents

	No. learned explorative patents (log)	**No. learned explorative patents (log)**	**No. learned explorative patents**	**No. learned explorative patents**	**No. learned explorative patents (log)**	**No. learned explorative patents (log)**	**No. learned explorative patents**	**No. learned explorative patents**
sdi (log)	0.032***	0.054***	0.211***	0.293***				
	-0.006	-0.008	-0.021	-0.029				
connection	-0.081***	0.185***	-0.605***	0.735***	-0.069**	0.031	-0.637***	-0.319***
	-0.029	-0.062	-0.077	-0.257	-0.029	-0.033	-0.076	-0.107
$sdi(log) \times connection$		-0.050***		-0.210***				
		-0.011		-0.042				
tzi					0.174***	0.305***	0.230***	0.422***
					-0.025	-0.038	-0.042	-0.065
$tzi \times connection$						-0.269***		-0.567***
						-0.052		-0.156
tech_distance	1.269***	1.271***	1.790***	1.797***	1.272***	1.273***	1.806***	1.811***
	-0.034	-0.034	-0.08	-0.08	-0.034	-0.034	-0.08	-0.08
inventors (log)	0.087***	0.090***	0.163***	0.167***	0.095***	0.101***	0.153***	0.158***
	-0.019	-0.019	-0.017	-0.017	-0.019	-0.019	-0.017	-0.018
RnD (log)	0.023***	0.023***	0.049***	0.049***	0.023***	0.023***	0.051***	0.051***
	-0.003	-0.003	-0.006	-0.006	-0.003	-0.003	-0.006	-0.006
R2	0.784	0.785			0.785	0.785		
Adjusted R2	0.758	0.758	0.916	0.916	0.758	0.758	0.915	0.916
N	21,365	21,365	19,549	19,549	21,365	21,365	19,549	19,549
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y

Robust standard errors: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.8: moderation on the number of learned patents

	No. learning patents (log)	**No. learning patents (log)**	**No. learning patents**	**No. learning patents**	**No. learning patents (log)**	**No. learning patents (log)**	**No. learning patents**	**No. learning patents**
sdi (log)	0.018***	0.036***	0.126***	0.208***				
	-0.004	-0.005	-0.017	-0.024				
connection	-0.086***	0.128***	-0.518***	0.738***	-0.080***	-0.005	-0.527***	-0.241**
	-0.019	-0.039	-0.075	-0.202	-0.019	-0.022	-0.074	-0.094
$sdi(log) \times connection$		-0.040***		-0.205***				
		-0.007		-0.034				
tzi					0.091***	0.188***	0.218***	0.411***
					-0.016	-0.025	-0.045	-0.068
$tzi \times connection$						-0.200***		-0.561***
						-0.034		-0.138
tech_distance	0.746***	0.747***	2.030***	2.038***	0.747***	0.748***	2.042***	2.047***
	-0.02	-0.02	-0.077	-0.077	-0.02	-0.02	-0.077	-0.077
inventors (log)	0.030**	0.032**	0.060***	0.065***	0.033***	0.037***	0.059***	0.063***
	-0.013	-0.013	-0.021	-0.021	-0.013	-0.013	-0.021	-0.021
RnD (log)	0.014***	0.014***	0.022***	0.022***	0.014***	0.014***	0.022***	0.022***
	-0.002	-0.002	-0.005	-0.005	-0.002	-0.002	-0.005	-0.005
R2	0.759	0.759			0.759	0.759		
Adjusted R2	0.729	0.729	0.743	0.743	0.729	0.729	0.743	0.743
Number of observations	21,365	21,365	19,549	19,549	21,365	21,365	19,549	19,549
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y

Robust standard errors: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.9: Moderation on the number of learning patents

3.5 Discussion

This paper investigates the innovative activities in geographically dispersed teams. We study how the extent of geographical dispersion influences the outputs, quality, and diffusions of the explorative patents within a firm, and how connections among clusters play as a moderator. With patent information from data sources PatentsView and OECD REGPAT Database and firm information from WRDS, we build an unbalanced panel of data of public companies headquartered in the US and inventors in companies that have filed at least one patent in all clusters. Our sample consists of $30,509$ observations covering $3,451$ firms during the year 1990 and year 2015.

We find that a higher degree of geographical dispersion increases the number of explorative patents. The average quality of explorative patents is not significantly affected by the level of dispersion, but the variance of such patents increases with the dispersion. By measuring the explicit citations and implicit learning of such patents by inventors in other clusters, we find a positive effect of dispersion on the diffusions and exploitations of such patents. Furthermore, the average quality and its variance of citing and learning patents are positively associated with the extent of dispersion. However, the connections established by prior co-patenting negatively influence knowledge exploitations and diffusions, which is opposed to our hypothesis. In the following research, we will investigate the potential reasons for the negative effect.

The paper enriches the literature on knowledge exploration and its quality in geographically dispersed teams. It provides another evidence on the research about the effects of geographical dispersion on innovation (Alcácer and Zhao, 2012; Gibson and Gibbs, 2006; Tzabbar and Vestal, 2015) and quality of innovation (Lahiri, 2010; Lanjouw and Schankerman, 2004). Additionally, the work contributes to the research on knowledge exploitations and diffusions in geographically dispersed teams and the quality of exploited and diffused patents. Extant research focuses on knowledge spillover to competitors in the same market that firms collocate with (Alcácer and Zhao, 2012; Jaffe et al., 2000; Lahiri, 2010; Thompson and Fox-Kean, 2005). Nevertheless, this paper pays attention to the internal circulation and integration of knowledge. It studies how inventors in other locations can also benefit from activities in other locations, which can improve the efficiency of innovative activities.

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Appendices

VARIABLES	N	mean	sd	min	max
tzi	30,509	0.498	0.498	0	5
No. explorative patents	30,509	5.404	14.79	0	477
No. cited explorative patents	30,509	1.962	8.671	0	207
No. citing patents	30,509	2.384	11.48	0	272
No. learned explorative patents	30,509	26.44	122.6	0	3,852
No. learning patents	30,509	4.073	13.22	0	373
connection	25,616	0.492	0.344	0	3.517
sdi (log)	30,509	5.236	2.731	0	8.979
RnD (log)	25,043	17.51	4.261	-3.64E-05	24.62
No. explorative patents (log)	30,509	1.082	1.059	0	6.17
average citations explorative patents have (log)	21,060	2.18	1.004	0	7.81
std citations explorative patents have (log)	21,057	1.444	1.295	0	7.027
No. cited explorative patents (log)	30,509	0.403	0.825	0	5.338
No. citing patents (log)	30,509	0.417	0.866	0	5.609
average citations citing patents have (log)	8,042	2.351	1.12	0	6.925
std citations citing patents have (log)	8,037	1.55	1.494	0	7.133
No. learned explorative patents (log)	30,509	1.287	1.675	0	8.257
No. learning patents (log)	30,509	0.781	1.039	0	5.924
average citations learning patents have (log)	15,088	2.229	1.035	0	7.81
std citations learning patents have (log)	15,087	1.405	1.31	0	7.071
inventors in the largest component (log)	30,509	3.871	0.66	0.456	4.605

Table A1: Descriptive Statistics

	-1	-2	-3	-4	-5	-6
(1) sdi (log)	1					
(2) tzi	0.69	1				
(3) RnD (log)	0.18	0.15	1			
(4) theta	0.39	0.22	0.17	1		
(5) connection	-0.11	-0.15	-0.11	-0.1	1	
(6) inventors in the largest component (log)	-0.36	-0.28	-0.11	-0.26	0.33	1

Table A2: Correlation Matrix

Consclusion

In a global economy characterized by rapid technological advancement, shifting labor dynamics, and intensifying competition, knowledge has emerged as the cornerstone of strategic management. The resource-based view of the firm posits that sustainable competitive advantage arises not merely from possessing valuable resources, but from leveraging those that are rare, imperfectly imitable, and non-substitutable (Barney, 1991). Among such resources, a firm's knowledge base—embedded in its individuals, teams, and organizational routines—has perhaps the greatest potential to serve as a source of sustainable differentiation (Dierickx Cool, 1989; Lippman Rumelt, 1982). Yet, this knowledge is neither static nor immune to disruption; it flows through mobility, collaboration, geography, and time. Accordingly, understanding how firms accumulate, retain, and deploy knowledge—and how this process is impacted by labor mobility, team composition, and structural design—is central to the strategic management of innovation.

This dissertation examines the strategic dimensions of knowledge-based resources across three critical contexts: involuntary mobility of inventors, knowledge recombination in entrepreneurial teams, and the effects of geographical dispersion on internal innovation processes. Across these distinct yet thematically interconnected studies, I explore how firms and individuals navigate the dynamic interplay between knowledge creation, disruption, and recombination, contributing to a more granular understanding of human capital as a strategic asset in the knowledge economy.

Chapter 1 investigates the underexplored domain of involuntary inventor mobility.

While previous research has extensively documented the productivity gains and knowledge spillovers associated with voluntary job changes, much less is known about the outcomes of inventors who are displaced due to layoffs or organizational restructuring. Using a novel dataset that combines LinkedIn career histories, USPTO patent records, and mass layoff data in the United States, this study finds that involuntary transitions lead to significant declines in post-mobility innovation output. However, the detrimental effects are mitigated when inventors maintain social capital through pre-existing collaborative ties. These findings suggest that social networks serve not only as repositories of tacit knowledge but also as critical buffers against the productivity shocks induced by unplanned separations. Strategically, this chapter underscores the importance of talent retention, knowledge continuity, and relational capital in innovation-intensive sectors.

Extending the focus on human capital, Chapter 2 shifts to the entrepreneurial context, where new ventures rely on the distinctive capabilities and complementary knowledge of their founding teams. This study explores how uncommon knowledge combinations—defined as the integration of diverse, non-overlapping expertise within founding teams—influence entrepreneurial outcomes. Analyzing comprehensive data on startups and founders, the chapter reveals a dual-edged dynamic: while teams with high levels of uncommon knowledge are more likely to secure venture capital and achieve successful exits, they also face a heightened risk of failure due to the cognitive and operational complexity of entering uncharted markets. These findings contribute to the literature on team formation and entrepreneurial strategy by illuminating the trade-offs associated with assembling cognitively diverse founding teams. They also offer practical insights into the structuring of entrepreneurial ventures and the strategic selection of co-founders based on complementary, yet potentially volatile, knowledge profiles.

Building on the micro-foundations of knowledge embedded in individuals and teams, Chapter 3 considers how organizational structure—specifically, geographical dispersion—affects firms' ability to explore and exploit knowledge across spatially distributed units. While geographical dispersion can facilitate access to diverse knowledge pools and local learning opportunities, it may also hinder coordination and cohesion. Drawing on panel data from U.S. public companies between 1990 and 2015, this chapter finds that dispersion enhances the generation and diffusion of exploratory patents, increasing both the quantity and breadth of innovative outputs. However, the quality of these patents becomes more variable, and prior co-patenting ties unexpectedly constrain the diffusion of ideas across dispersed locations. These findings highlight the organizational trade-offs between decentralization and innovation efficiency, offering nuanced insights into how spatial structures shape knowledge dynamics within firms. Strategically, the chapter informs decisions related to the design of multi-location R&D systems, cross-site collaboration, and the orchestration of internal knowledge flows.

Taken together, the three chapters of this dissertation converge on a central theoretical assertion: that knowledge, while inherently valuable, is contingent on its context—its mobility, its integration within teams, and its orchestration within organizational structures. The strategic management of knowledge is thus not a static exercise in resource allocation, but a dynamic and multifaceted process shaped by individual agency, relational embeddedness, and structural configuration.

Theoretically, this dissertation contributes to a more nuanced understanding of the microfoundations of strategy by integrating insights from human capital theory, organizational performance, and innovation studies. It advances the resource-based view by demonstrating how knowledge-related capabilities are built, disrupted, and recombined across multiple levels of analysis. Furthermore, it extends strategic management literature by highlighting underexplored contingencies, such as involuntary mobility and the effects of dispersion, that shape the outcomes of knowledge utilization.

Practically, the findings offer actionable implications for managers, entrepreneurs, venture capitalists, and policymakers. Firms should invest not only in acquiring top talent but also in sustaining their networks and fostering environments that support cross-boundary collaboration. Entrepreneurial ecosystems should be attuned to the cognitive composition of founding teams, balancing novelty with alignment. Organizations managing geographically dispersed operations must pay close attention to the mechanisms—both formal and informal—that enable knowledge sharing and integration.

In an era where knowledge is both a key driver of value and a source of vulnerability, the ability to manage its flow, structure its carriers, and mitigate its disruption becomes a defining competency. This dissertation, by unpacking the complex interplay between knowledge and its strategic context, aims to inform a more adaptive, integrative, and forward-looking approach to strategic management in the knowledge economy.