

Leveraging knowledge for competitive advantage

Aman Asija

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DOCTORAL THESIS

Title	Leveraging knowledge for competitive advantage
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“Sometimes you have to rethink the things
you thought you thought through”
A.A Milne (1882 – 1956)

I dedicate this Ph.D. thesis to all those who desire to learn.

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Table of contents

Acknowledgements	v
Table of contents	vii
List of figures	xi
List of tables	xiii
1. Introduction	1
1.1. Introduction to the Ph.D. dissertation	3
1.2. Structure and content of the Ph.D. dissertation	6
1.2.1. When firms acquire more (or less)? Industry fragmentation of technology ownership as a determinant of acquisitions	7
1.2.2. Anticipated knowledge worker mobility and R&D dynamism: Evidence from a natural experiment	8
1.2.3. A speed-accuracy tradeoff: Speed of expansion and replication accuracy in chain organizations	9
2. When firms acquire more (or less)? Industry fragmentation of technology ownership as a determinant of acquisitions	17
2.1 Abstract	19
2.2 Introduction	19
2.3 Theory and hypotheses	21
2.3.1. Acquisitions in fragmented markets for technology	21
2.3.2. Hypotheses development	23
2.4 Methods	27
2.4.1. Empirical context	27
2.4.2. Data and sample	30
2.4.3. Identifying relevant IP rights	31
2.4.4. Measures	32
2.4.4.1. Dependent variables	32
2.4.4.2. Independent variables	33
2.4.4.3. Control variables	35
2.5. Models	36
2.6. Results	38
2.6.1. Robustness checks	44
2.6.2. Supplementary analysis	45
2.7. Discussion	48
2.7.1 Limitations and future research	51
2.8. References	53
3. Anticipated knowledge worker mobility and R&D dynamism: Evidence from a natural experiment	63
3.1. Abstract	65
3.2. Introduction	65
3.3. Theory and hypotheses	67

3.3.1. Employee mobility and firm R&D appropriability	67
3.3.2. Anticipated employee mobility and firm R&D investment dynamics	69
3.4. Methods	72
3.4.1. Data and sample	72
3.4.2. Measures	73
3.4.2.1. Dependent variable	73
3.4.2.2. Independent variables	74
3.4.2.3. Control variables	75
3.5. Models	77
3.6. Results	78
3.6.1. Dynamic analysis	82
3.6.2. Alternate control and treatment groups	83
3.6.3. Cross-sectional variation in the impact of the threat of knowledge worker mobility	84
3.6.4. Impact on drastic increases and decreases in R&D	84
3.6.5. Additional robustness checks	85
3.7. Discussion	88
3.7.1. Limitations and future research	90
3.7.2. Conclusion	91
3.8. References	92
4. A speed-accuracy tradeoff: Speed of expansion and replication accuracy in chain organizations	105
4.1. Abstract	107
4.2. Introduction	107
4.3. Theory and hypotheses	110
4.3.1. The dual role of middle managers in multiunit chain organizations	110
4.3.1.1. Expansion role of middle managers: Expanding the number of units in a region	111
4.3.1.2. Monitoring role of middle managers: Ensuring that required practices are replicated accurately	111
4.3.2 Hypotheses development	112
4.4. Methods	118
4.4.1. Data and sample	118
4.4.2. Measures	124
4.4.2.1. Dependent variable	124
4.4.2.2. Independent variables	125
4.4.2.3. Control variables	127
4.5. Models	129
4.6. Results	130
4.6.1. Robustness checks	132
4.6.1.1. Instrumental variables estimations	132
4.6.1.2. Alternate model specifications: Poisson regressions	134
4.6.1.3. Alternate measurements	137
4.7. Discussion	140
4.7.1. Limitations and future research	142
4.7.2. Conclusion	144
4.8. References	145

5. Conclusion	157
5.1. Discussion	159
5.1.1. Theoretical contributions	160
5.1.2. Managerial implications	161
5.1.3. Limitations	162
5.1.4. Directions for future research	162
5.2. Conclusion	164
5.3. References	166

List of figures

2. When firms acquire more (or less)? Industry fragmentation of technology ownership as a determinant of acquisitions

Figure 2.1. Predicted relationship between industry fragmentation of IP rights on technology acquisitions 42

Figure 2.2. Predicted relationship between industry fragmentation of IP rights and technology acquisitions by firms' risk of being fenced in 43

Figure 2.3. Predicted relationship between industry fragmentation of IP rights and probability of being acquired 44

4. A speed-accuracy tradeoff: Speed of expansion and replication accuracy in chain organizations

Figure 4.1. Store locations of the franchise chain in the USA (end of year data) 120

List of tables

1. Introduction

Table 1.1. The three essays of this dissertation	10
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2. When firms acquire more (or less)? Industry fragmentation of technology ownership as a determinant of acquisitions

Table 2.1. Descriptive statistics and correlations	39
Table 2.2. Fixed effects panel regression models of technology acquisitions	41
Table 2.3. Logistic regression model of the likelihood of being acquired	44
Table 2.4. Supplementary analysis: Fixed effects panel regression models of technology acquisitions	47

3. Anticipated knowledge worker mobility and R&D dynamism: Evidence from a natural experiment

Table 3.1. Sample distribution across U.S. states	80
Table 3.2. Descriptive statistics and correlations	81
Table 3.3. Difference-in-differences regression models of R&D volatility	82
Table 3.4. Difference-in-differences regression models of R&D volatility using alternate control and treatment groups	86
Table 3.5. Difference-in-differences regression models to examine cross-sectional variation in R&D volatility	87

4. A speed-accuracy tradeoff: Speed of expansion and replication accuracy in chain organizations

Table 4.1. Descriptive statistics and correlations	131
Table 4.2. Fixed effects panel regression models of replication	133
Table 4.3. First stage instrumental variable regressions of replication accuracy	135
Table 4.4. Second stage instrumental variable regressions of replication accuracy	136
Table 4.5. Poisson regression models of replication accuracy	138

1.

Introduction

This chapter introduces the Ph.D. dissertation. It discusses the existing research, identifies the research gaps, and presents the specific research objectives that will be addressed in chapters 2, 3, and 4.

Introduction to the Ph.D. dissertation

Knowledge is considered as an important resource (Kogut & Zander, 1992), and its accumulation and protection is critical for the firm (Nelson & Winter, 1982; Teece, Pisano, & Shuen, 1997)¹. Accordingly, strategy scholars have focused their attention on explaining firms' choice between generating or internalizing knowledge and accessing outside knowledge (Conner, 1991; Conner & Prahalad, 1996; Kogut & Zander, 1992; Madhok, 1996). However, in his classic paper (Grant, 1996) on the knowledge-based theory of the firm, Grant posits that the primary role of the firm is knowledge exploitation rather than knowledge accumulation.

While exploiting knowledge within the firm is fundamental to realizing competitive advantage (Argote & Ingram, 2000; Zander & Kogut, 1995), it has been a fundamental and persistent challenge (Grant, 1996; Kogut & Zander, 1992). Ensuring appropriation and effective replication of knowledge are pertinent to the exploitation of knowledge within the firm (Grant, 1996). So, to effectively exploit knowledge, firms use different strategies to improve the appropriability (Arrow, 1962; Teece, 1986, 1987) and replicability (Szulanski, 1996; Winter & Szulanski, 2001) of their knowledge (Winter, 1995). Consequently, a large number of studies have paid attention to firm strategies that have implications for knowledge appropriation and replication. For instance, building on Teece (1986), previous studies have examined how firms acquire (Arora & Ceccagnoli, 2006; Ziedonis, 2004) and retain complementary resources (Agarwal, Audretsch, & Sarkar, 2007; Campbell, Ganco, Franco, & Agarwal, 2012) to improve appropriability of their knowledge base. Besides, previous studies on replication strategy (Winter & Szulanski, 2001) have examined the antecedents to replication performance of knowledge, such as the presence of a hierarchical manager (Knott, 2001), knowledge discreteness (Williams, 2007), and template performance (Lawrence, 2020).

This dissertation consists of three essays, which focus on the strategies that firms use to exploit their knowledge effectively. In doing so, this dissertation adds, overall, to the research on knowledge-based view (Grant, 1996; Kogut & Zander, 1992; Spender &

¹ The concept of knowledge is used broadly in this dissertation. The specific components of knowledge - know-how, know-why, and know-what (Garud, 1977) - are emphasized as needed.

Grant, 1996), and, specifically, to the research on the threats to knowledge appropriation (Arora, Fosfuri, & Gambardella, 2002; Teece, 1986) and determinants of replication performance (Szulanski, 1996; Winter & Szulanski, 2001) by focusing on the specific deterrents to knowledge exploitation and corresponding strategies to deal with them that have not been fully considered in the existing research. This dissertation is significant for strategy research because firms can employ diverse strategies to exploit their knowledge effectively (Winter, 1995), and for practitioners as challenges to the exploitation of existing knowledge can cause firms to lose value to competitors or even fail (Almeida & Kogut, 1999; Heller & Eisenberg, 1998; Winter, Szulanski, Ringov, & Jensen, 2012). The practical relevance of studying the strategies to effectively exploit existing knowledge is illustrated by the situation of Bristol-Myers Squibb as it had to abandon its plans of applying its knowledge on cancer: *“Peter Ringrose, former chief science officer at Bristol-Myers Squibb, told the New York Times that the company would not investigate some 50 proteins that could be cancer-causing, because patent holders would either decline to cooperate or demand big royalties”*.² Strategizing to avoid value fragmentation because of unreasonable royalty demands from complementary patent holders could have allowed Bristol-Myers Squibb to continue its research.

The essays that follow examine three main points related to the effective exploitation of knowledge by the firm. In the first two essays of this dissertation, the focus is on strategies that firms use to deal with the threats to the appropriability of their knowledge base. The first two essays follow Teece’s approach (Teece, 1986) to the appropriability of knowledge and view appropriability as the degree to which a firm can capture the value created when exploiting its knowledge. The first essay of this dissertation aims to study whether and how firms use technology acquisitions to improve the appropriability of their innovation efforts as the industry fragmentation of Intellectual Property (IP) rights increases. The second essay of this dissertation aims to study how firms adjust their R&D investments to deal with the challenges to the appropriability of their innovation efforts posed by the threat of knowledge worker mobility. In the third essay of this dissertation, the focus is on the exploitation of existing knowledge by replication (Winter & Szulanski, 2001). The third essay of this dissertation aims to study the role of managers on replication

² <https://www.forbes.com/forbes/2008/0811/030.html?sh=23ab5e11ea7b>

performance. Specifically, it examines the impact of middle managers' speed of expansion on replication accuracy and how managers learn to balance this "speed-accuracy" tradeoff.

While the connecting point of the three essays is to understand the strategies to exploit knowledge effectively, the essays in this dissertation build on different streams of literature and analytical frameworks. The first essay builds on the literature on the fragmentation of IP rights (Heller & Eisenberg, 1998; Ziedonis, 2004) and technology acquisitions (Ahuja & Katila, 2001), and the framework on appropriability (Teece, 1986; Williamson, 1991) to theorize and examine the impact of industry fragmentation of IP rights on the use of technology acquisitions. The second essay builds mainly on the literature on knowledge worker mobility (Agarwal, Ganco, & Ziedonis, 2009; Almeida & Kogut, 1999) and R&D dynamics (Kor & Mahoney, 2005; Mudambi & Swift, 2014), and the framework on appropriability (Campbell, Ganco, Franco, & Agarwal, 2012; Teece, 1986), to theorize and examine the impact of the threat of losing knowledge worker on the volatility of R&D investments. The third essay builds on the literature on replication of organizational practices (Winter & Szulanski, 2001) and organizational learning (Argote, 1999; Argote & Miron-Spektor, 2011) and uses attention-based view (Ocasio, 1997, 2011) as the framework to theorize and examine the impact of middle managers' speed of expansion on replication accuracy at units under their supervision.

The essays in this dissertation rely on different datasets to approach the above research objectives empirically. The first essay relies mainly on the data from Recombinant Capital's Biotech Alliance (Recap). Recap is known as one of the most accurate and comprehensive sources of information regarding M&A deals and technology exchange involving biopharmaceutical firms (Schilling, 2009). At least three main reasons make this context (biopharmaceutical firms) particularly appropriate to test the hypotheses proposed in the first essay. First, the biopharmaceutical industry has been experiencing increasing fragmentation of its IP rights, which deters innovation (Huang & Murray, 2009). Second, development costs and failure rates are high in this industry (Nerkar & Roberts, 2004), which creates significant uncertainty over firms' capacity to recover their investments (Munos, 2009) and pushes firms to improve the appropriability of their knowledge actively. Third, technology acquisitions are commonly used in this industry (e.g., Danzon, Epstein, & Nicholson, 2007; Higgins & Rodriguez, 2006; Ruckman, 2005). The data from

Recap were combined with the data from four other sources: Pharmaprojects for the data on drug pipeline, Compustat North America for data on financials, and the NBER patent project for data on patenting activity. The second essay relies on Compustat North America for the main dataset to test the proposed hypotheses on U.S. manufacturing firms. The manufacturing industry forms an appropriate context for this essay because it exhibits high R&D (Hall, Jaffe, & Trajtenberg, 2005; Mudambi & Swift, 2014) and employee mobility, which weakens the appropriability of firms' innovation efforts. The data from Compustat North America were combined with the data from five other sources: PatentsView for the data on patenting activity, Public Access to Court Electronic Records for the data on patent infringement lawsuits, Boardex for the data on corporate governance, Thomson Reuters Institutional (13f) Holdings for the data on institutional ownership, and Bureau of Economic Analysis for the data on state-level characteristics. The third essay relies on a proprietary dataset that tracks middle managers' speed of expansion and replication accuracy at the units of one of the largest U.S.-based non-food franchise chains over eleven years to test the proposed hypotheses. Franchising provides an appropriate context to empirically test the hypotheses as franchise chains expand by replicating a set of required practices in units in different regions (Winter & Szulanski, 2001; Winter et al., 2012). To obtain greater insights into the functioning of the focal franchise chain, the archival data was informed with qualitative data obtained via semi-structured interviews with senior managers, middle managers, and franchisees of the chain. Finally, the internal franchise data were supplemented with publicly available information on units' local geographic markets drawn from the United States Census Bureau's County Business Patterns database (<https://www.census.gov>) and ESRI Inc.'s annual Sourcebook of America and Sourcebook of Zip Code Demographics. The novel combination of datasets in the three essays of this dissertation was critical to address the questions unexamined by previous research.

1.2. Structure and content of the Ph.D. dissertation

This dissertation comprises three essays that develop conceptual and empirical applications of the different phenomenon of interest for knowledge exploitation. A detailed structure of this Ph.D. dissertation is presented below. Chapter 2 comprises the first essay of this dissertation. It addresses whether and how firms mitigate the challenges to the

appropriability of their innovation efforts in fragmented markets for technology by engaging in technology acquisitions. Chapter 3 comprises the second essay of this dissertation. It addresses how firms adjust their R&D investments in response to the appropriability threats posed by anticipated knowledge worker mobility. Chapter 4 comprises the third essay of this dissertation. It addresses how the speed of expansion of a middle manager affects replication accuracy at the units under her supervision. Finally, chapter 5 concludes the dissertation with an integrated discussion of the theoretical contributions, managerial implications, limitations, and future research opportunities emanating from the three essays that comprise chapters 2, 3, and 4. The reference list is presented at the end of each chapter. The objectives of the three essays and the methods used to test the proposed hypotheses are presented in Table 1.1 The three essays are summarized below:

1.2.1. Essay 1: When Firms Acquire More (or Less)? Industry Fragmentation of Technology Ownership as a Determinant of Acquisitions

The first essay of this dissertation examines the relationship between industry fragmentation of IP rights and technology acquisitions. Firms innovate by combining technological knowledge generated within the firm and inputs generated outside the firm (Foss, 1996; Helfat, 1994; Kogut & Zander, 1992). However, the arduous task of assembling all relevant IP rights can prevent firms from innovating as they risk being “fenced in” by other technology holders (Ziedonis, 2004). Thus, appropriability is a significant challenge for innovating firms in fragmented markets for technology, i.e., when IP rights in an industry are dispersed among a large number of firms (Heller & Eisenberg, 1998; Huang & Murray, 2009; Ziedonis, 2004). Accordingly, one of the keys to a successful innovation strategy is strengthening appropriability by securing access to relevant IP rights (Ceccagnoli, 2009; Grimpe & Hussinger, 2014; Ziedonis, 2004). Technology acquisitions are a means to this end, yet we know little about the use of acquisitions in fragmented markets for technology. This essay investigates whether and how firms mitigate the challenges to the appropriability of their innovation efforts in fragmented markets for technology by engaging in technology acquisitions. It posits that the level of industry fragmentation of IP rights is curvilinearly (inverted U-shape) related to the rate at which firms engage in technology acquisitions and that this relationship is

weaker for firms that have a higher risk of being “fenced in” by owners of external IP rights. Furthermore, firms with relatively more valuable IP rights are more likely to be acquired as fragmentation increases. The hypotheses are empirically supported using a unique longitudinal dataset on the biopharmaceutical industry from 1986 to 2004. Primarily, this essay contributes to the literature on determinants of acquisitions and appropriability in fragmented markets for technology by viewing technology acquisitions as a means of strengthening appropriability in industries with fragmented IP rights.

1.2.2. Essay 2: Anticipated Knowledge Worker Mobility and R&D Dynamism: Evidence from a Natural Experiment

The second essay of this dissertation examines the relationship between the threat of losing knowledge workers and firm R&D dynamics. According to the knowledge-based view of the firm, privately held knowledge is a key source of competitive advantage (Grant, 1996; Kogut & Zander, 1992; Teece et al., 1997). Firms generate knowledge by investing in R&D (Jaffe, 1986; Pakes, 1985), yet appropriating returns from R&D depends on firms’ ability to retain key talent. The outbound mobility of knowledge workers leads to loss of valuable knowledge from the source firm and its leakage to competitors (Agarwal et al., 2009; Almeida & Kogut, 1999), which weakens the appropriability of R&D. While prior research has examined the impact of employee mobility on firm strategies, such as location strategies (Alcácer & Chung, 2007), the design of employment contracts and financial incentives (Cappelli, 2000; Starr, 2019), or CSR strategies (Flammer & Kacperczyk, 2019), we know little about the impact of anticipated loss of employees on firm R&D strategy. This essay investigates how the threat of knowledge worker mobility affects the dynamics of firm R&D. It proposes that the appropriability challenges posed by the threat of knowledge worker outbound mobility give rise to a “caution effect” on firm R&D strategy, such that the threat of losing knowledge workers dampens R&D dynamism (reduces the volatility of firm R&D investments). Yet, the dampening of R&D dynamism is less pronounced for firms that have alternate mechanisms for mitigating the threat of knowledge worker mobility, such as firms that have established a reputation for litigiousness. The hypotheses are empirically supported using a natural experiment in the context of the U.S. manufacturing industry over the period 1991-2018. Primarily, this essay contributes to the literature on appropriability challenges posed by knowledge

worker mobility (Agarwal et al., 2009; Conti, 2014; Ganco, Ziedonis, & Agarwal, 2015) and R&D dynamism (Kor & Mahoney, 2005; Mudambi & Swift, 2014) by arguing and providing evidence that the threat of losing knowledge workers causes firms to dampen R&D dynamism.

1.2.3. Essay 3: A Speed-Accuracy Tradeoff: Speed of Expansion and Replication Accuracy in Chain Organizations

The third essay of this dissertation examines the relationship between middle managers' speed of expansion and the replication accuracy at units under their supervision. Expanding rapidly by replicating a set of required practices in different geographic locales is the primary growth strategy of multiunit chain organizations such as Starbucks, IKEA, Uber, or WeWork (Greve & Baum, 2001; Winter & Szulanski, 2001; Winter et al., 2012). Yet, a fundamental and persistent challenge for such "replicating" organizations has been ensuring that required practices are replicated accurately across all of their geographically dispersed units at any given time (Winter & Szulanski, 2001; Winter et al., 2012). While early work on replication strategy has suggested that monitoring by middle managers mitigate the problem of inaccurate replication of practices (Winter & Szulanski, 2001), more recent replication research has shown that problem of inaccurate replication can persist when such managers are present (El Akremi, Mignonac, & Perrigot, 2011; Winter et al., 2012). This essay sheds light on the issue by arguing that the competing claims on middle managers' scarce attention created by their dual expansion and monitoring role pose a "speed-accuracy tradeoff" such that when middle managers' speed of expansion increases, compliance with required organizational practices at units under their supervision decreases. It further argues that experiential learning, namely middle managers' learning from their expansion and failure experience as well as individual units' learning from their operating experience, ameliorates the tradeoff. The hypotheses are empirically supported using a proprietary dataset that tracks middle managers' speed of expansion and replication accuracy at the units of a large U.S.-based non-food franchise organization over eleven years. Primarily, this essay contributes to the literature on determinants of replication (Winter & Szulanski, 2001; Winter et al., 2012) and attention-based view (Ocasio, 1997, 2011) by identifying the role of middle managers' attention

allocation and experiential learning as key drivers of the accuracy with which required practices are replicated in multiunit chain organizations.

Table 1.1. The three essays of this dissertation

	Essay 1	Essay 2	Essay 3
Title	When Firms Acquire More (Or Less)? Industry Fragmentation of Technology Ownership as a Determinant of Acquisitions	Anticipated Knowledge Worker Mobility and R&D Dynamism: Evidence from a Natural Experiment	A Speed-Accuracy Tradeoff: Speed of Expansion and Replication Accuracy in Chain Organizations
Research Question	Whether and how firms mitigate the challenges to the appropriability of their innovation efforts in fragmented markets for technology by engaging in technology acquisitions?	How firms adjust their R&D to deal with the challenges to the appropriability of their innovation efforts posed by the threat of knowledge worker mobility?	How does middle managers' speed of expansion affect replication accuracy at units under their supervision?
Primary Literature	IP fragmentation and technology acquisitions	Knowledge worker mobility and R&D dynamics	Replication and organizational learning
Tool Literature	Appropriability	Appropriability	Attention-based view
Methodology	Quantitative	Quantitative	Quantitative
Empirical Context	U.S. biopharmaceutical industry	U.S. manufacturing industry	One of the largest U.S. non-food franchise chain
Datasets	Recap, Pharmaprojects , Compustat North America, and NBER patent project	Compustat North America, PatentsView, Public Access to Court Electronic Records, Boardex, Thomson Reuters Institutional (13f) Holdings, and Bureau of Economic Analysis	Dataset from one of the largest U.S. non-food franchise chain, qualitative data obtained via semi-structured interviews with managers, franchisor, and franchisee of the focal chain, U.S. Census Bureau's County Business Patterns, and ESRI Inc.'s annual Sourcebook of America and Sourcebook of Zip Code Demographics

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2.

When Firms Acquire More (Or Less)? Industry Fragmentation of Technology Ownership as a Determinant of Acquisitions

This chapter examines whether and how firms use technology acquisitions to improve the appropriability of their knowledge as the industry fragmentation of intellectual property rights increases.

2.1. Abstract

This paper examines how the ownership fragmentation of intellectual property (IP) rights in an industry affects technology acquisitions. We theorize that the level of industry fragmentation of IP rights is curvilinearly (inverted U-shape) related to the rate at which firms engage in technology acquisitions. We also propose that this relationship is weaker for firms that have a higher risk of being “fenced in” by owners of external IP rights. Furthermore, firms with relatively more valuable IP rights are more likely to be acquired as fragmentation increases. Using a unique longitudinal dataset on the biopharmaceutical industry from 1986 to 2004, we test and find empirical support for our hypotheses.

Keywords: Knowledge exploitation; IP fragmentation; technology acquisitions; appropriability; biopharmaceuticals.

2.2. Introduction

“Invention, and particularly modern invention...is a drama enacted on a crowded stage.”
— (Polanyi, 1944, p.71)

Firms innovate by combining technological knowledge generated through their R&D with inputs generated outside the firm (Foss, 1996; Helfat, 1994; Kogut & Zander, 1992). While seeking to use technology components in new ways, firms need to manage their innovation strategy to avoid infringing the intellectual property (IP) rights of other technology holders (Arora, Fosfuri, & Gambardella, 2001; de Rassenfosse, Griffiths, Jaffe, & Webster, 2020). Obtaining access to valuable IP rights is critical for firms to appropriate value from their investments in innovation as technology owners can demand unreasonable royalties and upfront payments or engage in costly litigation. Thus, appropriability is a significant challenge for firms in fragmented markets for technology characterized by widely dispersed ownership of IP rights (Heller, 2008; Heller & Eisenberg, 1998). In extreme cases, the arduous task of assembling all relevant IP rights can prevent firms from innovating as they risk being “fenced in” by other technology holders (Ziedonis, 2004).

Simply put, a firm has its R&D activities fenced in when outside owners of IP rights³ can block or impose prohibitively high remuneration conditions for technologies relevant to the firms' innovation activities.

Understanding how firms access and assemble valuable IP rights has increased in importance over the last few decades with the growing fragmentation of IP ownership (Ahuja, Lampert, & Tandon, 2008; Burk & Lemley, 2009). This phenomenon has driven firms to actively deploy strategies that allow them to access externally generated IP rights that can be subsequently incorporated into their ongoing R&D efforts (Cassiman & Valentini, 2016; Laursen & Salter, 2006; Zahringer, Kolympiris, & Kalaitzandonakes, 2017). Among these strategies, one of the most commonly observed is the use of technology-related acquisitions (Capron, 1999; Clarysse, Bruneel, & Wright, 2011; Valentini, 2012; Wubben, Batterink, Kolympiris, Kemp, & Omta, 2015) in which the acquirer firm takes ownership of the target firm to access its IP rights (Ahuja & Katila, 2001; Schweizer, 2005).

Yet, our understanding of how fragmented ownership of IP rights in an industry relates to firms' use of technology acquisitions is still limited. Our paper sheds light on this issue. We theorize that an industry's structure of IP ownership is an essential determinant of the use of technology acquisitions as a value-appropriation mechanism. We argue that the fragmentation of IP rights in an industry is curvilinearly (inverted U-shape) related to firms' rate of technology acquisitions. Furthermore, this curvilinear relationship becomes weaker (more linear) for firms at a higher risk of being fenced in by owners of external IP rights. Moreover, the level of IP rights fragmentation in an industry also relates to the likelihood of firms becoming the targets of technology acquisitions. Specifically, we argue that firms that hold more valuable IP rights relative to their portfolio size are more likely to be acquired as the fragmentation of IP rights in an industry increases. Using a unique longitudinal dataset on the biopharmaceutical industry from 1986 to 2004, we test and find empirical support for our hypotheses.

³ Since we are interested in examining how firms protect their R&D activities from being fenced in, we focus on one particular type of IP rights, patent rights, which grant the patentee the right to exclude others from using the patented invention for a some time. We use the terms IP rights and patent rights interchangeably hereon.

Our study makes several contributions to the literature. First, it contributes to the literature on the determinants of technology acquisitions (Ahuja & Katila, 2001; Schweizer, 2005; Valentini, 2012; Valentini & Di Guardo, 2012). While this literature has focused primarily on learning and capability development benefits as determinants of technology acquisitions, to our knowledge, this is the first paper to identify the fragmented ownership of IP rights at the industry level as a driver of firms' use of technology acquisitions. In doing so, we provide a novel theoretical perspective on the antecedents of one of the most commonly observed strategies innovative firms use to access and assemble needed IP rights: technological acquisitions. Second, we further contribute to the literature on technology acquisitions by examining the relationship between the fragmentation of ownership of IP rights in an industry and firms' likelihood to be the targets of technology acquisitions. Third, we contribute to the literature on value appropriation in markets for technology (Arora et al., 2001; Grimpe & Hussinger, 2014; Ziedonis, 2004) by examining the use of technology acquisitions as a means of strengthening appropriability in industries with fragmented ownership of IP rights. Overall, this paper advances understanding of technology acquisitions by introducing the fragmentation of ownership of IP rights within an industry as a critical determinant of technology acquisition decisions.

2.3. Theory and hypotheses

2.3.1. Acquisitions in fragmented markets for technology

IP rights protect knowledge elements (Bessen & Meurer, 2008; Levitas & Chi, 2010) that firms combine and recombine to create value (Kneeland, Schilling, & Aharonson, 2020; Kogut & Zander, 1992). Firms assemble IP rights for innovation purposes through acquisitions (Ahuja & Katila, 2001), alliances (Mowery, Oxley, & Silverman, 1998; Rosenkopf & Schilling, 2007), or licensing contracts (Arora et al., 2001; Laursen, Moreira, Reichstein, & Leone, 2017). However, assembling the necessary IP rights can be challenging when such IP rights in an industry are highly fragmented and dispersed across many firms (Heller, 2008; Heller & Eisenberg, 1998). Having to negotiate with multiple technology owners simultaneously exposes the innovating firm to environmental uncertainty and risk of opportunistic behaviour from other firms, resulting in coordination issues and prohibitive costs (Diestre & Rajagopalan, 2012).

Therefore, how IP rights are distributed within an industry has important implications for firms' ability to appropriate value from innovation. As the ownership of IP rights in an industry becomes more fragmented, firms' ability to appropriate value from innovation becomes increasingly threatened by the risk that external IP owners may "fence in" a firm's innovation activities (Heller & Eisenberg, 1998; Ziedonis, 2004). The dispersion of IP rights, and resulting uncertainty over ownership, makes it harder to assemble the IP rights that the innovating firm might be infringing (von Graevenitz, Wagner, & Harhoff, 2013). For instance, the pharmaceutical firm Bristol-Myers Squibb announced that "*it would exclude from its drug research and would, thus, not pursue any investigations into more than 50 proteins possibly involved in cancer. The patent holders, the company explained, either would not allow it or were demanding unreasonable royalties.*" (Heller, 2008:1). As this example illustrates, even if the highly dispersed owners can be identified and contacted, the potentially severe metering and royalty stacking (Lemley & Shapiro, 1991) can render the piecemeal access of necessary technologies through licensing contracts infeasible.

The problem posed by fragmented ownership of IP rights is similar to the "hold-up" problem featured in the transactions cost literature (Foss & Foss, 2008; Klein, Crawford, & Alchian, 1978; Williamson, 1985). In the context of innovation, hold-up occurs when a firm expropriates rents from another firm, weakening its ability to appropriate value from its innovation. Transaction cost theory suggests that firms should respond to the appropriability threats posed by an increased fragmentation of IP rights by building a larger portfolio of IP rights to be able to "exchange hostages", thereby improving their bargaining positions vis-à-vis other firms (Cuypers, Hennart, Silverman, & Ertug, 2020; Williamson, 1983). Indeed, innovative firms often seek to mitigate value appropriation threats and improve their bargaining position by patenting aggressively (Ceccagnoli, 2009; Ziedonis, 2004). However, generating IP rights internally through own R&D tends to have long development cycles and uncertain outcomes (Chesbrough, 2003). Therefore, generating IP rights internally from scratch may not provide the firm, particularly in the short-term, with access to the specific technology rights it needs to protect and commercialize its existing innovations and continue innovating.

An alternative strategy innovative firms can use to amass a larger IP portfolio is to pursue technology acquisitions. Through technology acquisitions firms can acquire and access the entire IP portfolio of target firms and, thus, build a “*patent fence*” (Cohen et al., 2000; Ziedonis, 2004) around their innovation activities which enhances appropriability (Grimpe & Hussinger, 2014). Yet, despite their value appropriation benefits, the use of technology acquisitions may not always be a feasible or optimal strategy for securing needed IP rights due to their potentially considerable costs, such as the direct and the indirect costs associated with unrealized gains from trade with specialized firms (Ziedonis, 2004). In what follows, we develop theory and hypotheses on how the fragmentation of ownership of IP rights in an industry relates to firm’s technology acquisition behavior by shaping the benefits and costs of technology acquisitions as a value appropriation mechanism.

2.3.2. Hypotheses development

While accessing external IP rights in a fragmented market for technology, firms get exposed to the risk of opportunistic behaviour by other technology owners who may impose prohibitively high remuneration conditions for technologies that are relevant to the innovating activities of the focal firm. In such a situation firms seek to safeguard their investments (Ceccagnoli, 2009; Grimpe & Hussinger, 2014; Reitzig & Puranam, 2009; Ziedonis, 2004). Yet, ex-ante solutions to the problem are restricted because IP boundaries are not easy to demarcate and some of the IP related to “cumulative chain of innovation” are often unknown in advance (Merges & Nelson, 1990). Further, the potential costs and delays arising from a myriad of negotiations with diffused IP owners (Ziedonis, 2004) before developing or commercializing an innovation render ex-ante solutions to threats to value appropriation infeasible. As ex-ante contractual solutions are less feasible, firms respond to the appropriability threats posed by an increased fragmentation of IP rights by amassing IP rights that improves their bargaining positions vis-à-vis other firms (Cuypers et al., 2020; Williamson, 1983).

The acquisition of firms that own valuable IP rights is a key strategy an innovative firm can use to promptly augment its portfolio of IP rights needed to sustain and profit from innovation. The strategy of using technology acquisitions to consolidate needed IP rights, and thereby strengthen a firm’s value appropriation ability, is vividly illustrated by the

following statement made by John Maraganore, CEO of Anylam Pharmaceuticals: *“The reason we did the IP consolidation strategically was to avoid the fragmentation of value that occurred in the settings of other big platform technologies and to be the leading company for pharma collaborations... In one case we acquired a company... because they had some critical patents. So, it was a very explicit strategy to bring it all together ... frankly there was not as much data to support its potential ... we had the persistence and the conviction that we wanted to consolidate IP this way, which would give us the whole lion’s share of the value (Shih & Chai, 2010: 4).”*

Technology acquisitions can improve a firm’s ability to protect its innovations from the value-capture efforts of others via enhanced bargaining power resulting from a greater ability to cross-license (Cohen et al., 2000) or threaten reciprocal suits (Cohen et al., 2000; Hall & Ziedonis, 2001). Furthermore, acquiring a firm holding valuable IP rights can promptly reduce the need to engage in extensive individual negotiations for specific IP components, or can facilitate the development of needed technology in-house from scratch. Thus, the incentives for a firm to engage in technology acquisitions depend on the value they place on improving their bargaining positions in the face of potential threats to their innovation efforts in the future. Therefore, if the fragmentation of IP rights weakens the appropriability of innovations, one would expect firms to engage in more technology acquisitions as the fragmentation of IP rights in an industry increase.

However, firms will use acquisitions as a strategic mode for dealing with the threats posed by the industry fragmentation of IP rights as long as the realized gains from acquiring the entire IP portfolio of another firm outweigh the costs involved in the acquisition itself (Ziedonis, 2004). In other words, the number and significance of relevant IP rights accessed through the acquisition must carry more strategic value than the costs involved. We argue that the benefits associated with technology acquisitions increase at a decreasing rate, whereas the corresponding costs increase linearly as the level of industry fragmentation of IP rights increases. When the fragmentation of IP rights in an industry is severe, the benefits associated with technology acquisitions increase at a decreasing rate as a firm’s ability to enhance its bargaining position via technology acquisitions is limited by the small number of IP rights that it can obtain through each deal. Moreover, as the level of industry fragmentation of IP rights increases, the costs of engaging in technology

acquisitions increase. As fewer firms possess enough valuable IP rights for the strategic benefits of acquiring them to outweigh the costs, it will be harder for acquirers to find suitable targets, leading to substantial screening and due-diligence costs (Harvey & Lusch, 1995).

In addition, higher levels of IP rights fragmentation in an industry can also imply higher post-acquisition costs related to infringement issues involving the IP portfolio of the newly acquired firm. Research has shown that plaintiffs file IP related lawsuits strategically when their chances of monetization are highest (Cohen, Gurun, & Kominers, 2019; Feldman & Frondorf, 2015). For instance, the transfer of IP rights ownership to a larger firm could function as such a trigger, by increasing the incentives of other firms to assert their IP rights. The need for comprehensive due diligence to identify possible infringement issues and the likelihood of discovering after the acquisition that other IP rights are needed to obtain freedom to operate increase the costs of acquisitions as a value appropriation mechanism.

In sum, the net effect of benefits of technology acquisitions which increase at a decreasing rate and their costs which increase linearly as the industry fragmentation of IP rights increases suggest a curvilinear, inverted U-shape relationship (Haans, Pieters, & He, 2016) between the level of fragmentation of IP rights in an industry and firms' technology acquisition rate. Thus, we hypothesize:

***Hypothesis 1 (H1):** Industry fragmentation of IP rights is curvilinearly (inverted U-shape) related to the rate at which firms engage in technology acquisitions.*

Furthermore, using technology acquisitions when the ownership of IP rights in an industry is fragmented should be particularly important when a firm is at a higher risk of being fenced in, i.e., at a higher risk of facing restrictions or prohibitively high remuneration conditions by outside owners of IP rights for using technologies relevant to its innovation activities. Firms holding IP rights that are less valuable relative to industry peers will be more vulnerable to the value capture efforts of other firms as the fragmentation of ownership of IP rights in an industry increases (Noel & Schankerman, 2013; Ziedonis, 2004). They will find themselves in a relatively weaker bargaining position when negotiating access to others' IP rights in the future and thus are exposed to the risk of

opportunistic behaviour by other technology owners. This means that for a firm that faces a higher risk of having its innovation activities fenced in by competitors, the potential benefits of acquisitions will be relatively higher than for a firm that is less exposed to such a threat.

While aggressively applying for IP rights can enhance firms' bargaining position (Ziedonis, 2004), firms holding less valuable IP rights portfolios might lack the capability to pursue this option (Reitzig & Puranam, 2009). Even if they succeed, they might face threats to value appropriation from the owners of backdated IP rights (Lemley & Shapiro, 2005). Therefore, to improve their bargaining position and safeguard investments in innovation and commercialization, for any given level of costs associated with a technology acquisition, firms holding less valuable IP rights will be more likely to pursue acquisitions as a way of accessing relevant IP rights.

Conversely, firms with more valuable IP rights portfolios than those of competitors will be better positioned to protect their innovation efforts. Valuable IP rights provide firms with a flexible set of "hostages" for use in negotiations. Therefore, even if some of the critical IP rights are owned by other firms, the owners of a valuable IP rights portfolio will have the bargaining power to engage in cross-licensing (Cohen et al., 2000) or to threaten a reciprocal lawsuit (Cohen et al., 2000; Hall & Ziedonis, 2001). As the number of potential IP rights that can be accessed through an acquisition goes down with higher levels of industry IP rights fragmentation, the benefits of an additional acquisition become very similar to those of contractual mechanisms such as cross-licensing (Grindley & Teece, 1997) for firms with valuable IP portfolios.

Based on the arguments above, we expect that for firms with a high risk of being fenced in, the benefits of technology acquisitions will be high for any level of industry IP rights fragmentation. Therefore, we suggest that as the risk of being fenced in increases, the relationship between the industry level of fragmentation of IP rights and firms' acquisition rate will grow more linear and, hence, less curvilinear (inverted U-shape). Thus, we hypothesize:

***Hypothesis 2 (H2):** Firms that face an increasing risk of being fenced in by owners of external IP rights will exhibit a weaker curvilinear (more linear) relationship between the industry fragmentation of IP rights and their technology acquisition rate.*

In addition, we posit that firms owning more valuable IP rights relative to their portfolio size will be more likely to be acquired when their industry's IP rights landscape exhibits increasing fragmentation. As the fragmentation of IP rights increases, firms will be more concerned about protecting themselves from the value capture efforts of other firms within the industry (Heller, 1998; Ziedonis, 2004). Given the infeasibility of ex-ante contractual solutions to the appropriability threats posed by the fragmentation of IP rights, firms tend to amass valuable IP rights to improve their bargaining positions vis-à-vis other firms (Cuypers et al., 2020; Williamson, 1983) using technology acquisitions. However, when valuable IP rights become diluted across several technology holders, very few potential target firms will hold a large enough number of relevant IP rights in their portfolio. In this context, the number of potential target firms for which the benefits of an acquisition outweigh the costs of an acquisition decreases. This results in the most sought-after targets being firms with a relatively high share of valuable IP rights in their portfolio. Therefore, the higher the level of IP rights fragmentation in an industry, the more acquisitions will be focused on firms with more valuable IP rights portfolios. Thus, we hypothesize:

***Hypothesis 3 (H3):** The higher the relative IP rights value of a firm, the more likely the firm will be acquired under conditions of increasing industry fragmentation of IP rights.*

2.4. Methods

2.4.1. Empirical context

To test our hypotheses, we used data on firms operating in the biopharmaceutical industry. We chose this empirical setting for several reasons. First, the biopharmaceutical industry has been experiencing increasing fragmentation of its IP rights. This has been largely driven by the fact that, since the early 1990s, the industry has seen a steady influx of new players dedicated to the identification and development of new molecules and treatments

(Pisano, 2006). Although many firms in this industry, particularly smaller ones, may have no intention of pushing new drugs through FDA clinical trials approval, their investments in R&D often result in patents (Gunther McGrath & Nerkar, 2004; Henderson & Cockburn, 1994). This results in a wide variety of firms holding strategic IP rights. Furthermore, the industry accounts for one of the largest shares of patents granted in the U.S. (Lim, 2004). In line with our theoretical predictions, we expect that, particularly for biopharmaceutical firms, innovation costs will be strongly related to increasing number of patent holders. Indeed, in this industry the “*proliferation of intellectual property rights upstream may be stifling life-saving innovations further downstream in the course of research and product development*” (Heller and Eisenberg, 1998, p. 698). These characteristics push firms into using a different range of mechanisms, such as acquisitions, to deal with dispersion of ownership across the industry.

It is also worth noting the deleterious effect of increasing IP fragmentation on the innovation activities of biopharmaceutical firms. For example, despite the strategic importance of gene therapy for the development of several new treatments, “*no single company or organization, however, has the resources to develop any significant fraction of the genetic information present in an organism. If proprietary information is not freely available or licensed in an affordable manner, researchers will be precluded from using these protected nucleic acids to develop new therapeutics and diagnostics*” (Jeanne, Piccolo, Stanton, & Tyson, 2000: 3). In the absence of proprietary technologies, firms can turn to technology licensing, which partly explains the large number of deals commonly observed in this industry. Although the market for technology in the biopharmaceutical industry is relatively well developed (Anand & Khanna, 2000), technology holders frequently ask for prohibitively expensive remuneration conditions (Laursen et al., 2017; Moreira, Cabaleiro, & Reichstein, 2018). In extreme situations, for specific therapeutic areas, firms may find themselves excluded from innovating and from making strategic R&D investments due to the costs or infeasibility of accessing multiple IP rights⁴.

⁴ We extended our theoretical perspective by testing whether alternative mechanisms to augment patent portfolios are complementary to, or substitutes for, technology acquisitions in a context of increasing industry fragmentation of IP rights (see appendix).

In fact, the issues related to ownership fragmentation of IP rights faced by biopharmaceutical firms has been extensively documented and described in prior studies. For example, Heller and Eisenberg (1998) apply the “tragedy of the commons” metaphor to explain how the presence of multiple technology holders and IP rights may damage the R&D investments and developments in this industry by holding back development of fewer and less useful drugs and treatments. In another example, Huang and Murray (2008) document how the presence of multiple technology holders related to the IP ownership of the human genome hinders the future development of scientific work in this area.

Second, not only are R&D costs in this industry high, but so are failure rates (Nerkar & Roberts, 2004). This creates significant uncertainty over firms’ capacity to recover their investments in R&D (Munos, 2009). One way for firms to mitigate this risk is by ensuring legal access to relevant IP rights. For example, firms will not embark on clinical trials without either applying for patents related to the underlying technologies that will be tested or acquiring access to the patents protecting them. Indeed, as prior studies have pointed out, *“If the innovating company begins FDA process before USPTO filing, then it runs the risk of another company patenting the invention before them. Consequently, the innovating company would have to license the biopharmaceutical, losing royalties, market exclusivity, and company value; or would have to abandon the FDA process and forfeit millions spent in research and development”* (Fernandez & Huie, 2004: 510). This pushes firms to actively manage their innovation and IP strategy to improve appropriability of their innovations.

Finally, several studies have shown that acquisitions are prevalent in this industry (e.g. Danzon, Epstein, & Nicholson, 2007; Higgins & Rodriguez, 2006; Ruckman, 2005). Biopharmaceutical firms are commonly involved in acquisitions, whether as acquirer or target (Munos, 2009). While the industry saw many horizontal mergers between large firms in the 1980s, the acquisition of smaller companies due to strategic R&D decisions became more prevalent from the 1990s (Danzon et al., 2007). This offers an appropriate empirical context in which to examine whether IP ownership fragmentation is a driver of biopharmaceutical firms’ tendency to acquire or be acquired.

2.4.2. Data and sample

Our database was compiled based on information combining four main data sources: Recap Deal Builder, Pharmaprojects, Compustat North America, and the NBER patent project. The combination of these four different data sources gave us a unique dataset that allowed us to perform a longitudinal analysis for the period 1986–2004. We defined 1986 as the starting year based on the availability of consistent acquisition data from Recap, and 2004 as the ending year based on the availability of patent data in NBER. The NBER data is compiled based on patents granted by the United States Patent and Trademark Office (USPTO). We decided to rely on this version of the patent data because, to the best of our knowledge, it is the most accurate dataset to identify the IP rights holder of a patent at a given point in time *unambiguously*. Indeed, this *particular* dataset allows us to follow longitudinal changes in IP ownership *dynamically* (Bessen, 2009). This is critical, as patents are often repeatedly reassigned through sale or M&A events.

We began constructing our sample by identifying public firms listed in Compustat that belong to either SIC code 2834, *Pharmaceutical Preparations*, or 2836, *Biological Products*. These two are the most relevant SIC codes for companies that operate in the biopharmaceutical industry. The public firms operating in these SICs are the most relevant industry players in terms of patenting activity and acquisitions. Furthermore, these are the firms responsible for the largest share of new drugs at the U.S. Food and Drug Administration (FDA) and of patenting activity, which are critical in this industry.

We used the firm names listed on Compustat to connect each observation in the sample with Recap Deal Builder. Recap is known as one of the most accurate and comprehensive sources of information regarding M&A deals and technology exchange involving biopharmaceutical firms (Schilling, 2009). Using the Recap dataset, we could identify all deals in which a focal firm was listed as an acquirer or a target during our period of observation. This dataset also provided access to important control variables, such as licensing and alliance activities. It allowed us to access detailed information regarding the M&A deals, and also to unambiguously identify the acquirer and acquired firm for a given deal. Having connected these two datasets, we were able to access detailed information regarding each acquisition. We only included completed deals where the acquirer bought

a *majority stake* in a target that was not already a subsidiary. This ensured that the IP rights of the target were transferred to the acquirer upon acquisition.

Next, we captured information regarding firms' innovation activity and patent portfolio using the NBER patent database (Hall, Jaffe, Trajtenberg, & Berglass, 2001). To avoid noise produced by differences in evaluation procedures across countries, we focused on the patents granted by the USPTO. Given that the U.S. represents one of the world's main markets for new drugs and treatments, firms have strategic incentives to apply for patents at the USPTO as early as possible (Henderson & Cockburn, 1994).

Finally, we matched the firms in our sample with Pharmaprojects, which contains pharmaceutical trial data regarding the development of new drugs at the FDA. Using this database, we extracted the R&D pipeline for each firm in our sample to capture its drug-development activities (Hess & Rothaermel, 2011). Based on trial data, we could track and identify the firms that had been actively involved in drug development.

The resulting sample was structured as a panel in which we observe each firm i in a given year t . Therefore, we use the firm-year combination as our unit of analysis. The final sample comprised 306 unique firms appearing 6.5 times on average (min: 2; max: 18). The empirical analysis was performed based on 1,984 firm-year observations 1986–2004.

2.4.3. Identifying Relevant Industry IP Rights

Our core argument is that when ownership of industry IP rights becomes fragmented, firms will react by engaging in more acquisitions. However, we only expect to observe this relation for fragmentation in the focal industry's most important technology areas (strategic IP rights). In other words, we don't expect that fragmentation of general or unspecific IP rights will drive more acquisitions⁵. Strategic IP rights tend to be specialized, and to demand significant R&D investments, while general IP rights with a broad set of

⁵ This assumption is tested in the robustness checks section of the paper, where we also report the results using an alternative measure of industry fragmentation of IP rights that uses all patent classes in which the firms patented in a given year.

unspecific applications tend to be less complex, and more likely to be available for licensing on markets for technology (Gambardella & McGahan, 2010). Furthermore, given that general IP rights tend to have a large set of substitutes and also to be employed in different industries, technology holders of such rights are unlikely to succeed in fencing in other firms' innovation activities, making it less likely that acquisitions will be deployed as a strategic reaction.

To identify the strategic IP rights for the firms in the biopharmaceutical industry, we used patent classes reported in NBER and identified each patent that fell into categories 424/514, *Drug, Bio-Affecting and Body Treating Compositions*; 435, *Chemistry: Molecular Biology and Microbiology*; and 604, *Surgery*. These three classes have also been previously identified by several studies as being the most relevant to the dynamics of innovation and IP rights in the biopharmaceutical industry (e.g., Bogner, Thomas, & McGee, 1996; Lim, 2004; Penner-Hahn & Shaver, 2005; Rothaermel & Thursby, 2007). These classes do not just represent the specific technological fields in which firms in this industry most frequently patent but are also highly specific to the R&D activities of the industry. These classes are different, for example, from general chemistry patent classes, which are used by firms in many different industries.

2.4.4. Measures

2.4.4.1. Dependent variables

To test *hypotheses 1* and *2*, we used the number of technology acquisitions as our dependent variable, while for *hypothesis 3*, our dependent variable was based on a dummy that equals 1 when a firm is acquired and 0 otherwise. The two dependent variables were computed as follows:

Technology acquisitions. We scrutinized Recap to identify each acquisition deal that was connected to the firms in our sample. Because we were interested in identifying the acquisitions driven by industry fragmentation of IP rights, we excluded deals that involved targets that had *no patents accumulated* in the preceding seven years. We did this by also connecting all the target firms described in our sample with the NBER patent database.

Furthermore, we also removed from the sample *reverse* and *minority acquisitions*, as these types of deals are unlikely to be motivated by the intention to access strategic IP rights. Our measure captures the total number of acquisitions that firm i had engaged in year t as the acquirer firm. Finally, we follow prior studies (e.g., Hagedoorn & Duysters, 2002; Servaes & Zenner, 1996) and reduce the skewness of the variable by using the logarithm of (*Technology acquisitions* + 1) as our final measure.

Likelihood of being acquired. To operationalize this second dependent variable, we first identified all biopharmaceutical firms that had at least one patent in one of the strategic patent classes for this industry during our period of observation. We then tracked these firms longitudinally using Recap to determine whether they had been acquired. This dependent variable was then computed using a dummy taking the value of 0 if firm i had not been acquired in year t , and 1 if it had.

2.4.2.2. Independent Variables

Industry fragmentation of IP rights. the generic patents for the firms in our sample (i.e., patent classes 424/514, 435, and 604), we computed the level of industry fragmentation of IP rights based on the dispersion of strategic IP rights ownership among technology holders. To compute industry fragmentation, we used a similar measure to Ziedonis (2004)⁶. Our measure was intended to capture the level of fragmentation in the ownership rights of the patents in the strategic technological classes of the biopharmaceutical industry in a given year. We computed it with the following formula:

$$\text{Industry fragmentation of IP rights} = \left[1 - \sum_{i=1} \left(\frac{N_{it}}{N_t} \right)^2 \right]$$

where $\frac{N_{it}}{N_t}$ represents the share of patents owned by firm i in year t . We take as the reference year the year in which patents were successfully applied for. We multiplied the variable

⁶ The fragmentation measure introduced by Ziedonis (2004) captures the fragmentation of IP rights within an *individual firm's* portfolio. We leverage her approach to construct a measure of the fragmentation of IP rights at the *industry* level.

by a correction factor of $\frac{PA_t}{PA_t-1}$, where PA_t is the total number of patent applicants in the strategic technological classes of the biopharmaceutical industry in the focal year.

Risk of being fenced in. To capture the risk of a focal firm being fenced in, we looked at the value of its IP portfolio. This measure was computed to vary by each firm cross-sectionally and longitudinally. The rationale is that firms with a stronger IP portfolio are more likely to build future innovations based on their own technologies, as opposed to using other firms'. To compute this variable, we first constructed the portfolio of patents owned by firm i in a given year t . We defined a firm's patent portfolio using a 10-year moving window. Next, we identified the value of each patent based on the number of forward citations it had received. We then summed the total value of a firm's portfolio and compared it to the average value of the portfolios of other firms operating in the same SIC code in a given year. Because we wanted to compute the risk of being fenced in, we inverted this variable by multiplying it by (-1). Accordingly, increasing values indicate a higher risk of being fenced in⁷.

Relative IP rights value for a potential target. We used a 3-year moving window to calculate the cumulative number of patents that the firms accumulate in strategic patent classes. We used this time window because acquirer firms are most likely to be interested in more recent IP rights, since older ones may already be obsolete. We then computed the ratio between a firm's value of its IP portfolio (proxied by the total forward citations) and the number of patents it had accumulated in the same period. The final measure was calculated based on the logarithm of (*Relative IP rights value for a potential target* + 1) to reduce skewness.

⁷ To facilitate interpretation and graphical representation, we categorized this variable into quartiles (lower, lower-median, median-upper, and upper). The estimation results are virtually identical if we use the continuous variable or quantiles instead.

2.4.4.3. Controls

We controlled for a number of variables that may be simultaneously related to firms' rate of technology acquisitions and our independent variables. For acquiring firm innovation characteristics, we controlled for firm *Patenting experience* as accumulated experience in managing and generating IP rights using the number of years from the firm's first patent application to year t . As R&D investments of a firm can impact its acquisition decisions, we controlled for a firm *R&D intensity* by dividing its total amount of R&D investment divided by the total number of employees of the firm in year t . Another characteristic that can impact acquisition strategy of a firm is its *Drug pipeline*. We controlled for Drug pipeline using a dummy variable that took a value of 1 if a firm had at least one drug in its pipeline in year t , and 0 otherwise. To account for the extent to which firms build on their own technologies, we include in our econometric models the *Knowledge base specificity* as the ratio of self-citations to total citations received by a firms' IP portfolio in the three years prior to the year t . As alliance activities can both increase firm innovation output and facilitate acquisitions, we also account for *Strategic alliances* measured as the cumulative number of alliances that a firm had within three years from year t . We further controlled for *Litigation* by including a dummy variable that took a value of 1 if a firm had been sued at least once for infringing another firm's patents within three years prior to year t , and 0 otherwise. Finally, we controlled for two strategies that the firms use to mitigate the risks of fragmentation. First, based on Recap data, we compute *Technology licensing* using the cumulative number of technology licensing-in deals, that a firm had within three years from year t . Second, we account for patenting activity (Ziedonis, 2004) as the logarithm of the number of patent applications filed by a firm i in year t .

For acquiring firm resources and capabilities characteristics, we controlled for *Downstream commercial capabilities* as the amount that a firm had spent on Selling, General, and Administrative Expenses (SG&A) in year t (Rothaermel & Boeker, 2008). We also incorporate in our models a firm's *Size* using natural logarithm of reported total assets for a firm in year t . Additionally, we also account for *Slack*, i.e., the amount of firms' unused resources, based on the ratio between current liabilities and total assets of a firm in year t . As the equity valuation of a firm impacts its acquisition strategy, we take into account the *Price to book ratio* using the ratio of market value to book value of a firm in

year t . We controlled for the financial status of the acquirer using *Return on assets* and *Leverage*. *Return on assets* is measured as the ratio of earnings before interest, tax, depreciation and amortization to total assets of firm in year t while *Leverage* is measured as the ratio of long-term debt to total assets of a firm in year. We also controlled for *Capital intensity*, which is measured as ratio of the net property, plant, and equipment to the total number of employees at the end of the previous year. Since, acquiring firms might follow different rhythms of acquisitions over time, we controlled for *Time since last acquisition*. We also account for competition and industry characteristics faced by the acquiring firm. We controlled for *Firm market share*, measured as the share of the market a firm had in year t , and *Advertisement intensity*, measured as the ratio of advertisement expenses to total sales for a firm in year t . Additionally, we also control for *Industry growth* based on the change in total sales achieved by firms in the same SIC code as the focal firm between years $t-1$ and t .

Finally, to test *hypothesis 3*, which concerns the likelihood of a potential target firm being acquired, we used a different set of control variables based on the target's patenting activity. Because most targets are not public firms and are significantly smaller than their acquirers, we relied on a smaller set of control variables based on the available data: *Patenting experience*, *Average age of patent portfolio*, and *Size of patent portfolio*. The model specification used to test this hypothesis is explained in greater depth below.

2.5. Models

To test our *hypotheses 1* and *2*, we use fixed-effects regressions with robust standard errors. We opted to use firm fixed effects to account for firm-related time-invariant unobservable heterogeneity that could correlate with our error term and our main explanatory variables simultaneously. We also captured time trends employing period fixed effects. To avoid issues related to reverse causality, we lagged the explanatory variables in our model by one year relative to the dependent variable. We use the models below to test *hypotheses 1* and *2*:

$$H1: TA_{i,t} = f(F_{t-1}) = F_{t-1} + F_{t-1}^2 + Controls_{i,t-1} + \gamma_i + \gamma_t + \varepsilon_{i,t}$$

$$H2: TA_{i,t} = f(F_{t-1}, R_{i,t-1}) = F_{t-1} + F_{t-1}^2 + F_{t-1} \times R_{i,t-1} + F_{t-1}^2 \times R_{i,t-1} + \\ Controls_{i,t-1} + \gamma_i + \gamma_t + \varepsilon_{i,t}$$

In these estimations, our dependent variable corresponds to the number of *Technology acquisitions* in which firm i engages at year t . The two main explanatory variables in this model are *Industry fragmentation of IP rights*, indicated by F_{t-1} , and the squared term for *Industry fragmentation of IP rights*, represented by F_{t-1}^2 . To test *hypothesis 2*, we use the term $R_{i,t-1}$, capturing the *Risk of being fenced in*, interacted first with F_{t-1} and then with F_{t-1}^2 .

We ruled out using a poisson or a negative binomial model to test our first two hypotheses because with a firm fixed-effects specification these estimators would exclude firms for which the dependent variable—in this case, *Technology acquisitions*—has no within-firm variation for the period of analysis (Allison & Waterman, 2002). In the final sample, 232 firms do not engage in technology acquisitions during the period of study, and for these firms technology acquisition has no within-firm variation. Therefore, in our context, employing these models could induce significant sample selection issues in our estimations⁸ (Cameron & Trivedi, 2010: 623). Furthermore, concerning the use of a negative binomial model specifically, this estimator does not allow the use of robust standard errors in conjunction with fixed effects, which is an important specification to account for heteroscedasticity (Allison & Waterman, 2002).

To test *hypothesis 3*, we predicted firm i 's likelihood of being acquired at year t $\Pr [Acq_{i,t} = 1 | F_{t-1}, RV_{i,t-1}]$ using a logistic regression model with random effects. We opted for random effects to test this hypothesis because a fixed-effects estimator would not allow us to use non-acquired firms as a reference group to compute the likelihood of a firm being acquired. In the model described below, the dependent variable is estimated as

⁸ Despite this limitation on the use of a count model in our empirical setup, the results we report in the paper regarding the relationship between *Industry fragmentation of IP rights* and *Technology acquisitions* are very similar in terms of statistical significance to those obtained using a poisson or negative binomial estimator.

a function of *Industry fragmentation of IP rights* captured by F_{t-1} and $RV_{i,t-1}$, representing the relative IP rights value for a potential target. Differently from our first model predicting the number of acquisitions a firm undertakes in a given year, this model estimates the likelihood of a given firm i being *acquired* at year t .

$$H3: \Pr [Acq_{i,t} = 1 | F_{t-1}, RV_{i,t-1}] = f(F_{t-1}, RV_{i,t-1}) = 1 / (1 + \exp(-(F_{t-1} \times RV_{i,t-1} + F_{t-1} + RV_{i,t-1} + Controls_{i,t-1} + \gamma_t + \varepsilon_{i,t}))$$

To implement this model, we identified a group of non-acquired firms that were also at risk of becoming a target within our study period. We first selected assignee firms that had at least one of the industry's main patent classes using the NBER patent database⁹, and restricted this sample to U.S. corporations only (i.e., we removed individuals, universities, government institutes, hospitals etc. that filed for patents in the above patent classes). Lastly, we merged the resulting list with Recap data to identify which firms were acquired during the period of our analysis. We estimate these models putting all the firms in this sample at risk of acquisition in a given year.

2.6. Results

Table 2.1 reports the descriptive statistics and simple pairwise correlations between the variables used to test our hypotheses. We mean-center *Industry fragmentation of IP rights* before using the variable in the regression models and, thereby, report descriptive statistics and correlations of the transformed variable. Except for the correlations between *Size* and *Patenting experience*, the results of pairwise correlations raised no significant concerns regarding multicollinearity involving our explanatory variables. The high correlation among the above control variables is in line with theoretical expectations, but to test

⁹ We use the NBER database to identify potential targets because relying on a dataset such as Compustat would only allow us to base our analysis on public firms. This would not be the best sample criterion, as most acquisitions in the pharma industry involve smaller, not publicly listed, firms.

Table 2.1. Descriptive statistics and correlations

Variables	Mean	S.D.	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
[1] Technology acquisitions	0.05	0.19	1										
[2] Industry fragmentation of IP rights	0.01	0.06	0.07	1									
[3] Risk of being fenced in	1.52	1.11	-0.14	0.04	1								
[4] Patenting experience	8.26	7.52	0.23	-0.03	-0.51	1							
[5] R&D intensity	125.2	123.1	-0.01	0.26	0.11	-0.33	1						
[6] Drugs in pipeline	0.77	0.42	0.09	0.32	-0.18	-0.01	0.36	1					
[7] Knowledge specificity	0.10	0.12	0.02	-0.06	-0.44	0.29	-0.08	0.1	1				
[8] Technology licensing	2.87	5.30	0.29	0.10	-0.34	0.53	-0.09	0.21	0.11	1			
[9] Strategic alliances	0.35	0.96	0.21	0.15	-0.30	0.34	0.00	0.16	0.09	0.52	1		
[10] Patenting activity	19.07	49.63	0.23	-0.04	-0.45	0.65	-0.21	0.07	0.28	0.65	0.34	1	
[11] Litigation	0.19	0.39	0.15	0.03	-0.33	0.49	-0.22	0.03	0.11	0.39	0.23	0.40	1
[12] Capital intensity	62.85	50.79	0.09	0.06	-0.24	0.22	0.03	0.14	0.14	0.28	0.21	0.20	0.24
[13] Return on assets	-0.02	0.04	0.11	-0.11	-0.19	0.42	-0.47	-0.19	0.07	0.22	0.12	0.28	0.29
[14] Leverage	0.01	0.02	0.11	-0.04	-0.13	0.15	-0.05	0.01	0.09	0.06	0.08	0.05	0.09
[15] Advertisement intensity	0.01	0.04	0.03	-0.13	-0.11	0.27	-0.20	-0.11	0.09	0.08	0.00	0.16	0.15
[16] Size	11.64	2.14	0.30	-0.02	-0.52	0.69	-0.23	0.10	0.24	0.60	0.36	0.65	0.54
[17] Slack	0.03	0.08	0.02	-0.07	-0.07	0.15	-0.08	-0.02	0.03	0.09	0.04	0.13	0.09
[18] Downstream commercial capabilities	0.81	0.86	0.17	-0.14	-0.23	0.60	-0.51	-0.20	0.11	0.37	0.16	0.46	0.40
[19] Price to Book value	6.44	6.70	0.00	0.03	-0.05	0.02	0.09	0.12	0.05	0.05	0.06	0.05	0.01
[20] Market share	0.01	0.04	0.12	-0.11	-0.33	0.35	-0.15	0.00	0.08	0.31	0.20	0.37	0.36
[21] Time since last acquisition	3.46	3.38	-0.27	0.14	-0.19	0.37	-0.12	0.05	0.15	-0.09	-0.04	-0.04	0.11
[22] Industry growth	0.15	0.00	-0.09	-0.07	-0.14	-0.18	0.00	-0.08	-0.00	-0.11	-0.07	-0.11	-0.08

Variables	Mean	S.D.	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	[21]	[22]
[12] Capital intensity	62.85	50.79	1										
[13] Return on assets	-0.02	0.04	0.18	1									
[14] Leverage	0.01	0.02	0.17	0.06	1								
[15] Advertisement intensity	0.01	0.04	-0.09	0.11	0.08	1							
[16] Size	11.64	2.14	0.38	0.54	0.20	0.2	1						
[17] Slack	0.03	0.08	-0.02	-0.08	0.04	0.09	0.05	1					
[18] Downstream commercial capabilities	0.81	0.86	0.13	0.47	0.14	0.29	0.62	0.12	1				
[19] Price to Book value	6.44	6.70	-0.07	-0.20	0.19	0.04	-0.11	0.06	-0.02	1			
[20] Market share	0.01	0.04	0.28	0.26	0.00	0.08	0.45	0.05	0.38	0.03	1		
[21] Time since last acquisition	3.46	3.38	0.09	0.11	0.02	0.00	0.03	0.00	0.13	0.04	-0.01	1	
[22] Industry growth	0.15	0.00	-0.07	-0.07	-0.10	-0.07	-0.14	-0.04	-0.16	0.02	0.09	-0.130	1

whether this was a concern, we estimated our models entering these control variables separately, and our main results remained unchanged. Additionally, the mean of Variance Inflation Factors (VIF) associated with our variables does not raise further concerns (Mean VIF= 2.61).

Table 2.2 reports the results of fixed-effects panel-regression estimations in four different specifications (Models 1 to 4) to test *hypotheses 1* and 2. Model 1 reports a baseline estimation that does not include industry fragmentation of IP rights. Next, Model 2 reports the linear term of *Industry fragmentation of IP rights*. In Model 3, we introduce both the linear and square terms for *Industry fragmentation of IP rights* to test *hypothesis 1*. The coefficient estimates from this model provide support for *hypothesis 1*. The coefficient of *Industry fragmentation of IP rights* is positive and statistically significant ($\beta = 0.382$, $p - value < 0.01$), while the coefficient of its squared term is negative and statistically significant ($\beta = -6.213$, $p - value < 0.01$). Figure 2.1 plots the curvilinear (inverted U-shape) relationship between *Industry fragmentation of IP rights* and the rate at which firms engage in *Technology acquisitions* based on the coefficient estimates from Model 3. The maximum of the curve is within the range of the *Industry fragmentation of IP rights*; the number of observations beyond the turning point amounts to 33.55% of the sample. Following the recommendations of Haans, Pieters, & He (2016), we further confirm the presence of an inverted-U shaped relationship between *Industry fragmentation of IP rights* and firms' *Technology acquisitions* rate by calculating the slope of the curve to the right and left of the turning point. When *Industry fragmentation of IP rights* is equal to its 10th percentile, the slope of the curve is positive and significant (1.26, $p - value < 0.01$); when it is equal to its 90th percentile, the slope is negative and significant (-0.86 , $p - value < 0.05$). These results provide further support for *hypothesis 1*.

In Model 4, we introduce interaction terms to test *hypothesis 2*. The interaction term between the *Industry fragmentation of IP rights* and firms' *Risk of being fenced in* is negative and significant ($\beta = -0.344$, $p - value < 0.01$), while the interaction term between the squared term of *Industry fragmentation of IP rights* and firms' *Risk of being fenced in* is positive and significant ($\beta = 3.740$, $p - value < 0.01$). Figure 2.2

illustrates that firms facing a higher *Risk of being fenced in* exhibit a weaker inverted U-shape

Table 2.2. Fixed effects panel regression models of technology acquisitions

Variables	Model [1]	Model [2]	Model [3]	Model [4]
Industry fragmentation of IP rights		0.266** (0.105)	0.382*** (0.121)	0.912*** (0.208)
Industry fragmentation of IP rights square			-6.213*** (2.242)	-11.700*** (3.469)
Industry fragmentation of IP rights X Risk of being fenced in				-0.344*** (0.090)
Industry fragmentation of IP rights square X Risk of being fenced in				3.740** (1.572)
Risk of being fenced in	0.022** (0.011)	0.022* (0.011)	0.023** (0.011)	0.011 (0.011)
Patenting experience	0.003 (0.004)	0.000 (0.004)	-0.001 (0.004)	-0.001 (0.004)
R&D intensity	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Drugs in pipeline	-0.018 (0.018)	-0.021 (0.018)	-0.027 (0.018)	-0.037** (0.018)
Knowledge specificity	-0.025 (0.054)	-0.024 (0.054)	-0.015 (0.053)	-0.010 (0.052)
Technology licensing	0.005 (0.003)	0.005 (0.003)	0.005 (0.003)	0.004 (0.003)
Strategic alliances	0.018* (0.010)	0.017* (0.010)	0.018* (0.010)	0.015 (0.010)
Patenting activity	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Litigation	-0.020 (0.025)	-0.022 (0.025)	-0.025 (0.025)	-0.037 (0.025)
Capital intensity	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000* (0.000)
Return on assets	-0.497** (0.212)	-0.476** (0.210)	-0.468** (0.206)	-0.501** (0.209)
Leverage	0.438 (0.351)	0.480 (0.352)	0.471 (0.354)	0.530 (0.348)
Advertisement intensity	0.155 (0.175)	0.147 (0.179)	0.175 (0.175)	0.205 (0.169)
Size	0.005 (0.009)	0.003 (0.009)	0.007 (0.009)	0.007 (0.008)
Slack	-0.029 (0.043)	-0.021 (0.043)	-0.016 (0.043)	-0.014 (0.046)
Downstream commercial capabilities	0.008 (0.010)	0.007 (0.011)	0.006 (0.011)	0.007 (0.011)
Price to Book value	-0.000 (0.001)	-0.000 (0.001)	0.000 (0.001)	-0.000 (0.001)
Market share	0.359 (0.244)	0.388 (0.237)	0.374 (0.233)	0.399* (0.216)
Time since last acquisition	0.007** (0.003)	0.007** (0.003)	0.007** (0.003)	0.007** (0.003)
Industry growth	0.040 (0.051)	0.007 (0.049)	-0.002 (0.050)	0.005 (0.050)
Constant	-0.121 (0.100)	-0.078 (0.101)	-0.063 (0.101)	-0.033 (0.099)
Observations	1,984	1,984	1,984	1,984
R-squared	0.050	0.054	0.058	0.071
Number of Firms	306	306	306	306
Firm FE	YES	YES	YES	YES
Period FE	YES	YES	YES	YES

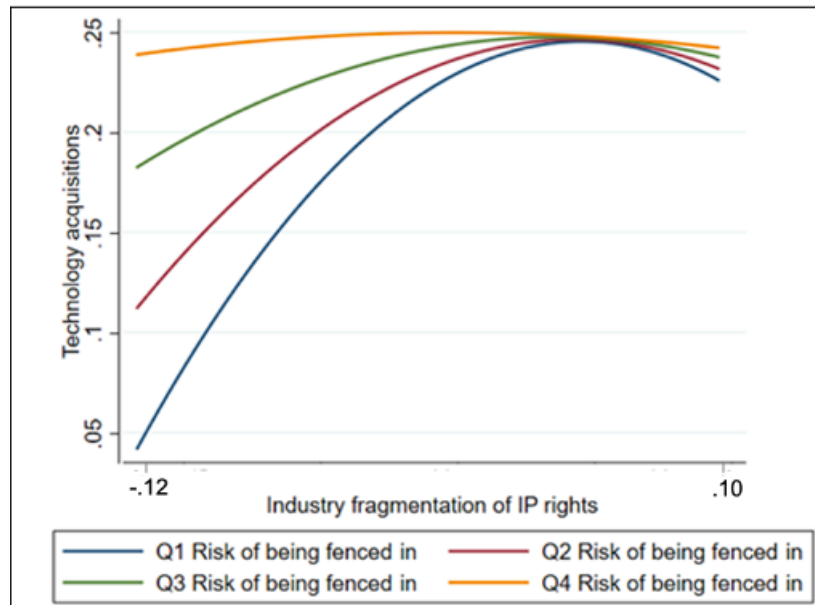
Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

relationship between *Industry fragmentation of IP rights* and their *Technology acquisitions* rate, such that they sustain higher acquisition rates for increasing levels of fragmentation. Specifically, as the *Risk of being fenced in* increases, the relationship between industry IP rights fragmentation and the acquisition rate becomes more linear, and less like an inverted U-shape. Using the coefficient estimates from Model 4, we find that for firms facing an extremely low risk of being fenced in (lower quartile), the slope of the curve when *Industry fragmentation of IP rights* is equal to its 90th percentile is negative and significant (-1.29 , $p - value < 0.05$). Conversely, for firms facing an extremely high *Risk of being fenced in* (upper quartile), the slope of the curve when *Industry fragmentation of IP rights* is equal to its 90th percentile is not significant (-0.340 , $p - value > 0.10$). These results provide further evidence in favor of *hypothesis 2*.

Figure 2.1. Predicted relationship between industry fragmentation of IP rights on technology acquisitions



Figure 2.2. Predicted relationship between industry fragmentation of IP rights and technology acquisitions by firms' risk of being fenced in



Note: Figure 2.1 and Figure 2.2 show the relationship between industry fragmentation of IP rights and firms' technology acquisitions and how this relationship is moderated by acquiring firms' risk of being fenced in. The Y-axis is logarithm scale (1 + number of technology acquisitions), which is the dependent variable for hypothesis 1 and hypothesis 2. Figures 2.1 and 2.2 use coefficient estimates from Model 3 and Model 4 of Table 2.2, respectively, over the range of industry fragmentation of IP rights in our sample and at mean values for all other variables. Additionally, Figure 2.2 uses coefficient estimates by different quartiles of risk of being fenced in. Hence, the labels Q1, Q2, Q3, and Q4 correspond to the first, second, third, and fourth quartiles (first being lowest risk, fourth highest) of risk of being fenced in. The High and Low labels on the X-axis correspond to the extreme values of industry fragmentation of IP rights in our sample.

Table 2.3 reports the results of a logistic regression estimation used to test *hypothesis 3*. In Model 5, we use a dummy dependent variable that equals 1 if a firm is acquired in a given year and 0 otherwise. We also include an interaction term between the *Relative IP rights value of the potential targets* and the *Industry fragmentation of IP rights*. The estimated coefficient on the interaction term is positive and significant ($\beta = 2.076$, $p - value < 0.05$), supporting *hypothesis 3*, which predicts that firms with higher relative IP rights value are more likely to be acquired as fragmentation increases. In line with our expectations, industry fragmentation of IP rights does not directly predict *which individual firm* will be acquired in a given year ($\beta = 0.780$, $p - value > 0.10$). However, as described above, once we account for the heterogeneity among potential targets based on

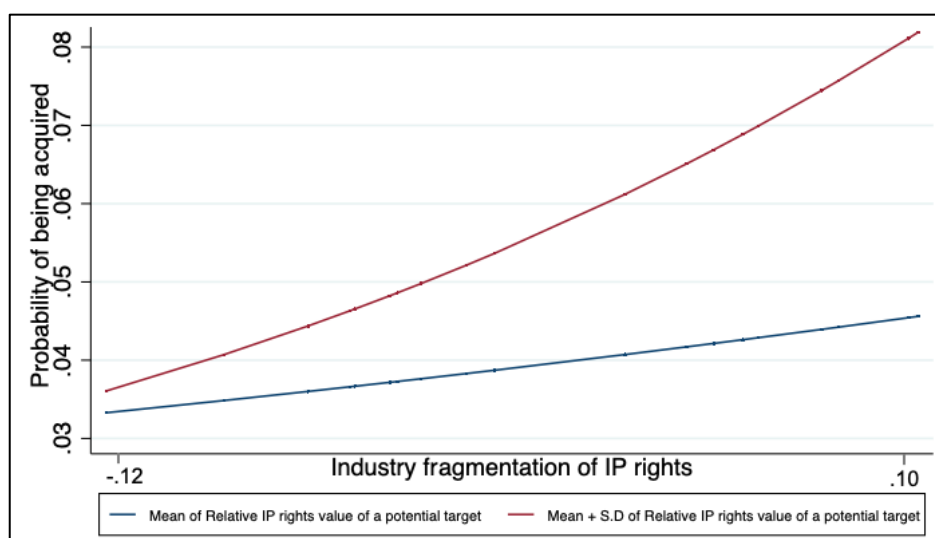
the relative value of their IP rights portfolio, fragmentation relates positively and significantly to the likelihood of being acquired. Figure 2.3 depicts the results obtained in Model 5.

Table 2.3. Logistic regression model of the likelihood of being acquired

Variables	Model [5]
Industry fragmentation of IP rights X Relative IP rights value for a potential target	2.076** (0.837)
Relative IP rights value for a potential target	0.323*** (0.068)
Industry fragmentation of IP rights	0.780 (0.941)
Patenting experience	0.016 (0.012)
Average age of patent portfolio	-0.055*** (0.018)
Size of patent portfolio	0.000** (0.000)
Constant	-8.485*** (0.439)
Observations	101,189
Number of firms	8,392
Period FE	YES

Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Figure 2.3. Predicted relationship between industry fragmentation of IP rights and probability of being acquired



2.6.1. Robustness tests

We checked the robustness of our results with additional tests and alternative specifications. One potential concern is that we measured IP fragmentation at the industry level, focusing on the most relevant patents classes for the industry. This choice is grounded in our theoretical argument that increasing levels of fragmentation make it harder for firms to secure their position in the technology space. Accordingly, we expect that firms are likely to face problems when having to deal with strategic IP rights, while generic and unspecific IP rights can be more easily traded or invented around. To test whether that is the case, we computed an alternative measure for industry fragmentation of IP rights that includes all patent classes in which firms in the pharmaceutical industry patent. In line with our expectations, the result of this alternative measure was not statistically significant. The coefficient of both the *Industry fragmentation of IP rights* ($\beta = 0.187$, $p - value > 0.10$) and its square term ($\beta = 1.520$, $p - value > 0.10$) with the alternative measurement are positive and not significant. This finding suggests that the fragmentation of general (unspecific) IP rights is not associated with more acquisitions.

We also performed a robustness check by adding the fragmentation measure at the firm patent portfolio level proposed by Ziedonis (2004) as a control variable in our econometric models used to test *hypotheses 1* and *2*. In line with our expectations, controlling for fragmentation at the level of a firm's patent portfolio did not change our results of the relationship between fragmentation and firms' decision to engage in technology acquisitions. For the model testing *hypothesis 1*, the coefficient of *Industry fragmentation of IP rights* is negative and significant ($\beta = 0.367$, $p - value < 0.01$), while the coefficient of its squared term is positive and significant ($\beta = -5.577$, $p - value < 0.01$).

Finally, we tested whether our results were sensitive to the way we measured our main dependent variable. We generated a new dummy dependent variable that took a value of 1 if firm i made at least one technology acquisition in a given year t , and 0 otherwise. We re-estimated Models 1–3 with this alternative dependent variable using a panel logit model

with random effects and the same independent and control variables as those reported in Table 2.2. For the specification equivalent to Model 3, the coefficient of *Industry fragmentation of IP rights* is negative and significant ($\beta = 10.408$, $p - value < 0.01$), while the coefficient of its squared term is positive and significant ($\beta = -173.412$, $p - value < 0.01$). The results are comparable to those reported earlier. In sum, all of the above tests yielded further evidence in support of the robustness of our findings.

2.6.2. Supplementary analyses

Many prior studies have examined different mechanisms through which firms can generate and acquire IP rights as part of their innovation strategy, including licensing contracts (Contractor & Reuer, 2014; Laursen et al., 2017), strategic alliances (Oxley, 1999), and increasing patenting activity (Reitzig & Puranam, 2009; Ziedonis, 2004). We extended our theoretical perspective by testing whether these three specific mechanisms are complementary to, or substitutes for, technology acquisitions in a context of increasing industry fragmentation of IP rights. We used Recap to compute, first, the number of licensing contracts that a focal firm i has entered into in a given year t as a licensee, and second, the number of research alliances for the same period. Finally, using the NBER database, we calculated the patents a firm has applied for in a given year.

Table 2.4 reports the results, using the same sample and empirical setup as in Table 2.2. Model 9, 10, and 11 introduce the interaction between the linear and square term of *Industry fragmentation of IP rights* and *Technology licensing*, *Strategic alliances*, and *Patenting activity*, respectively. In model 9, the coefficient of the interaction term of *Technology licensing* and *Industry fragmentation of IP rights* is positive and significant ($\beta = 0.093$, $p - value < 0.01$), while the coefficient of the interaction term of *Technology licensing* and the square term of *Industry fragmentation of IP rights* is negative and significant ($\beta = -1.371$, $p - value < 0.01$). The results suggest that firms consider technology acquisitions and license-in deals as complements at lower to medium levels of industry fragmentation of IP rights, while as substitutes at higher levels of fragmentation. In model 10, the coefficients of the interaction terms between the linear and square term of *Industry fragmentation of IP rights* and Strategic alliances are not significant at conventional levels. These results provide no evidence as to whether

Table 2.4. Supplementary analysis: Fixed effects panel regression models of technology acquisitions

Variables	Model [9]	Model [10]	Model [11]
Industry fragmentation of IP rights	0.397*** (0.113)	0.345*** (0.129)	0.371*** (0.107)
Industry fragmentation of IP rights square	-7.330*** (2.245)	-6.713*** (2.271)	-5.072** (2.026)
Industry fragmentation of IP rights X Technology licensing	0.093*** (0.024)		
Industry fragmentation of IP rights square X Technology licensing	-1.371** (0.590)		
Industry fragmentation of IP rights X Strategic alliances		0.079 (0.158)	
Industry fragmentation of IP rights square X Strategic alliances		0.658 (3.262)	
Industry fragmentation of IP rights X Patenting activity			0.011*** (0.002)
Industry fragmentation of IP rights square X Patenting activity			-0.115** (0.045)
Technology licensing	0.007** (0.003)	0.005 (0.003)	0.004 (0.003)
Strategic alliances	0.017 (0.010)	0.012 (0.017)	0.013 (0.010)
Patenting activity	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Risk of being fenced-in	0.021* (0.011)	0.022** (0.011)	0.016 (0.010)
Patenting experience	0.001 (0.004)	-0.000 (0.004)	-0.003 (0.004)
R&D intensity	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Drugs in pipeline	-0.027 (0.018)	-0.027 (0.018)	-0.030* (0.018)
Knowledge specificity	-0.010 (0.051)	-0.016 (0.053)	-0.015 (0.052)
Litigation	-0.024 (0.025)	-0.025 (0.025)	-0.032 (0.024)
Capital intensity	-0.000 (0.000)	-0.000 (0.000)	-0.000* (0.000)
Return on assets	-0.494** (0.211)	-0.474** (0.207)	-0.484** (0.208)
Leverage	0.497 (0.348)	0.511 (0.348)	0.489 (0.343)
Advertisement intensity	0.186 (0.171)	0.180 (0.174)	0.245 (0.169)
Size	0.007 (0.008)	0.006 (0.008)	0.008 (0.008)
Slack	-0.035 (0.044)	-0.017 (0.043)	-0.027 (0.043)
Downstream commercial capabilities	0.004 (0.011)	0.006 (0.011)	0.009 (0.010)
Price to Book value	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Market share	0.441** (0.216)	0.387 (0.236)	0.419* (0.220)
Time since last acquisition	0.007** (0.003)	0.007** (0.003)	0.008*** (0.003)

Industry growth	-0.014 (0.049)	0.000 (0.050)	-0.006 (0.048)
Constant	-0.077 (0.097)	-0.055 (0.099)	-0.042 (0.095)
Observations	1,984	1,984	1,984
R-squared	0.072	0.059	0.080
Number of Firms	306	306	306
Firm FE	YES	YES	YES
Period FE	YES	YES	YES

Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

alliances will be deployed as complements or substitutes of acquisitions under increasing fragmentation. In model 11, the coefficient of the interaction term of *Patenting activity* and *Industry fragmentation of IP rights* is positive and significant ($\beta = 0.011$, $p - value < 0.01$), while the coefficient of the interaction term of *Patenting activity* and the square term of *Industry fragmentation of IP rights* is negative and significant ($\beta = -0.115$, $p - value < 0.05$). The results indicate that, under increasing industry IP rights fragmentation, firms that patent more will also be more likely to engage in acquisitions. However, at higher levels of industry fragmentation of IP rights firms use aggressive patenting and technology acquisitions as substitutes.

To sum up, these tests provide evidence that technology licensing and patenting activity act as complements for technology acquisitions at lower to medium levels of industry fragmentation of IP rights, and as substitutes at higher levels of industry fragmentation of IP rights. Furthermore, we find no evidence that strategic alliances are used as complements or substitutes for technology acquisitions as the fragmentation of ownership of IP rights in an industry increases.

2.7. Discussion

This paper examines how the ownership structure of IP rights in an industry is related to technology acquisitions. In particular, we examine how the fragmentation of IP rights in an industry is related to both the rate at which innovative firms engage in technology acquisitions and their likelihood of being acquired. We argue that the fragmentation of IP rights in an industry is curvilinearly (inverted U-shape) related to firms' rate of technology acquisitions. We also argue that this relationship varies across firms, such that it is weaker (more linear) for firms that have a higher risk of being fenced in by owners of external IP

rights. Furthermore, we argue that the firms with relatively more valuable IP rights are more likely to be acquired as the level of IP rights fragmentation in their industry increases. Using a unique longitudinal dataset on acquisitions in the biopharmaceutical industry over the period 1986 to 2004, we operationalize and find empirical support for our theoretical perspective and hypotheses.

Our study makes several contributions. First, we contribute to the literature on the determinants of technology acquisitions (Ahuja & Katila, 2001; Schweizer, 2005; Valentini, 2012; Valentini & Di Guardo, 2012). While this stream of literature has focused on the learning and capability development motives of technology acquisitions, we examine the value appropriation motive of technology acquisitions. We theorize and show empirically that the fragmentation of IP rights in an industry is an important determinant of the use of technology acquisitions as a value-appropriation mechanism. Moreover, our theory and results suggest that the risk of being fenced in by owners of external IP rights is an important moderator of the relationship between industry fragmentation of IP rights and the rate at which firms engage in technology acquisitions.

Second, we leverage our theoretical perspective to also shed light on the relationship between the fragmentation of IP rights in an industry and firms' likelihood to be a target of technology acquisitions. While the extant literature on target selection primarily focuses on the characteristics of a target's technology base (Ahuja & Katila, 2001; Chondrakis, 2016; Sears & Hoetker, 2014), we highlight how the fragmentation of IP rights in an industry interacts with targets' IP-rights characteristics in determining their attractiveness to potential acquirers.

Third, we contribute to the literature on value appropriation in markets for technology (Arora et al., 2001; Grimpe & Hussinger, 2014; Ziedonis, 2004). While this stream of literature has largely focused on IP filing strategies that firms use to deal with appropriability challenges, it has given limited attention to the use of technology acquisitions as a value appropriation mechanism. An important exception is Grimpe & Hussinger (2014), who examine how the price that acquirer firms pay for targets is influenced by the value-appropriation benefits offered by the target's patent portfolio. We extend this stream of literature by examining the use of technology acquisitions as a means

of strengthening appropriability in industries with fragmented IP rights.

Our theory and results have broader implications for other research streams as well, such as research at the nexus of the resource-based view and economics of property rights. While the resource-based view (Barney, 1991; Foss, Klein, Kor, & Mahoney, 2008; Rumelt 1984; Wernerfelt, 1984) presupposes value appropriation (Reitzig & Puranam, 2009), research on the economics of property rights (Alchian & Demsetz, 1973; Demsetz, 1974; Foss & Foss, 2005) has suggested that value appropriation is threatened by potential constraints on the usage rights of the elements that constitute a resource. Indeed, recent research has started to explore in greater depth how firms strategize to improve their value appropriation by securing or protecting usage rights over value-generating resources (Ceccagnoli, 2009; Townsend & Busenitz, 2008; Ziedonis, 2004). Our study has implications for this line of work. In particular, our theory and findings shed light on the industry- and firm-level conditions that govern the balance between the benefits and costs of value appropriation through technology acquisitions and on the scenarios (e.g., severe IP-rights fragmentation) under which the costs of such value appropriation efforts may exceed the corresponding benefits.

Our study also has implications for research on IP rights that has been primarily concerned with licensing and alliance deals as market mechanisms to grant access to IP rights generated by other firms (Contractor & Reuer, 2014; Laursen et al., 2017; Oxley, 1999). We extend this research stream by providing evidence that technology acquisitions are also a mechanism that firms use to manage their access into markets for technology. We also propose that under high levels of industry fragmentation of IP rights, there can be gaps in a firm's IP portfolio that are best filled through technology acquisitions.

Furthermore, our study also has implications for the literature on "M&A waves". While the extant literature on M&A waves has focused on wave determinants such as valuation levels (Rhodes-Kroph & Viswanathan, 2004), exogenous industry shocks (Harford, 2005), or behavioral biases (Auster & Sirower, 2002), our study points to the fragmentation of IP rights in an industry as an additional driver of M&A activity and clustering.

2.7.1. Limitations and Future Research

While this paper deepens our understanding of the use of technology acquisitions as a mechanism for value appropriation in fragmented markets for technology, it has limitations that future research could address. First, our study focuses on a single mechanism for strengthening a firm's ability to appropriate value under conditions of increasing industry dispersion of relevant IP rights: technology acquisitions. Future research could compare the use of different value-appropriation mechanisms and examine how they are combined, sequenced, and interrelated. For instance, do firms that apply for IP rights aggressively also engage in more technology acquisitions as industry fragmentation of IP rights increases, or are these two mechanisms combined, sequenced, and/or prioritized differently at different levels of fragmentation? These questions are fundamental from both a policy and managerial perspective and warrant additional research. In our paper, we have made an initial step towards exploring this question by performing supplementary analyses extending our main theoretical perspective.

Second, although we employ an extensive list of relevant control variables in our econometric models, endogeneity problems might still be an issue. For instance, one could regress firms' rate of acquisitions on some measure of distribution of IP rights among other firms. Yet, in such regression, unobservable firm characteristics may drive a spurious relationship between the two variables of interest. However, we believe that our empirical strategy substantially reduces concerns over unobserved heterogeneity and omitted variables bias. In addition to a range of control variables, we also use firm and period fixed-effects, which should deal with unobserved heterogeneity coming from both time-trends and individual firm time-invariant characteristics such as industry affiliation. Furthermore, we expect that it is very unlikely that a single firm in our sample can significantly influence the level of IP rights fragmentation in an industry. Nevertheless, future studies could test our predictions in different empirical settings and using different research designs (i.e., quasi-natural experiments), where it is possible to fully isolate the effect of industry IP rights fragmentation on a firm's likelihood to make or be the target of technology acquisitions.

Third, our study examines how the fragmentation of IP rights relates to technology acquisitions in just one sector (biopharmaceuticals). While biopharmaceuticals provide an appropriate context, future research could examine the generalizability of our findings to other technological or industrial settings such as semiconductors or software. Another direction would be to examine which of our arguments and findings generalize to a setting where standard development organizations can make essential IP rights available to everyone on Fair, Reasonable, and Non-Discriminatory (FRAND) terms and conditions. For instance, the introduction of FRAND commitments in cellular phone development and manufacturing significantly mitigated the value appropriation challenges firms face (Teece, 2018). Thus, future research could also examine the relationship between the industry fragmentation of IP rights and the prevalence and value impact of technology acquisitions in FRAND contexts.

Furthermore, our theory and findings suggest that firms at greater risk of being fenced in are more likely to expend resources on costly appropriation efforts in the form of technology acquisitions. Yet, a firm could also invent around the IP positions of other firms to alleviate potential threats, which may be easier for firms possessing a decomposable knowledge base that provides greater malleability or capacity for change (Yayavaram & Ahuja, 2008). Future research could examine the interactions between the characteristics of a firm's knowledge base and its risk of being fenced in and, thereby, shed light on the optimal value-appropriation strategy in a given IP landscape. Furthermore, our theory development is from the point of view of the acquirer, yet research has shown that targets also seek benefits from being acquired (Huang & Walkling, 1987) and actively try to make themselves more attractive to potential acquirers (Zingales, 1995). Therefore, future studies could extend the current theorization to the benefits sought and actions undertaken by potential targets at different levels of industry IP rights fragmentation. More broadly, future research is needed to improve our understanding of the contextual and competitive conditions impacting the benefits and costs of alternative value-appropriation strategies.

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3.

Anticipated Knowledge Worker Mobility and R&D Dynamism: Evidence From a Natural Experiment

This chapter examines how firms adjust their R&D investments in response to appropriability challenges posed by the threat of losing knowledge workers.

3.1. Abstract

This study examines how the threat of knowledge worker mobility affects the dynamics of firm R&D. We argue that the appropriability challenges posed by the threat of knowledge worker mobility give rise to a “caution effect” on firm R&D strategy. In particular, we posit that the threat of losing knowledge workers dampens R&D dynamism, i.e., reduces the volatility of firm R&D expenditure. Yet, the dampening of R&D dynamism is less pronounced for firms that have alternate mechanisms for mitigating the threat of knowledge worker mobility, such as firms that have established a reputation for litigiousness. Using a natural experiment and a difference-in-differences methodology in the context of the US manufacturing industry over the period 1991-2018, we empirically test and find evidence supporting our hypotheses.

Keywords: Knowledge exploitation; R&D; knowledge workers; innovation; appropriability; risk and uncertainty

3.2 Introduction

According to the knowledge-based view of the firm, privately held knowledge is a key source of competitive advantage (Grant, 1996; Kogut & Zander, 1992; Teece et al., 1997). As innovative firms rely on R&D to create knowledge and explore for new competitive advantages (Jaffe, 1986; Pakes, 1985), the flexibility and adaptability of their R&D investments is increasingly essential to their ultimate success (Roussel, Saad, & Erickson, 1991). Yet, scholars have found R&D investments to be highly autocorrelated (Bloom, 2007) and the overall R&D expenditures of US firms to have even stagnated from 2.5 to 2.8 percent of GDP over the last decade (UNESCO Institute of Statistics, 2019)¹⁰.

A key feature of R&D investments is that profiting from them depends on firms' ability to retain key talent. The departure of knowledge workers leads to loss of valuable knowledge from the source firm and its leakage to competitors (Agarwal et al., 2009; Almeida & Kogut, 1999), which weakens the appropriability of R&D. Therefore, the threat of knowledge worker departures might change the very nature of firm R&D if firms choose

¹⁰ <https://data.worldbank.org/indicator/GB.XPD.RSDV.GD.ZS?locations=US>

R&D investments that enable them to avoid or minimize the appropriability challenges posed by employee mobility (Alcácer & Zhao, 2012; Zhao, 2006).

While prior research has examined the impact of employee mobility on firm strategies, such as location strategies (Alcácer & Chung, 2007), the design of employment contracts and financial incentives (Cappelli, 2000; Starr, 2019), or CSR strategies (Flammer & Kacperczyk, 2019), our understanding of the impact of anticipated employee mobility on firm R&D strategy is still limited. Recent research has begun developing our knowledge on the subject by suggesting and finding that employment protection laws affect firm innovation outcomes (Conti, 2014; Francis, Kim, Wang, & Zhang, 2018; Keum, 2020). Yet, to our knowledge, no prior work has examined the impact of employee mobility on the dynamics of firm R&D inputs.

This paper sheds light on the issue. We examine how the threat of knowledge worker mobility affects the dynamics of firm R&D expenditure. Exploring this question also sheds light on the well-documented puzzle posed by the surprisingly high persistence of R&D investment over time which at the firm level is about three times more autocorrelated than capital investment (Bloom, 2007; Triguero & Córcoles, 2013). We argue that the appropriability challenges posed by the threat of knowledge worker mobility give rise to a “caution effect” on firm R&D strategy. In particular, we posit that the threat of knowledge worker mobility undermines the appropriability of R&D, reducing firms’ incentives to engage in major upward or downward adjustments in R&D expenditure. As a result, firms gradually adjust their R&D, i.e., dampen their R&D dynamics by reducing the volatility of their R&D expenditures. Furthermore, we argue that the dampening of R&D dynamics is less pronounced for firms that have alternate mechanisms for mitigating the threat of knowledge worker mobility, such as firms that have established a reputation for litigiousness. We leverage the natural experiment created by the staggered rejection of “Involuntary Disclosure Doctrine” (IDD) laws in different U.S. states to empirically test our hypotheses in the context of the US manufacturing industry over the period 1991-2018. The rejection of IDD removes a crucial mobility restriction for knowledge workers (Flammer & Kacperczyk, 2019; Kahnke & Bundy, 2013; Kahnke, Bundy, & Liebman, 2008). It poses a threat in the sense that it restricts employers’ ability to prevent employees with valuable knowledge to work for a competitor in the immediate future.

This paper makes four contributions to extant literature. First, it contributes to the literature on the impact of employee mobility on firm R&D strategy (Conti, 2014; Hall & Soskice, 2001; Keum, 2020) by providing novel theory and evidence that firms reduce the volatility of their R&D to address the appropriability challenges posed by the threat of knowledge worker mobility (Agarwal et al., 2009; Conti, 2014; Ganco, Ziedonis, & Agarwal, 2015). This “caution effect” on firm R&D is mitigated for firms that have alternative mechanisms for preventing knowledge worker mobility and associated knowledge spillovers, such as an established reputation for litigiousness. Second, it contributes to the literature on the determinants of R&D volatility (Kor & Mahoney, 2005; Mudambi & Swift, 2014; Triguero & Córcoles, 2013) by identifying anticipated employee mobility and reputation for litigiousness as hitherto underexamined determinants of firm R&D dynamics. Third, this study also contributes to the growing stream of research on the relationship between firm strategy and the institutional context (e.g., Furman, 2003; Ingram & Silverman, 2002; Pe'er & Gottschalg, 2011). Finally, this paper also contributes to the literature on dynamic capabilities (Eisenhardt & Martin, 2000; Teece et al., 1997) by identifying important antecedents of the dynamism of firm R&D.

3.3. Theory and hypotheses

3.3.1. Employee mobility and firm R&D appropriability

Investing in R&D is one of the primary methods firms use to create new knowledge. Yet, a lot of firm knowledge is embedded in people (Simon, 1991). Firms investing in R&D face the risk of losing the valuable knowledge that they created as their employees can join a rival or create a new venture (Coff, 1997; Ganco et al., 2015; Kacperczyk, 2012; Starr, Balasubramanian, & Sakakibarac, 2018). These are serious concerns as they reduce the ability of firms to appropriate returns from investments in R&D.

First, firm knowledge often resides in individual employees. Simon (1991) emphasized that “all learning takes place inside individual human heads” and that organizations learn primarily by their employees’ learning. Employees apply codified elements of knowledge that are objective, rational, and created in the “then and there” to learn tacit elements that are subjective, experiential, and created in the “here and now.” (Nelson & Winter, 1982;

Nonaka & Takeuchi, 1995; Polanyi, 1966). Successful R&D activities require use of both codified knowledge such as technical manuals and tacit knowledge that is embedded in individuals (Droege & Hoobler, 2003; Zucker, Darby, & Brewer, 1998). Tacit knowledge that is above and beyond what firm has documented can be lost when employees leave. A firm that has financed R&D creating tacit knowledge cannot prevent its employees from taking the knowledge with them when they quit (Coff, 1997). Therefore, mobility of knowledge workers is a fundamental threat to a firm's ability to appropriate value from its R&D investments.

Second, the departure of employees is likely to lead not only to the loss of knowledge embedded in departing employees but also disrupt established organizational knowledge creation routines, hamper previously well-functioning teams and networks, and thereby undermine key organizational capabilities in technology development (Grabowski, 1968; Hambrick, MacMillan, & Barbosa, 1983). The loss of knowledge workers may require remaining members of the team to allocate time away from knowledge creation towards adjusting and adapting to the organizational disruption caused by mobility (Hale, Ployhart, & Shepherd, 2016; Zellmer-Bruhn, 2003). Moreover, the attention of remaining employees can be drawn “away from the standard progression of the work” (Bechky & Okhuysen, 2011: 239) towards thoughts of leaving their employer (Lee, Hom, Eberly, Jason, & Mitchell, 2017) as turnover has been shown to be “contagious” in teams (Felps et al., 2009) and result in cascading disruptions of knowledge creation routines. Disruption in knowledge creation routines can severely affect the productivity of the remaining knowledge workers, suggesting that the benefits originating from a firm's long-term investment in knowledge creation routines would not be effectively appropriated.

Third, the mobility of knowledge workers can lead to the leakage of valuable firm knowledge to direct competitors (Agarwal et al., 2009; Almeida & Kogut, 1999). Firms actively hire knowledge workers to gain access to their previous employers' knowledge and technology (Rao & Drazin, 2002; Stern & James, 2016), helping them overcome the limitations of ‘local search’ (Rosenkopf & Almeida, 2003; Song, Almeida, & Wu, 2003) and, thereby, erode their rivals' competitive advantages. As the saying goes, “if you have trouble with the competition, simply raid its talent (Kerstetter, 2000: 44)”. Thus, the loss

of knowledge workers to other firms could have a significant adverse effect on source firms' ability of to appropriate returns from R&D (Agarwal, Croson, & Mahoney, 2010).

3.3.2. Anticipated employee mobility and firm R&D investment dynamics

The expected appropriability of R&D investments can be expected to influence firms' willingness to significantly increase investment in R&D (Bloom, 2007). Because the threat of knowledge worker mobility affects appropriability, firms can be expected to adjust their R&D investments based on their expectations about potential loss of knowledge and leakage to rivals. Zhao (2006) and Alcácer & Zhao (2012) find that firms facing appropriability risks invest in R&D projects characterized by strong linkages with other corporate proprietary knowledge—because this interdependence creates knowledge that is hard for competitors to replicate. Relatedly, Conti (2014) finds that firms usually choose risky R&D projects when they are able to reduce knowledge outflows by restricting mobility of inventors.

Anticipated knowledge worker mobility reduces the expected appropriability of R&D investments and, thus, lowers firm incentives to significantly increase R&D in three main ways. First, if knowledge workers are more mobile, R&D appropriability concerns arise as the knowledge embedded in individual employees is more vulnerable to loss (Coff, 1997). Second, the loss of knowledge workers also disrupts valuable knowledge creation routines which threatens intra-firm dynamics (Campbell, Ganco, Franco, & Agarwal, 2012; Castanias & Helfat, 2001), undermining technology development. Third, after hiring and training employees and investing in R&D programs, engineers and scientists may leave to exploit the discoveries they made while being employed by the focal firm at rival firms. Thus, knowledge worker departures can lead to significant knowledge spillover to rivals (Rosenkopf & Almeida, 2003; Song et al., 2003), facilitating imitation and adversely affecting the expected returns from significant increases in R&D by the focal firm.

On the other hand, significant decreases in R&D investments can be problematic for knowledge workers (Gino & Pisano, 2006), inducing them to quit their jobs. To prevent such departures, and thereby to mitigate the risk of knowledge worker mobility, firms can be expected to not engage in significant R&D cuts when legal regimes expose firms to a

higher threat of knowledge mobility. The projects that suffer from reduced financing tend to be the ones that are more exploratory, more fundamental in nature, involving the “good science” beloved by knowledge workers (Dasgupta & David, 1994; Gittelman & Kogut, 2003), i.e., projects that are intellectually engaging and earn greater esteem within their professional guild. Knowledge workers prefer to continue existing projects until results are obtained (Bernardo, Cai, & Luo, 2001) as making a significant scientific discovery can lead to the receipt of important rewards (Dasgupta & David, 1994; Merton, 1957; Sorenson & Fleming, 2004). Moreover, ending an ongoing project places a researcher at a distinct disadvantage with respect to performance appraisals, hurting researcher morale (Balachandra, Brockhoff, & Pearson, 1996). In addition, upon facing cuts in R&D, knowledge workers become more concerned about the future strategic direction of the firm and its implications for their career progression (Balachandra et al., 1996; Bernardo et al., 2001; Dasgupta & David, 1994; Sorenson & Fleming, 2004). Insufficient support during this time can fuel career uncertainty, feelings of resentment and alienation, and lack of trust in the management that can induce knowledge workers to potentially voluntarily quit their jobs (Holtom, Mitchell, Lee, & Inderrieden, 2005; Lee et al., 2017; Morgeson, Mitchell, & Liu, 2015).

Investments in R&D are a part of firms’ long-term strategy and the decision to significantly decrease R&D involves understanding the benefits of R&D cuts compared to the long-term decrease in the value of previous R&D investments as successful innovation at the firm level requires consistent investments and accumulation of knowledge over time (Dierickx & Cool, 1989; Grabowski, 1968; Hambrick et al., 1983; Kor & Mahoney, 2005). The departure of knowledge workers leads to the loss of valuable knowledge that can disrupt the R&D function of the firm for many years to come. Research workers tend to have highly specialized skills that make them particularly well suited to certain research projects (Wang, He, & Mahoney, 2009) and finding replacements for knowledge workers that leave can be difficult and time-consuming, hampering the accumulation of knowledge over time. The issue becomes especially pertinent when barriers to employee mobility are lowered. Therefore, when legal barriers to knowledge worker mobility are removed, firms can be expected to avoid significant decreases in R&D to mitigate the threat of losing specialized knowledge workers and disrupting their long-term R&D investment strategy.

In sum, the above arguments suggest that higher mobility-induced appropriability challenges reduce firm R&D dynamism, dampening firm incentives to engage in major upward or downward adjustments in R&D expenditure and favoring more cautious, gradual adjustments to R&D, thus lowering the volatility of firm R&D expenditure. Thus, we hypothesize:

Hypothesis 1 (H1): The threat of knowledge worker mobility has a negative effect on firm R&D volatility.

Yet, firms may possess alternate mechanisms for mitigating R&D appropriability concerns arising from the threat of employee mobility. One such mechanism documented by prior research is establishing a reputation for litigiousness (Agarwal et al., 2009; Ganco et al., 2015).

A firm's aggressiveness in patent enforcement through litigation can deter employees' decision to quit to join or form rival companies. Enforcing patent rights through litigation is costly and attracts media attention (Graham, Merges, Samuelson, & Sichelman, 2009). Thus, it serves as a costly and observable action that can be used by third parties as a sorting function (Connelly, Certo, Ireland, & Reutzel, 2011; Spence, 1974). If a former employer has invested in prior litigation to bar direct market rivals from unauthorized use of its patent protected technologies, hiring organizations and employees may perceive that the firm is tough rather than passive in protecting its knowledge (Toh & Kim, 2013). Employees and their potential hirers can therefore gauge which firms are likely to adopt a more protective stance against unauthorized uses of proprietary technologies. Prior litigiousness of the focal firm credibly informs the expectations of future action of potential hirers of its employees and of its employees, thus deterring employee mobility (Ganco et al., 2015).

Moreover, even if employees do join other firms, reputation for litigiousness deters employees from disclosing their prior employers' valuable knowledge upon joining. Indeed, Agarwal et al. (2009) find that employees and hiring organizations have lower

incentives to misappropriate technologies from firms that have established reputations for litigiousness.

In sum, establishing a reputation for litigiousness helps mitigate concerns of R&D appropriability by (i) reducing employees' propensity to join a rival firm, and (ii) reducing employees' propensity to disclose the firm's valuable knowledge even if they join a rival firm. Thus, a firm that has established a reputation for litigiousness should, *ceteris paribus*, be less prone to the “caution”, dampening effect that anticipated knowledge worker mobility has on firm R&D dynamism. Thus, we hypothesize:

Hypothesis 2 (H2): The negative effect of the threat of knowledge worker mobility on R&D volatility is weaker for firms that have established a reputation for litigiousness.

3.4. Methods

3.4.1. Data and sample

To test our hypotheses, we use data of publicly traded U.S. manufacturing firms. The manufacturing industry exhibits high R&D (Hall et al., 2005; Mudambi & Swift, 2014) and employee mobility, which weakens appropriability of R&D. Our initial sample is generated from the Compustat Annual North America database (Standard & Poors, 2009). We obtain financial and R&D related data for U.S. manufacturing firms (SIC codes 2,000 to 3,999) from Compustat. This dataset covers the years 1991-2018. Each observation represents one firm-year. After removing observations with missing values, the dataset contains 900 unique firms and 15,000 firm-year observations. This dataset is merged with data from PatentsView for information on patenting activities of the firms, Public Access to Court Electronic Records for information on patent infringement lawsuits filed by the firms, Boardex for information on corporate governance, Thomson Reuters Institutional (13f) Holdings for information on institutional ownership, and Bureau of Economic Analysis for information on the state-level characteristics.

3.4.2. Measures

3.4.2.1. Dependent variable

The dependent variable is the *R&D volatility*. Volatility in R&D expenditures is an observable marker of unexpected changes in firms' R&D expenditures because of proactive R&D management (Mudambi & Swift, 2011, 2014). We measure it using the time varying conditional variance estimate derived from an Autoregressive Conditional Heteroskedastic (ARCH) time trend of R&D spending that the firm exhibits over the period of the study. We use this R&D expenditure trend to estimate the extent to which a firm's R&D spending diverges from the predicted R&D spending obtained using the ARCH model (Anderson & Tushman, 2001; Folta & O'Brien, 2004; Oriani & Sobrero, 2008). In other words, this measure captures the unexpected changes in R&D spending net of R&D expenditure growth and also identifies the extent of changes in R&D spending relative to all of the changes that the firm exhibits during the study period.

The calculation is performed using a two-step process. First, to make the time-series of firm-level R&D expenditures stationary, we transform the R&D expenditures to log changes in R&D for each year (Hamilton, 1994). Second, we use the transformed time-series to estimate the R&D expenditure trend over time using an ARCH model. To capture the unexpected changes in the R&D expenditures, we measure the time-varying volatility of R&D expenditures using the conditional variance estimates for each year obtained from the ARCH model. The ARCH model can be represented as follows:

$$r_{i,t} = \beta \cdot r_{i,t-1} + \varepsilon_{i,t}$$
$$Var(\varepsilon_{i,t}) = Var_{i,t} = \alpha_0 + \delta \cdot \varepsilon_{i,t-1} + v_t$$

where $r_{i,t}$ is the continuous changes in R&D expenditures of a firm i at time t , and $Var(\varepsilon_{i,t})$ is the conditional variance of the error term $\varepsilon_{i,t}$. v_t is independent and identically distributed.

The conditional variance of the error term captures the volatility of a firm R&D expenditures for each year. Finally, to deal with the skewed distribution of the conditional variance of firm R&D expenditures, we take of the conditional variance estimate.

3.4.2.2. Independent variables

Our main independent variable is the *Threat of Knowledge Worker Mobility*, and we measure it by exploiting the changes in the inevitable disclosure doctrine laws across U.S. states. The inevitable disclosure doctrine prevents employees with valuable know-how from working for a competitor or founding a rival firm on the grounds that they would inevitably disclose trade secrets (Lowry, 1988). A rule in the favour of inevitable disclosure doctrine provides employers with a strong mechanism to reduce the inter-firm mobility of their inventors by obtaining a court injunction against departing inventors (e.g., Castellaneta, Conti, Veloso, & Kemeny, 2016; Contigiani, Hsu, & Barankay, 2018; Gilson, 1999; Png, 2017). Conversely, a rule against the inevitable disclosure doctrine removes this important mobility restriction for inventors, increasing their mobility (Flammer & Kacperczyk, 2019).

We measure the *Threat of Knowledge Worker Mobility* using the rejection of the inevitable disclosure doctrine, which occurs when a U.S. state court rules that the doctrine is not enforceable in the state. The inevitable disclosure doctrine does not apply to the state of incorporation but to the state of location, which we proxied using the state of headquarters' location provided in Compustat. The *Threat of Knowledge Worker Mobility* is a dummy variable that equals one for subsequent years if the firm is located in the state that has rejected the inevitable disclosure doctrine by year t . Since the rejection of inevitable disclosure doctrine offers an exogenous variation in firm's exposure to the threat of knowledge worker mobility, it allows us to how firms adjust their R&D strategy in response to such a threat. During the period of observation, i.e., 1991 to 2013, 14 states in the U.S. had rejected the IDD (Flammer & Kacperczyk, 2019; Kahnke & Bundy, 2013; Kahnke et al., 2008)¹¹.

¹¹ The states rejecting inevitable disclosure laws are Virginia (1991), Florida (2001), California (2002), Michigan (2002), Maryland (2004), Ohio (2008), Arkansas (2009), New York (2009), Wisconsin (2009), New Hampshire (2010), Massachusetts (2012), New Jersey (2012), Washington (2012),

Our second independent variable is *Litigiousness*. A firm's reputation of being litigious in enforcing its patent rights deters employees to voluntarily quit their jobs and to use or disclose the valuable knowledge of their previous employer in case they do so (Agarwal et al., 2009; Ganco et al., 2015). Thus, litigiousness serves as a knowledge protection mechanism that helps mitigate concerns related to R&D appropriability. Following prior research (ibid.), we measure *Litigiousness* based on the observed enforcement of exclusionary rights that a firm accumulated by patenting its technologies. In particular, we use a five-year cumulative count of the number of unique patent infringement lawsuits launched by a source firm.

3.4.2.3. Control variables

We control for several factors that may be simultaneously related to our dependent variable and independent variables. As large firms may find it easier to finance their R&D, we control for the *Size* of the firm as the log of its total assets in a given year. We also control for the financial status of the focal firm using *Return on Assets*, *Cash Balance*, and *Leverage*. *Return on Assets* is measured as the ratio of earnings before interest, tax, depreciation and amortization to total assets of a firm in year *t*. *Cash Balance* is measured as the ratio of cash and cash equivalents to total assets of a firm in year *t*. *Leverage* is measured as the ratio of long-term debt to total assets of a firm in year *t*. Further we control for focal firms' *Capital Intensity*, which is the ratio of the net property, plant, and equipment to the total number of employees at the end of the previous year (Hall & Ziedonis, 2001).

A set of relevant control variables is firm knowledge base characteristics. In particular, we control for *Knowledge Base Size*, *Knowledge Base Diversity*, and *Knowledge Base Complexity*. *Knowledge Base Size* is measured as the count of the number of patents that a firm has obtained between years *t-5* and *t*. *Knowledge Base Diversity* is the number of patent classes that a firm has obtained a patent in between years *t-5* and *t*. *Knowledge Base*

Georgia (2012). The years of rejection of the of the inevitable disclosure doctrine in the above states and the relevant court rulings are adopted from Kahnke et al. (2008) and Flammer & Kacperczyk (2019).

Complexity is the average number of patent classes that patents obtained between years t-5 and t by a firm are assigned into.

In our estimations, we also account for the competition and industry characteristics faced by a firm. We control for *Downstream Expenses* using the amount that a firm had spent on Selling, General, and Administrative Expenses (SG&A) in year t (Rothaermel & Boeker, 2008). Another relevant control variable is *Advertisement Intensity*, which we measure as the ratio of advertisement expenses to total sales in year t (Ellis, Fee, & Thomas, 2012). We also control for *Firm Growth Rate* measured as the percentage change in sales achieved by a firm between years t-1 and t. Further, we control for *Industry Growth* and *Industry Concentration*. *Industry Growth* is measured based on the change in total sales achieved by firms in the same SIC code as the focal firm between years t-1 and t. While *Industry Concentration* is measured using the Herfindahl index of sales of firms in the same SIC code as the focal firm in year t.

We also control for firms' governance characteristics that may affect its R&D allocation. Specifically, we control for *Board Size*, *Board Independence*, *CEO Duality*, *Number of Institutional Investors*, and *Ownership by Institutional Investors*. We measure *Board Size* as the number of members in firms' board in year t. We measure *Board Independence* as the ratio of the outside independent directors, i.e., directors who have never served as executive director, executive officer or employee of the firm, on the board (Anand & Khanna, 2000; Desender, Aguilera, Lópezpuertas-Lamy, & Crespi, 2016). *CEO Duality* is an indicator of CEO power relative to the board (Campbell, Campbell, Sirmon, Bierman, & Tuggle, 2012; Haynes & Hillman, 2010), and we measure it as a dummy variable that takes a value of 1 when CEO is the chairman of the board in year t, otherwise 0. As institutional investors affect firms' corporate governance and strategies (Aggarwal, Erel, Ferreira, & Matos, 2011; Chaganti & Damanpour, 1991), we control for the *Number of Institutional Investors* and *Ownership by Institutional Investors*. We measure the *Number of Institutional Investors* as the number of institutional investors that own shares of a firm

in year t and *Ownership by Institutional Investors* as the percentage of shares of a firm owned by the institutional investors in year t ¹².

Finally, to account for the possibility that state-level characteristics that may affect firm R&D dynamics, we control for the log of the GDP of the state in which the firm is headquartered. Another state-level variable that we control for is the strength in the enforcement of non-competes across states as it would affect a firm's ability to retain knowledge workers (Garmaise, 2011; Starr, 2019).

3.5. Models

Empirically, it is difficult to estimate how the threat of knowledge worker mobility affects firm R&D dynamics. For instance, one could regress a measure of firm R&D on some measure of knowledge workers mobility. Yet, such regression is subject to a classic endogeneity problem, that is, unobservable firm characteristics may drive a spurious relationship between the two. To rule out such alternative explanations, it is necessary to leverage a research design that provides exogenous shifts in the threat of knowledge worker mobility. The specific source of exogenous variation we used in this paper is the rejection of the inevitable disclosure doctrine. To examine whether the threat of knowledge worker mobility affects firms' R&D dynamics, we use a difference-in-differences methodology based on staggered rejection of involuntary disclosure doctrine by 14 U.S. states. We follow the difference-in-differences methodology in the presence of staggered treatments at the state level as applied by Bertrand & Mullainathan (2003) and estimate the models using firm fixed effects ordinary least squares regressions.

Moreover, we control for time trends by including year dummies in all the models. Further, to account for the serial correlation of the error terms, we cluster the standard errors at the state-of-firm-location level (Imbens & Wooldridge, 2009). The main specification that we estimate is as follows:

$$R\&DVolatilty_{i,t} = \alpha_i + \alpha_t + \alpha_j X_{j,t} + \alpha_r X_{r,t} + \beta.Treatment_{s,t} + \lambda.Z_{i,t} + \gamma.X_{i,s,t} + \varepsilon_{i,t} \quad (1)$$

¹² The data on institutional investors that is available on Thomson Reuters Institutional (13f) Holdings is based on the information from SEC form 13f, which is filed by institutional investment managers with at least USD 100 million in equity assets under management.

where i indexes the firm, t indexes the time, j indexes the two-digit SIC industries, s indexes the state of the firms' headquarters, and r indexes Bureau of Economic Analysis regions; α_i are firm fixed effects; α_t are year fixed effects; $\alpha_j X \alpha_t$ are industry by year fixed effects; and $\alpha_r X \alpha_t$ are region by year fixed effects, respectively.¹³ Treatment is the *Threat of Knowledge Worker Mobility*, measured using the rejection of inevitable disclosure doctrine; $Z_{i,t}$ is the vector of other independent variables, in this case, *Litigiousness*; $X_{i,s,t}$ is the vector of control variable; $\varepsilon_{i,t}$ is the error term.

In the regression equation (1), α_i accounts for unobserved heterogeneity at the firm level¹⁴. The inclusion of $\alpha_j X \alpha_t$ accounts for time varying industrial effects that may correlate with the treatment. Similarly, the inclusion of $\alpha_r X \alpha_t$ accounts for time varying regional effects that may correlate with the treatment (We did not include interaction terms between state and year in the regression because the treatment is at the state-year level).

As the rejection of the inevitable disclosure doctrine is staggered over time across states, in all the regressions the composition of both the treatment group and the control group changes over time as more states are progressively treated.

3.6. Results

Table 3.1 provides the distribution of the entire sample. It presents the year of rejection of Inevitable Disclosure Doctrine (a proxy for the main independent variable, Threat of Knowledge Worker Mobility) in the U.S. states, frequency of firm-year observations in each state in our sample and the percentage of firm-observations that are post rejection of Inevitable Disclosure Doctrine in each state. The number of firm-years located in the 14 states that rejected the Inevitable Disclosure Doctrine is 9,702, representing about 64.31% of the total sample size. The firm-year observations are reasonably well distributed across

¹³ For the mapping of states to regions, see Bureau of Economic Analysis: <https://apps.bea.gov/regional/docs/regions.cfm>.

¹⁴ Controlling for firm-fixed effects subsumes state-fixed effects, and thus are not included separately in the regression.

these states, but a large number of observations are from California (3,660). Table 3.2 reports descriptive statistics and simple pairwise correlations between the variables used to test our hypotheses. The results of pairwise correlations and the mean of variance inflation factors (mean VIF: 1.52) associated with our explanatory variables raised no significant concerns regarding multicollinearity.

Table 3.3 reports the results of difference-in-differences ordinary least squares regressions that test our hypotheses. In all the regressions the dependent variable is *R&D Volatility*. Models 1-2 show the main results of the analysis testing hypothesis 1 (H1) and hypothesis 2 (H2). In the estimation for model 1 the control group at a given time consists of all the firms in the sample that are not treated up to year t . Supporting H1, in model 1 the coefficient of the *Threat of Knowledge Worker Mobility* is negative and significant ($-0.116, p < 0.01$). The results in model 2 support H2 as the coefficient of the interaction term between the *Threat of Knowledge Worker Mobility* and *Litigiousness* is positive and significant ($-0.05, p < 0.05$).

3.6.1. Dynamic analysis

We perform several robustness checks to validate our empirical results. Casual interpretations using difference-in-differences methodology rely on the parallel trends assumption, i.e., the treatment and control group follow parallel trends before the treatment occurs, in this case, rejection of the Inevitable Disclosure Doctrine (Bertrand & Mullainathan, 2003). In model 3, we inspect the parallel trend assumption of the difference-in-differences methodology. We test the parallel trends assumption by including the Threat of Knowledge Worker Mobility (-1), Threat of Knowledge Worker Mobility (0) Threat of Knowledge Worker Mobility (+1), and Threat of Knowledge Worker Mobility (+2), which equal 1 if the firm is headquartered in a state that will reject the inevitable disclosure doctrine in two years, will reject the inevitable disclosure doctrine in one year, rejected the inevitable disclosure doctrine in the current year, rejected the inevitable disclosure doctrine one year ago, rejected the inevitable disclosure doctrine two years ago, respectively, otherwise 0 (Flammer & Kacperczyk, 2019). There is no evidence of an existing pre-trend as the coefficients of the *Threat of Knowledge Worker Mobility* (-

1) (0.004, $p > 0.10$) and the *Threat of Knowledge Worker Mobility* (0) (-0.052 , $p > 0.10$) are insignificant. While the coefficients of the *Threat of Knowledge Worker Mobility* (1) (-0.074 , $p < 0.05$), and the *Threat of Knowledge Worker Mobility* (2) (-0.145 , $p < 0.01$) are negative and significant, suggesting that an increase in the *Threat of Knowledge Worker Mobility* (as proxied by the rejection of the *Inevitable Disclosure Doctrine*) reduces R&D Volatility of the treated firms.

Table 3.1. Sample distribution across U.S. states

State	Year of Rejection of Inevitable Disclosure Doctrine *	Firm-Year Observations	Percentage of Observations Post Rejection of Inevitable Disclosure Doctrine
AL		42	0.00
AR	2009	18	0.00
AZ		185	0.00
CA	2002	3,660	0.58
CO		248	0.00
CT		453	0.00
DC		26	0.00
DE		49	0.00
FL	2001	523	0.58
GA	2013	250	0.11
HI		26	0.00
IA		41	0.00
ID		26	0.00
IL		783	0.00
IN		235	0.00
KS		9	0.00
KY		61	0.00
MA	2012	1,248	0.14
MD	2004	282	0.47
ME		42	0.00
MI	2002	533	0.56
MN		603	0.00
MO		149	0.00
MT		15	0.00
NC		219	0.00
NE		43	0.00
NH	2010	128	0.12
NJ	2012	716	0.14
NV		42	0.00
NY	2009	1,089	0.24
OH	2008	474	0.31
OK		20	0.00
OR		223	0.00
PA		662	0.00
RI		132	0.00
SC		64	0.00
SD		7	0.00
TN		118	0.00
TX		670	0.00
UT		190	0.00
VA	1999	192	0.65
WA	2012	270	0.17
WI	2009	319	0.27

* The years of rejection of the of the inevitable disclosure doctrine in the above states and the relevant court rulings are adopted from Kahnke et al. (2008) and Flammer & Kacperczyk (2019).

Table 3.2. Descriptive statistics and correlations

Variables	Mean	S.D.	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
[1] R&D Volatility	-2.55	1.49	1											
[2] Threat of Knowledge Worker Mobility	0.28	0.45	-0.04	1										
[3] Litigiousness	0.39	1.28	-0.11	0.04	1									
[4] Size	5.11	2.48	-0.43	0.09	0.29	1								
[5] Capital Intensity	0.49	1.43	0.04	0.00	-0.01	-0.04	1							
[6] Downstream Expenses	0.66	1.57	0.05	0.03	-0.01	-0.07	0.36	1						
[7] Dividend	0.02	0.26	0.02	0.01	0.00	-0.05	0.00	0.15	1					
[8] Cash	0.29	0.27	0.26	0.16	-0.08	-0.31	0.06	0.05	0.01	1				
[9] Leverage	0.26	0.46	-0.01	0.01	.000	0.02	0.00	0.00	-0.01	0.00	1			
[10] Return on Assets	-0.08	0.57	-0.06	-0.05	0.02	0.17	-0.02	-0.50	-0.03	-0.06	0.01	1		
[11] Industry Growth	0.08	0.25	0.05	-0.08	0.00	-0.06	0.01	0.00	0.00	0.04	0.00	0.00	1	
[12] Industry Concentration	0.25	0.19	-0.14	-0.02	-0.01	0.07	-0.03	-0.03	0.00	-0.25	0.01	0.02	-0.03	1
[13] Advertisement Intensity	0.01	0.16	0.02	-0.01	0.01	-0.02	0.07	0.17	0.06	0.02	0.00	-0.01	0.00	0.00
[14] Knowledge Base Size	46.33	178.34	-0.10	0.03	0.29	0.24	-0.01	-0.01	0.00	-0.05	0.00	0.01	-0.01	-0.03
[15] Knowledge Base Complexity	1.67	2.18	-0.10	0.01	0.24	0.15	-0.01	0.06	-0.01	-0.05	0.01	0.01	-0.01	-0.05
[16] Knowledge Base Diversity	6.23	15.86	-0.19	0.06	0.42	0.39	-0.02	-0.01	0.00	-0.12	0.00	0.02	-0.02	0.01
[17] Board Size	5.43	4.21	-0.29	0.02	0.17	0.51	-0.01	-0.04	-0.01	-0.05	0.01	0.06	-0.07	0.05
[18] Board Independence	0.15	0.23	-0.04	-0.12	0.00	0.03	-0.02	-0.02	-0.02	0.00	0.01	0.03	0.03	0.02
[19] CEO Duality	0.37	0.48	-0.14	-0.02	0.10	0.24	-0.01	-0.02	-0.01	-0.1	0.00	0.04	-0.01	0.02
[20] CEO Tenure	3.94	5.64	-0.12	0.06	0.02	0.11	-0.01	-0.02	-0.02	-0.03	0.00	0.03	0.01	-0.02
[21] Ownership by Institutional Investors	0.32	0.35	-0.32	0.18	0.18	0.55	-0.04	-0.04	-0.03	-0.08	0.01	0.06	-0.04	0.06
[22] Enforcement of Non-competes	3.54	2.44	-0.02	-0.31	-0.05	0.00	0.01	0.01	0.01	-0.19	0.00	0.00	-0.01	0.08
[23] State GDP	13.08	0.97	0.00	0.53	0.07	0.07	0.00	0.00	0.00	0.24	0.00	-0.01	-0.02	-0.07

Variables	Mean	S.D.	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	[21]	[22]	[23]
[13] Advertisement Intensity	0.01	0.16	1										
[14] Knowledge Base Size	46.33	178.34	0.00	1									
[15] Knowledge Base Complexity	1.67	2.18	0.00	0.14	1								
[16] Knowledge Base Diversity	6.23	15.86	0.00	0.78	0.34	1							
[17] Board Size	5.43	4.21	0.01	0.12	0.09	0.23	1						
[18] Board Independence	0.15	0.23	0.00	-0.02	0.02	-0.01	0.11	1					
[19] CEO Duality	0.37	0.48	-0.01	0.06	0.07	0.12	0.40	0.23	1				
[20] CEO Tenure	3.94	5.64	0.00	0.00	0.04	0.02	0.27	0.17	0.32	1			
[21] Ownership by Institutional Investors	0.32	0.35	-0.02	0.11	0.12	0.21	0.45	0.05	0.2	0.15	1		
[22] Enforcement of Non-competes	3.54	2.44	0.00	-0.03	-0.03	-0.04	0.02	0.06	0.05	-0.02	-0.02	1	
[23] State GDP	13.08	0.97	0.00	0.04	0.04	0.07	0.15	-0.09	-0.02	0.07	0.11	-0.60	1

Table 3.3. Difference-in-differences regression models of R&D volatility

VARIABLES	Model [1]	Model [2]	Model [3] Parallel Trends Assumption
Threat of Knowledge Worker Mobility	-0.116*** (0.038)	-0.126*** (0.038)	
Threat of Knowledge Worker Mobility X Litigiousness		0.020** (0.009)	
Litigiousness	-0.011* (0.006)	-0.019** (0.009)	-0.011* (0.006)
Threat of Knowledge Worker Mobility (-1)			0.004 (0.075)
Threat of Knowledge Worker Mobility (0)			-0.052 (0.042)
Threat of Knowledge Worker Mobility (+1)			-0.074* (0.041)
Threat of Knowledge Worker Mobility (+2)			-0.145*** (0.040)
Size	-0.036** (0.014)	-0.036** (0.014)	-0.036** (0.014)
Capital Intensity	-0.002 (0.004)	-0.002 (0.004)	-0.002 (0.004)
Downstream Expenses	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Dividend	-0.040 (0.082)	-0.040 (0.082)	-0.039 (0.082)
Cash	0.141* (0.077)	0.140* (0.077)	0.140* (0.078)
Leverage	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)
Return on Assets	0.001 (0.002)	0.001 (0.001)	0.001 (0.001)
Industry Growth	0.050 (0.034)	0.051 (0.034)	0.051 (0.034)
Industry Concentration	-0.031 (0.142)	-0.032 (0.143)	-0.030 (0.143)
Advertisement Intensity	0.340*** (0.091)	0.339*** (0.091)	0.338*** (0.091)
Knowledge Base Size	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Knowledge Base Complexity	-0.028*** (0.009)	-0.028*** (0.009)	-0.029*** (0.009)
Knowledge Base Diversity	-0.003* (0.002)	-0.003* (0.002)	-0.003* (0.002)
Board Size	-0.008 (0.008)	-0.008 (0.008)	-0.008 (0.008)
Board Independence	-0.066 (0.089)	-0.066 (0.089)	-0.065 (0.090)

CEO Duality	0.028 (0.035)	0.028 (0.035)	0.027 (0.034)
CEO Tenure	-0.005* (0.003)	-0.005* (0.003)	-0.005* (0.003)
Ownership by Institutional Investors	-0.163*** (0.052)	-0.164*** (0.052)	-0.162*** (0.052)
Enforcement of Non-competes	-0.135 (0.096)	-0.134 (0.096)	-0.134 (0.095)
State GDP	-0.569*** (0.204)	-0.578*** (0.205)	-0.555*** (0.189)
Constant	5.480** (2.522)	5.582** (2.538)	5.296** (2.333)
Observations	15,085	15,085	15,085
Number of Firms	913	913	913
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Industry X Year FE	YES	YES	YES
Region X Year FE	YES	YES	YES

Robust standard errors clustered at State-level are in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%

3.6.2. Alternate Control and Treatment Groups

Another potential concern regarding the casual evidence is that our findings may be driven by the differences between the states that rejected the Inevitable Disclosure Doctrine and those that did not. To test the robustness of our design choice, we re-run our main models, on just the subsample of firms that are headquartered in the 14 states that rejected the Inevitable Disclosure Doctrine. In model 4 and model 5 we restrict the control group at a given time to all the firms in the sample that are not treated up to year t but would be eventually treated during our period of observation. The results of model 4 and model 5 are qualitatively similar in size and significance to the main results, and thus provide additional support for H1 and H2.

We also perform tests to rule out the possibility that our results are driven by large number of firm-year observations in a state that rejected the Inevitable Disclosure Doctrine. For this robustness check, we exclude all the firms from California and Massachusetts, the two states with the largest number of firm-year observations in our sample. In Table 3.4, model 6 and model 7 present the results testing H1 with a subsample of firms that are headquartered in states other than California and Massachusetts, respectively. The results

of model 6 and model 7 are qualitatively similar in size and significance to the main results, and thus provide additional support for H1.

3.6.3. Cross-sectional variation in the impact of the threat of knowledge worker mobility

Moreover, we explore the heterogeneity in the relationship between the *Threat of Knowledge Worker Mobility* and *R&D Volatility*. Specifically, we examine how the treatment effect varies by the strength of enforcement of non-compete covenants and presence of geographically proximate rival R&D. First, as the enforcement of non-compete covenants in a state is expected to improve firms' ability to retain knowledge workers (Garmaise, 2011; Marx, Strumsky, & Fleming, 2009), we checked how the strength of non-compete enforceability affect the relationship between threat of knowledge worker mobility and R&D volatility. We use the strength of non-compete enforceability as provided by Starr (2019). As enforceability of non-compete covenants restrict employee mobility, we expect that the effect of the threat of knowledge worker mobility on R&D volatility would be weaker for firms that are located in states that have a higher value of the strength of non-compete enforceability index Starr (2019). However, the moderation effect of the strength of non-compete enforceability is not significant (see model 8 in Table 3.5). Second, since prior research has documented that employees are more likely to depart and to join geographically proximate rival firms (Almeida & Kogut, 1999), we checked if geographically proximate rival R&D moderate the main relationship. We measure *Geographically Proximate Rival R&D* for a focal firm as the ratio of the cumulative R&D expenditures to cumulative total assets of all the firms that are located in the same state as the focal firm and belong to the same four-digit sic code as that of the focal firm (McGahan & Silverman, 2006). In line with our theory, *Geographically Proximate Rival R&D* weakens the negative relationship between the *Threat of Knowledge Worker Mobility* and *R&D Volatility* (see model 9 in Table 3.5).

3.6.4. Impact on drastic increases and decreases in R&D

To provide further support to our proposed theory, we perform separate checks to examine the impact of the *Threat of Knowledge Worker Mobility* on drastic increases and decreases

in R&D. We compute drastic increases and decreases in R&D using residuals from the ARCH models of R&D expenditures (as discussed in the section on Variable Definition). In order to determine whether the changes in R&D expenditures are significant, we develop indicator variables. The indicator variable capturing drastic increases in R&D expenditures is set to a value of 1 if the residuals obtained using ARCH model of R&D for a focal firm are in the top 10 percent by value (i.e., high positive values). Similarly, the indicator variable capturing drastic decreases in R&D expenditures is set to a value of 1 if the residuals obtained using ARCH model of R&D for a focal firm are in the bottom 10 percent by value (i.e., high negative values). In addition, we compute the above-described indicator variables using different cut-off values such as top and bottom 25, 15, and 5 percent of residuals for a firm.

To examine the impact of the *Threat of Knowledge Worker Mobility* on drastic changes in firm R&D expenditures, we use firm fixed effect logistic regressions and the indicator variables for drastic increases and decreases of R&D as dependent variables. Supporting our arguments, we find that the coefficient of the *Threat of Knowledge Worker Mobility* predicting drastic increases in R&D is negative and significant. The coefficient of the *Threat of Knowledge Worker Mobility* predicting drastic decreases in R&D is not significant.

3.6.5. Additional robustness checks

Finally, we perform two additional robustness checks. We measure the *Threat of Knowledge Worker Mobility* using the rejection of the Inevitable Disclosure Doctrine in the state of the focal firms headquarter location as obtained from Compustat. Such a measure raises issues because Compustat does not track the location of the headquarter of firms over time and provides only the latest headquarter location. Another issue with the measure is that as many firms are dispersed across multiple states, then different employees at these firms are subjected to different legal regimes. We perform a robustness check by limiting the sample to firms that have at least 80 percent of their operations in the state of headquarter location. For this robustness check, we use the data provided by García & Norli (2012) on the state-wise dispersion of firm operations based on the 10-K

filings. The results for the restricted sample are qualitatively similar in size and significance to the main results, and thus provide additional support for H1.

To further support our hypotheses, we re-run the models with the adoption of Inevitable Disclosure Doctrine in the U.S. states as the independent variable. As documented by prior research, the adoption of the doctrine provides the employers with a strong mechanism to restrict the mobility of their knowledge workers (e.g., Castellaneta et al., 2016; Contigiani et al., 2018; Gilson, 1999; Li, Lin, & Zhang, 2018). We use the data on the adoption of Inevitable Disclosure Doctrine in the U.S. states as provided by Li et al. (2018). In line with our theory, the results show that the adoption of Inevitable Disclosure Doctrine has a positive impact on firm R&D volatility.

Table 3.4. Difference-in-differences regression models of R&D volatility using alternate control and treatment groups

Variables	Model [4] For the firms that experienced the transition in inevitable disclosure doctrine laws	Model [5]	Model [6] Excluding firms in California	Model [7] Excluding firms in Massachusetts
Threat of Knowledge Worker Mobility	-0.092** (0.040)	-0.107** (0.041)	-0.088* (0.052)	-0.148*** (0.048)
Threat of Knowledge Worker Mobility X Litigiousness		0.033** (0.012)		
Litigiousness	-0.011* (0.006)	-0.031** (0.013)	-0.011 (0.009)	-0.012* (0.006)
Size	-0.050*** (0.015)	-0.050*** (0.015)	-0.029 (0.019)	-0.037** (0.015)
Capital Intensity	-0.002 (0.003)	-0.002 (0.003)	-0.004 (0.003)	0.003 (0.004)
Downstream Expenses	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Dividend	0.025 (0.073)	0.025 (0.073)	-0.061 (0.092)	-0.025 (0.083)
Cash	0.096 (0.109)	0.094 (0.109)	0.156 (0.111)	0.176** (0.076)
Leverage	-0.004*** (0.000)	-0.004*** (0.000)	-0.003** (0.001)	-0.003*** (0.001)
Return on Assets	0.002* (0.001)	0.002* (0.001)	0.001 (0.002)	0.001 (0.002)
Industry Growth	0.059 (0.042)	0.064 (0.040)	0.043 (0.034)	0.029 (0.025)
Industry Concentration	-0.367** (0.138)	-0.374** (0.138)	0.054 (0.157)	-0.003 (0.160)
Advertisement Intensity	0.254** (0.108)	0.252** (0.106)	0.266 (0.185)	0.478*** (0.085)
Knowledge Base Size	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Knowledge Base Complexity	-0.032** (0.013)	-0.032** (0.013)	-0.028** (0.012)	-0.031*** (0.009)
Knowledge Base Diversity	-0.002 (0.003)	-0.002 (0.003)	-0.002 (0.002)	-0.004*** (0.002)

Board Size	-0.007 (0.013)	-0.006 (0.012)	0.000 (0.007)	-0.010 (0.008)
Board Independence	-0.163 (0.095)	-0.163 (0.095)	-0.004 (0.099)	-0.102 (0.082)
CEO Duality	0.044 (0.057)	0.043 (0.057)	-0.002 (0.036)	0.046 (0.031)
CEO Tenure	-0.003 (0.003)	-0.003 (0.003)	-0.006 (0.004)	-0.006** (0.003)
Ownership by Institutional Investors	-0.153* (0.081)	-0.155* (0.080)	-0.165** (0.070)	-0.153** (0.057)
Enforcement of Non-competes	-0.263*** (0.020)	-0.261*** (0.021)	-0.143 (0.094)	-0.012 (0.143)
State GDP	-0.694** (0.316)	-0.710** (0.318)	-0.458** (0.221)	-0.580** (0.271)
Constant	7.711* (4.045)	7.914* (4.066)	3.992 (2.635)	5.130 (3.257)
Observations	8,243	8,243	11,425	13,837
Number of Firms	459	459	681	834
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry X Year FE	YES	YES	YES	YES
Region X Year FE	YES	YES	YES	YES

Robust standard errors clustered at State-level are in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 3.5. Difference-in-differences regression models to examine cross-sectional variation in R&D volatility

VARIABLES	Model [8]	Model [9]
Threat of Knowledge Worker Mobility	-0.122 (0.089)	-0.084 (0.061)
Threat of Knowledge Worker Mobility X Enforcement of Non-competes	0.017 (0.029)	
Threat of Knowledge Worker Mobility X Geographically Proximate Rival R&D		-0.162** (0.076)
Geographically Proximate Rival R&D		0.051 (0.056)
Enforcement of Non-competes	-0.016 (0.146)	-0.042 (0.127)
Litigiousness	-0.012* (0.006)	-0.011* (0.006)
Size	-0.036** (0.014)	-0.034** (0.014)
Capital Intensity	0.003 (0.004)	-0.002 (0.004)
Downstream Expenses	0.000 (0.000)	0.000 (0.000)
Dividend	-0.025 (0.083)	-0.045 (0.081)
Cash	0.176** (0.076)	0.137* (0.075)
Leverage	-0.003*** (0.001)	-0.003*** (0.001)
Return on Assets	0.001 (0.002)	0.001 (0.002)
Industry Growth	0.029 (0.024)	0.049 (0.034)
Industry Concentration	-0.012 (0.160)	-0.043 (0.148)
Advertisement Intensity	0.472*** (0.084)	0.336*** (0.089)
Knowledge Base Size	0.000 (0.000)	0.000 (0.000)
Knowledge Base Complexity	-0.031***	-0.028***

	(0.009)	(0.009)
Knowledge Base Diversity	-0.004***	-0.003**
	(0.002)	(0.002)
Board Size	-0.010	-0.008
	(0.008)	(0.008)
Board Independence	-0.104	-0.064
	(0.082)	(0.089)
CEO Duality	0.044	0.031
	(0.031)	(0.034)
CEO Tenure	-0.006**	-0.005*
	(0.003)	(0.003)
Ownership by Institutional Investors	-0.155***	-0.163***
	(0.057)	(0.053)
State GDP	-0.518	-0.559**
	(0.339)	(0.268)
Constant	4.347	4.825
	(4.093)	(3.240)
Observations	15,085	15,085
Number of Firms	913	913
Firm FE	YES	YES
Year FE	YES	YES
Industry X Year FE	YES	YES
Region X Year FE	YES	YES

Robust standard errors clustered at State-level are in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%

3.7. Discussion

This study examines the impact of the threat of knowledge worker mobility on the dynamics of firm R&D. We propose that that the threat of knowledge worker mobility dampens R&D dynamism, i.e., reduces the volatility of firm R&D expenditure, and that this effect is less pronounced for firms that have alternate mechanisms for mitigating the threat of knowledge worker mobility, such as an established reputation for litigiousness. Using a natural experiment and a difference-in-differences methodology in the context of the US manufacturing industry over the period 1991-2018, we empirically test and find evidence supporting our hypotheses.

This paper makes four contributions to extant literature. First it contributes to the nascent literature exploring the impact of employee mobility on firm R&D strategy. While research has argued that employee protection increases the likelihood of achieving innovation outcomes that have a higher probability of being valuable (Conti, 2014), it has stopped short of examining how anticipated employee mobility affect a firms' decision to commit resources to R&D. We provide theory and evidence that the threat of knowledge worker mobility gives rise to a “caution effect” on firm investment in R&D. In particular, our results suggest that mobility-induced appropriability challenges (Agarwal et al., 2009;

Conti, 2014; Ganco, Ziedonis, & Agarwal, 2015) reduce firm R&D dynamism. We argue that the threat of knowledge worker mobility decreases firm incentives to engage in major upward or downward adjustments to R&D expenditures, and drives firms to make gradual adjustments to their R&D expenditures, thereby, lowering the volatility of firm R&D expenditures. Furthermore, we argue that that this “caution effect” is mitigated for firms that have alternative mechanisms for mitigating the threat of knowledge worker mobility or the associated knowledge spillovers, such as an established reputation for litigiousness.

Second, this study contributes to the literature on R&D dynamics (Kor & Mahoney, 2005; Mudambi & Swift, 2014; Swift, 2016). While prior research has examined the benefits of the persistence of R&D expenditures (Kor & Mahoney, 2005; Mudambi & Swift, 2011), little is known about the antecedents of R&D volatility. Given the well documented puzzle posed by the high persistence of R&D investment over time, which at the firm level is about three times more autocorrelated than capital investment (Bloom, 2007; Triguero & Córcoles, 2013), it is surprising that we know little about the drivers of the limited volatility of firm R&D expenditures. We extend the literature by identifying the threat of knowledge worker mobility and a firm’s reputation for litigiousness as hitherto underexamined determinants of firm R&D volatility.

Third, this study contributes to extant literature on the relationship between firm strategy and the institutional context (e.g., Furman, 2003; Ingram & Silverman, 2002; Pe’er & Gottschalg, 2011). With regard to innovation performance, prior research has found that employment protection laws, on average, increase radical innovation (Conti, 2014), while they decrease radical innovation for lagging firms (Keum, 2020). This study focuses instead on examining the link between anticipated employee mobility and firms’ commitment of resources to R&D, i.e., innovation inputs, rather than innovation performance/outputs. It provides theory and evidence that when the threat of employee mobility increases, the volatility of firm R&D decreases.

Fourth, this study also contributes to the literature on dynamic capabilities (Eisenhardt & Martin, 2000; Teece et al., 1997). Prior research on dynamic capabilities has identified factors that facilitate or hinder the development, maintenance, and usage of dynamic capabilities (Schilke, Hu, & Helfat, 2018). For instance, financial resources (El Akremi,

Perrigot, & Piot-Lepetit, 2015), technological resources (Anand, Oriani, & Vassolo, 2010), R&D investments (Kor & Mahoney, 2005), and slack resources (Danneels, 2008) have been found to be conducive to dynamic capabilities. Our findings contribute to this work by demonstrating that the threat of knowledge worker mobility can significantly hinder the creation of dynamic capabilities as mobility induced appropriability concerns make firms “cautious” about making significant changes to their R&D expenditures.

3.7.1. Limitations and future research

While this paper deepens our understanding of how exogenous changes in the threat of knowledge worker mobility affect the dynamism of firm R&D expenditures, it has limitations that future research could address. First, the generalizability of our results may be affected by contextual differences. Future studies can examine whether and how, for instance, national cultural differences in job hoping (Recht & Wilderom, 1998) and innovation (Shane, 1993, 1992) affect the way relaxation in legal barriers to employee mobility impact firm R&D volatility. Second, the generalizability of our results may be affected by the ownership structure of firms. In this study, we have restricted our sample to public firms. Future research could probe the extent to which our arguments and results generalize for private firms, non-profits or hybrid organizations. For instance, privately owned firms have different risk profiles and time horizons (Jensen & Meckling, 1976) and, thus, the threat of knowledge worker mobility might have a different effect for public relative to private firm decisions to commit resources to R&D activities. In sum, a replication of this study in different settings would help test the generalizability of our theory and results.

This paper suggests several avenues future research could explore. While we argue and show that the dampening effect of the threat of knowledge worker mobility on firm R&D volatility is attenuated for firms that have developed reputations for litigiousness, future research could explore additional contingencies. For instance, future research could examine the extent to which firms dynamically adjust their R&D expenditures when they possess alternate mechanisms for mitigating R&D appropriability concerns arising from the threat of knowledge worker mobility. In addition, research on innovation strategies would benefit from further theoretical advances in understanding the costs and benefits

resulting from a more cautious, less dynamic approach to R&D expenditures in firms that face anticipated knowledge worker mobility. Such theory would help us more comprehensively explain the high persistence of R&D expenditures across time (Bloom, 2007; Triguero & Córcoles, 2013).

3.7.2. Conclusion

The threat of knowledge worker mobility influences firm R&D inputs as firms choose R&D investments that enable them to avoid or minimize the appropriability challenges posed by employee mobility. We argue and find that the appropriability challenges posed by the threat of knowledge worker mobility give rise to a “caution effect” on firm R&D expenditure, decreasing R&D dynamism. Yet, the dampening of R&D dynamism is less pronounced for firms that have alternate mechanisms for mitigating the threat of knowledge worker mobility, such as an established reputation for litigiousness.

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4.

A Speed-Accuracy Tradeoff: Speed of Expansion and Replication Accuracy in Chain Organizations

This chapter examines how a middle managers' speed of expansion affect replication accuracy at units under her supervision.

4.1. Abstract

The replication of a successful set of practices in different geographic locales is the primary growth strategy of multiunit chain organizations such as Starbucks, McDonalds, or Marriott. Yet, despite decades of research and practice, ensuring that required practices are replicated accurately by their individual units continues to be a fundamental challenge for such “replicating” organizations. This paper sheds new light on the issue by arguing that the dual role of middle managers, expansion and monitoring, in multiunit chains and the resulting competing demands on their limited attention give rise to a “speed-accuracy tradeoff”. Thus, when middle managers’ speed of expansion increases, replication accuracy at units under their supervision decreases. We further argue that experiential learning, namely middle managers’ learning from their expansion and failure experience as well as individual units’ learning from their operating experience, ameliorates the tradeoff. Using unique data that tracks middle managers’ speed of expansion and replication accuracy at the units of a large U.S.-based non-food franchise organization over eleven years, we test and find empirical support for the above hypotheses.

Keywords: Knowledge exploitation; replication; organizational learning; attention-based view; multiunit chains

4..2. Introduction

The replication of a successful set of practices in different geographic locales is the primary growth strategy of multiunit chains such as Starbucks, McDonalds, or Marriott (Winter & Szulanski, 2001; Winter et al., 2012). Indeed, chain organizations have become prevalent in a wide array of industries spanning retail, hospitality, banking, real estate, health care, education, or consulting services (Argote & Fahrenkopf, 2016; D’Adderio, 2014; Greve, 2003; Winter et al., 2012). They have become a substantial economic phenomenon with chain’s overall share of U.S. GDP standing at a staggering *three times* that of the entire U.S. manufacturing sector (Gupta, Hoopes, & Knott, 2015) and franchise chains alone contributing 7.4 percent of U.S. private nonfarm GDP and 10.1 percent of U.S. private nonfarm employment (International Franchise Association 2016).

A fundamental and persistent challenge for such “replicating” organizations has been ensuring that required practices are replicated accurately across all of their geographically dispersed units at any given time (Winter & Szulanski, 2001; Winter et al., 2012)¹⁵. While early work on replication strategy hinted at the important monitoring role of middle managers in mitigating the problem of inaccurate replication of practices (Winter & Szulanski, 2001), more recent replication research has documented that replication accuracy at the individual units of multiunit chains can vary widely both in cross section and over time even when such managers are present (El Akremi et al., 2011; Winter et al., 2012). Yet, the question of why this is the case, i.e., what explains the differential effect middle managers have on the accuracy with which required practices are replicated, has received no attention in the literature on replication to date. This paper aims to shed light on the issue. Given that in multiunit chains middle managers are the ones directly in charge of monitoring the accurate replication of required practices in existing units (Bradach, 1998; Brickley & Dark, 1987; Kalnins & Lafontaine, 2013) as well as in charge of expanding the chain organization through the creation of new units in the region under their supervision (Bradach, 1998; Garvin & Levesque, 2008)¹⁶, the specific research question we ask is: How does middle managers’ speed of expansion affect replication accuracy at units under their supervision?

We draw on the attention-based view of the firm (Ocasio, 1997, 2011) to develop theory on how middle managers’ allocation of attention to expansion versus monitoring affects replication accuracy at units under their supervision. We argue that competing demands on middle managers’ attention create a “speed-accuracy tradeoff” such that, *ceteris paribus*, when middle managers’ speed of expansion increases, replication accuracy at

¹⁵ Scholars have also used other terms such as “fixed elements” (Jonsson & Foss, 2011), “mandatory elements” (Ansari, Reinecke, & Spaan, 2014), and “nonplastic practices” (Levinthal & Marino, 2015) to refer to required organizational practices.

¹⁶ Scholars have used different terms such as “middle managers”, “hierarchical managers”, “regional managers”, “area managers”, “area franchisees”, “district managers”, “regional headquarters” and “regional monitoring centers” (Bradach, 1998; Brickley & Dark, 1987; Garvin & Levesque, 2008; Kalnins & Lafontaine, 2013; Kalnins & Mayer, 2004; Winter et al., 2012; Yin & Zajac, 4). Bradach (1998: 208) notes that practitioners often use the above terms interchangeably. We use the term “middle managers”, yet our theory extends to the other aforementioned concepts as well.

units under their supervision decreases. This tradeoff serves as a baseline from which we then argue that the capacity to switch attention focus and better balance the tradeoff—what Ocasio (2011) refers to as executive attention—will be regulated by middle managers' past expansion experience (Kunisch, Bartunek, Mueller, & Huy, 2017; Weick & Sutcliffe, 2006) and past failure experience (Dahlin, Chuang, & Roulet, 2018) as well as by the focal unit's operating experience (Darr, Argote, & Epple, 1995; Desai, 2009). Using unique data that tracks middle managers' speed of expansion and replication accuracy at the units of a large U.S.-based non-food franchise chain over eleven years, we test and find empirical support for our hypotheses.

This study makes three contributions to the literature. First, we contribute to the literature on replication (Winter & Szulanski, 2001; Winter et al., 2012) by identifying novel determinants of replication accuracy, namely middle managers' speed of expansion, prior expansion and failure experience, as well as individual units' operating experience. While prior work has pointed to the presence of a hierarchical manager (Winter & Szulanski, 2001), unit age (D'Adderio, 2014), knowledge discreteness (Williams, 2007), and template performance (Lawrence, 2020) as antecedents of replication accuracy, we examine and find attention and experiential learning mechanisms that govern middle managers' ability to allocate and focus attention on expansion versus monitoring to be important determinants of the accuracy with which required practices are replicated in multiunit chain organizations.

Second, this paper contributes to the attention-based view of the firm (Ocasio, 1997, 2011). Although the importance of executive attention and attentional stability (vigilance) have been documented in prior research (Ocasio, 2011), it is rarely acknowledged that they may have countervailing implications for organizational behavior. As Ocasio and colleagues (2020: 8) note, these mechanisms are somewhat contradictory to each other in the sense that organizational members who vigilantly attend to a particular domain (i.e., exhibit attentional stability/vigilance) may find it difficult to flexibly switch their focus of attention to other domains (i.e., exercise executive attention), or vice versa. Yet, research in this area has yet to investigate the relationship between the two. Our study makes a step in that direction by pointing to important contingencies which moderate this relationship

– in particular, the role of experiential learning in the form of learning from expansion experience, learning from failure experience, and learning from operating experience.

Third, we contribute towards a better understanding of the effect of speed in organizations. While the theory of the growth of the firm (Penrose, 1959), research on the costs of rapid scaling (Chandler, 1990; Pierce & Aguinis, 2013; Sterman, Henderson, Beinhocker, & Newman, 2007), and on time-compression diseconomies (Dierickx & Cool, 1989; Hawk & Pacheco-de-Almeida, 2018) have documented the existence of a tradeoff between speed and other desired outcomes in organizations, this paper is the first to examine and find a relationship between middle managers' speed of expansion and the accuracy of replication of required practices at units under their supervision as well as to clarify the attention and experiential learning mechanisms that govern this relationship.

4.3. Theory and hypotheses

4.3.1. The dual role of middle managers in multiunit chain organizations

According to the variation-selection-retention framework (Burgelman, 1991; Campbell, 1969; Nelson & Winter, 1982), managers are involved in activities related to the variation, selection, and retention of initiatives and practices (Wooldridge, Schmid, & Floyd, 2008). In multiunit chain organizations, middle managers, located below top managers and above first-level supervision in the hierarchy (e.g., Dutton & Ashford, 1993; Uytendaele, 1972; Wooldridge, Schmid, & Floyd, 2008), play an important intermediary or bridging role between the headquarters and the individual units of a chain organization in a given region (Bradach, 1998; Garvin & Levesque, 2008; Kalnins & Lafontaine, 2013). While top management's role is discovering (i.e., variation and selection) a successful set of practices to replicate, middle managers' role is expanding the organization by opening new units as well monitoring that required practices are replicated accurately (i.e., retention) at existing units (Winter & Szulanski, 2001). Attention to activities associated with both objectives is of vital importance to chain organizations in the process of growth by replication: Expanding the chain organization by opening new units is typically their primary driver of revenue and profit growth, yet those expected benefits will not materialize if the

organization cannot ensure the accurate replication of required practices at its units (Ater & Rigbi, 2015; Bradach, 1997; Szulanski & Jensen, 2006).

4.3.1.1. Expansion role of middle managers: Expanding the number of units in a region

Expansion allows organizations to realize economies of scale (Knudsen, Levinthal, & Winter, 2014), increase legitimacy (Zimmerman & Zeitz, 2002), defend against or preempt would-be imitators (Eisenmann, Parker, & Van Alstyne, 2006), and compete with more established organizations (Schilling, 2002). Yet, expansion requires significant commitment of managerial attention (Garud, Kumaraswamy, & Karnøe, 2010) and when the allocation of this limited resource (Ocasio, 1997, 2011) is not managed judiciously, it can lead to errors, value destruction, and failure (Joseph & Wilson, 2018; Penrose, 1959). Managing the expansion process is particularly demanding in the case of geographically dispersed chain organizations (Eisenmann & Wagonfeld, 2012; Winter & Szulanski, 2001).

To overcome, or at least mitigate, the expansion and monitoring challenges posed by distance, chain organizations recruit middle managers to help expand the organization and oversee its operations in a given region. While expanding the network of units in their region, middle managers involve themselves in selecting and training unit owners/managers, selecting outlet sites, as well as helping with the design and construction of outlets (Bradach, 1998; Garvin & Levesque, 2008). These are critical decisions and activities that a middle manager has to make and perform before an individual unit's first day of operation, and they are fundamental to its subsequent success (Kalnins & Mayer, 2004; Salvaneschi, 1996).

4.3.1.2. Monitoring role of middle managers: Ensuring that required practices are replicated accurately

Monitoring the accuracy with which required practices are replicated is a second key role and responsibility for the middle managers of chain organizations. Monitoring is critical because the inaccurate replication of required practices is a major driver of unit failures in chain organizations (Winter et al., 2012). Rich Bachman, a KFC executive, described the challenge of monitoring accuracy of replication of required practices in the thousands of

geographically dispersed KFC franchise units in the following way: “*We are running thousands of identical factories. They need to be the same because customers need to get what they expect... the details of the business are crucial. Details are like a cancer: they start to grow out of control if you don't constantly monitor them.*” (Bradach, 1998: 85).

Failure to replicate the set of required practices in their entirety can impede unit performance in multiple ways. For one, it exposes the focal unit to the risk of being perceived as illegitimate and, thus, the unit might be penalized by relevant local audiences such as customers and/or suppliers (Barthélemy 2008; Hsu and Hannan 2005; Zuckerman 1999). Moreover, it makes the focal unit incompatible with the common operating, logistics, support, feedback, and control systems established by the chain organization, diminishing the ability of the unit to draw support and resources from the rest of the organization (Szulanski & Jensen, 2006). In addition, it also negatively affects the whole chain organization (El Akremi et al., 2011) by impairing brand name and reputation, increasing customer uncertainty, and lowering chain-wide economies of scale (Barthélemy, 2008).

To ensure replication accuracy and avoid the negative performance consequences of inaccurate replication at their geographically dispersed units, chain organizations rely on middle managers who monitor replication accuracy at the individual units in the region under their supervision. Middle managers monitor the accuracy with which required practices are replicated by units under their supervision through regular onsite visits, use of mystery shoppers, field audits, etc. (Bradach, 1997; Garvin & Levesque, 2008; Kalnins & Lafontaine, 2013). Thus, monitoring the accuracy of replication of required practices at units in their portfolio requires ongoing, deliberate allocation of attention by middle managers.

4.3.2. Hypotheses Development

According to the attention-based view of the firm, managers' perceptions and actions depend on the issues and activities on which they focus their attention (Ocasio, 1997). As managers are inherently limited in their attentional capacity, attention allocated to a particular activity inevitably limits the attention allocated to other activities. Accordingly, the focus of attention facilitates perception and action towards activities that are attended

to, while limiting perception and action towards those that are not. In attention-based view terms, the greater the attentional stability (vigilance) to one activity, the less attention that is available for the other (Ocasio, et al., 2020).

Scholars have documented that while attentional stability (vigilance) benefits the activity of focus (Ocasio, 2011; Ocasio & Joseph, 2014; Rerup, 2009; Weick & Sutcliffe, 2006), it also diverts attention from parallel activities (Huckman and Zinner, 2008; Joseph and Wilson, 2017; Robert Mitchell, Shepherd, & Sharfman, 2011; Yu, Engleman, & Van de Ven, 2005). Indeed, attentional stability promotes a “deep but relatively narrow awareness of what goes on in a specific context” (Rerup, 2009: 878), and makes it difficult to flexibly switch focus of attention to other activities (Ocasio & Wohlgezogen, 2010). This mechanism is especially critical since middle managers are limited in their attentional capacity (Ren & Guo, 2011), and tasking them with competing roles, e.g., expansion and monitoring, creates competing claims on their limited attention (Cyert & March, 1963; March & Simon, 1958; Ocasio, 1997, 2011; Simon, 1947).

Anecdotal evidence on multiunit chains suggests that rapid expansion indeed focuses middle managers’ attention on expansion-related tasks, reducing the attention available to monitoring tasks:

"We [at Pizza Hut] added three units to one market ... and it simply was too fast we're still trying to get things settled down there. Opening a new restaurant required a disproportionate amount of management time compared to managing existing units ... Debbie Stewart, a district manager at Hardee's, estimated that over half of her time for several weeks was devoted to opening a single unit. At the same time, she was responsible for the management of several existing units. She personified the Pizza Hut vice-president's worry that excessive growth could cause a firm to lose control of its base. Nugent, CEO of Jack in the Box, put it in even stronger terms: You can kill a company by growing it too fast." — (Bradach, 1998: 66)

Hence, other things being equal, committing more attention to expansion can be expected to adversely affect the level of attention available to a middle manager for the purpose of performing monitoring activities in a given period. As continuous monitoring disciplines

units to comply with required practices (Bradach, 1997, 1998; Garvin & Levesque, 2008; Kalnins & Lafontaine, 2013), less attention dedicated to monitoring by a middle manager can be expected to result in lower accuracy of replication of required practices at units under his/her supervision. Thus, we hypothesize:

***Hypothesis 1 (H1).** The speed of expansion of a middle manager will have a negative effect on the accuracy of replication of required practices at units under his/her supervision.*

While middle managers may stabilize attention on a particular activity at a given time, they may also exercise executive attention, i.e., switching between different foci of attention (O’Leary et al., 2011; Ocasio et al., 2020; W. C. Ocasio & Wohlgezogen, 2010). This executive attention reflects how managers detach their attention from one activity, reallocate it to a different activity, and then return to the first (Ocasio, 2011). Executive attention permits managers to go back and forth between activities more flexibly and thus, allows for the better balancing of tradeoffs.

The degree to which managers can regulate their attention focus between multiple activities quasi-simultaneously, as well deal with interruptions, may be a function of experience. Experience provides individuals and organizations with knowledge needed to alter behavior and improve processes (Argote & Miron-Spektor, 2011; Argote & Ophir, 2002). Experience gets encoded in the firms’ structures, routines, and practices and, thus, even with the passage of time (Argote, 1999; Haunschild & Sullivan, 2002), can significantly guide attentional processing. Here we detail three important types of experience which the literature suggests may be particularly relevant and important: experience with prior expansion, experience with failure, and operating experience of the units under a middle managers’ supervision. While these types of experience do not exhaust the potential regulators of attentional tradeoffs, they do reflect key theoretical categories highlighted in research on learning (Argote & Miron-Spektor, 2011).

The first type of experience that would affect how the allocation of a middle manager’s attention is regulated derives from how the focal manager has paced expansion in the past. Research in the cognitive neuropsychology of attention (e.g., Corbetta & Shulman, 2002;

Posner & Rothbart, 2007) confirms that mechanisms associated with attentional control can be improved with repetition and such improvements are associated with greater levels of competence (Rueda, Posner, & Rothbart, 2005). A middle manager's rhythm of prior expansion captures his/her temporal pattern of expansion, i.e. how concentrated in time is the expansion (Kunisch et al., 2017; Vermeulen & Barkema, 2002). A regular rhythm of expansion results in a relatively uniform distribution of units opened over time. Following a more regular rhythm of expansion, achieved through repeated scanning for expansion opportunities over time, requires managers to continually split their attention between expansion through the creation of new units and monitoring that required practices are replicated accurately at existing units in their portfolio. Thus, a more regular rhythm of expansion experience may limit managers' ability to fully channel attention to one or the other.

By contrast, an irregular rhythm of expansion, characterized by large expansion peaks and long periods of inactivity (Klärner & Raisch, 2013; Vermeulen & Barkema, 2002), suggests greater intentionality toward sequential attention and switching attention focus between expansion and monitoring goals (Ocasio, 2011). Irregular, and thus sequential, attention patterns in the past serve as cognitive acts which, over time, improve a middle managers' executive attention. As a result, managers are better able to focus on one goal at a time, reducing the cognitive effort otherwise needed to concurrently weigh the two goals against each other (Greve, 2008). An irregular expansion rhythm can, thus, be expected to help middle managers balance their allocation of attention between expansion and monitoring activities more effectively than a regular rhythm.

In sum, middle managers that experienced an irregular (sequential) rhythm of expansion over time can be expected to be better able to flexibly switch their focus of attention between expansion and monitoring. Thus, we hypothesize:

Hypothesis 2 (H2). *The more irregular the rhythm of expansion experience of a middle manager, the lower the negative effect of his/her speed of expansion on the accuracy of replication of required practices at units under his/her supervision.*

The second type of experience which may condition the impact that speed of expansion has on monitoring replication accuracy is the experience the focal middle manager has with the negative consequences of prior violations of replication accuracy at units in his/her portfolio such as unit failures associated with inaccurate replication. Learning from failure has a long history in the organizational learning literature and has been shown to improve quality and efficiency (Haunschild, Polidoro, & Chandler, 2015), and limit future failures (Baum & Dahlin, 2007; Haunschild & Sullivan, 2002). Such experience accumulates as middle managers face replication accuracy violations from units throughout their portfolio and are forced to learn to correct them. Failures provide opportunities, greater motivation, and greater capacity to learn (Dahlin et al., 2018) because they provide firms with a chance to reflect on what has gone wrong and how to improve routines.

Moreover, as the monitoring role of middle managers is critical for a chain organization, middle managers' attention to monitoring becomes more strongly scrutinized by the headquarters when an "unintended event emerges" (Martin, Lopez, Roscigno, & Hodson, 2013), i.e., when unit failures emerge as a consequence of middle managers not effectively performing their monitoring role. As middle managers desire to portray a positive self-image in their professional roles to top management (Burgelman 1991, Dutton et al., 1997; Dutton et al., 2001), greater scrutiny of their actions by headquarters can be expected to result in more attention to and learning from unit failures associated with inaccurate replication and, thus, improve middle managers' monitoring routines. As a result, middle managers will be better prepared to deal with future lapses in replication accuracy at units under their supervision and such lapses will be less disruptive to their attentional allocation patterns.

In sum, as experience with failures associated with lapses in replication accuracy accumulates, it is likely that managers will be able to learn from and address such problems more effectively. Failure prompts managers to re-examine the key assumptions of their causal models, leading to a deeper understanding of cause-effect linkages (Dahlin et al., 2018; Haunschild & Sullivan, 2002; Morris & Moore, 2000). Thus, it enables organizations to develop response repertoires to deal with such occurrences (Gaba & Joseph, 2013; Miller & Chen, 2004), which may economize on attention to any particular

subsequent problem that can cause failure. These repertoires could include selecting more effective threats of sanctions for deviant units or better assisting units with overcoming their replication accuracy issues. Thus, we hypothesize:

***Hypothesis 3 (H3).** The higher the number of past unit failures associated with inaccurate replication of required practices, the lower the negative effect of a middle manager's speed of expansion on the accuracy of replication of required practices at units under his/her supervision.*

A third type of experience that may regulate middle managers' capacity for switching attention between their expansion and monitoring role is the operating experience of a unit. Middle managers need to make choices about the basis on which to distribute their limited attention towards their monitoring role across the units in their portfolio. Units with greater operating experience may be easier to manage when replication accuracy issues arise, thereby requiring less attention overall and making tradeoffs in attention possible. Put differently, less attentional demands from any single activity creates greater capacity for switching attention between activities (in this case, between speed of expansion and monitoring of replication accuracy).

Unit operating experience provides a number of advantages for firms with performance problems related to the inaccurate replication of required practices. Research has shown that as organizations accumulate operating experience, they develop repositories of knowledge and expertise which serve as buffers when faced with adversity (Sorenson, 2003). In particular, they develop structures and routines in place to deal with complex problems and are less likely to rely on simplifying heuristics or shortcuts (Delmar & Wennberg, 2007). Such routines can lower costs, increase quality, and improve reliability (Darr et al., 1995; Levin, 2000). Organizational units that have longer operating experience also tend to have larger or higher quality managerial and other resources (Mitchell, 1994) and, as a result, are better able to address performance problems (Audia & Greve, 2006). This will lower the attentional demands placed on the middle manager to get involved with correcting inaccurate replication in such units.

Firms with greater operating experience may also have developed stronger ties and closer relationships with the middle managers in charge. This dynamic occurs because repeated exchanges over time lead to the development of trust which promotes the sharing of private information (Uzzi, 1996; Vanneste, Puranam, & Kretschmer, 2014). Thus, when it comes time to discuss replication accuracy issues, the trust and knowledge embedded in these relationships is likely to make it easier to coordinate activity and resolve deviance problems (Reagans, Argote, & Brooks, 2005). Appeals by the middle managers to address such problems may also be more readily accepted by the focal unit manager, making it easier for middle managers to balance attention between monitoring replication accuracy and the responsibilities associated with their other key role, expansion. Thus, we hypothesize:

***Hypothesis 4 (H4).** The negative effect of a middle manager's speed of expansion on the accuracy of replication of required practices at units under his/her supervision is attenuated for units with greater operating experience.*

4.4. Methods

4.4.1. Data and sample

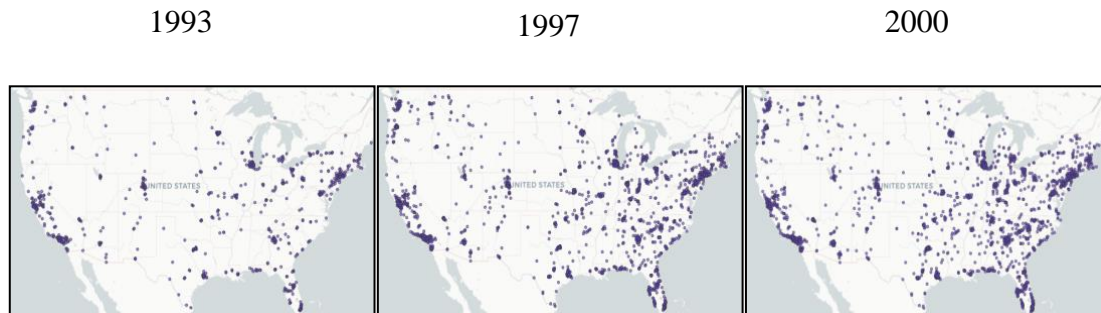
The empirical setting for our study is franchising. Franchise chains provide a natural laboratory for the study of how middle managers' attention allocation and learning to allocate attention may affect the accuracy with which required practices are replicated as franchise chains create and operate a large number of similar units in different geographic locations based on a common set of required practices (Szulanski & Jensen, 2006; Winter & Szulanski, 2001; Winter et al., 2012) and they use of middle managers to create and monitor their units in a given region (Bradach, 1998; Brickley & Dark, 1987; Kalnins & Lafontaine, 2013)¹⁷. The geographic dispersion of units, combined with the arms-length

¹⁷The franchise chain uses the term "area franchisees" to refer to the middle managers. Scholars have used different terms such as "middle managers", "hierarchical managers", "regional managers", "area managers", "area franchisees", "district managers", "regional headquarters" and "regional monitoring centers" (Bradach, 1998; Brickley & Dark, 1987; Garvin & Levesque, 2008; Kalnins & Lafontaine, 2013; Kalnins & Mayer, 2004; Winter et al., 2012; Yin & Zajac, 2004). Bradach (1998: 208) notes that practitioners often use the above terms interchangeably. We use the term "middle managers" in this essay.

interface between the franchisor and franchisees, implies that the franchisor cannot completely control and enforce the replication of required practices by the individual units of its franchise chain (El Akremi et al., 2011; Szulanski & Jensen, 2006; Winter et al., 2012). As a result, virtually all franchise chains recruit an intermediate layer of middle managers to monitor the implementation of required practices at units under their supervision. At the same time, middle managers are typically also responsible for expanding the franchise chain in their region by opening new units. As middle managers have the dual role of monitoring how required practices are replicated at units under their supervision and of expanding the franchise chain in their region through the creation of new units, franchise chains offer an appropriate context in which to examine how middle managers' attention allocation and learning to allocate attention among their two roles affects replication accuracy at units under their supervision.

The main data for this study come from a proprietary dataset obtained from a large, U.S.-based, non-food franchise chain specializing in services for individual consumers and the small-office/home-office (SOHO) market. The services in question span multiple SIC codes including Business Services (7389), Office Supplies (5112), and Photocopying Services (7334). The dataset comprises monthly updated indicators for all U.S. units of the franchise chain collected by the franchisor over the eleven-year period from 1991 to 2001. All units of the chain are franchised rather than company-owned with franchised units being opened and operated in all 50 U.S. states during the period of observation. Figure 4.1 depicts the distribution of the units of the franchise chain across the U.S. at three points in time during the period of observation. To obtain greater insight into the functioning of the franchise chain and the constructs underlying our theorizing and empirical investigation, we informed our quantitative data gathering and analysis with qualitative data obtained via semi-structured interviews with senior managers, middle managers, and franchisees of the focal chain. The qualitative data were collected during a visit to the headquarters of the franchise organization, a visit to one of its annual conventions, and visits to several area franchisees (middle managers) and franchisees (units). The executives interviewed at the company headquarters and annual convention were in charge of functions that included general management, operations, training, and franchisee relations. The average interview lasted about an hour.

Figure 4.1. Store locations of the franchise chain in the USA (end of year data)



representative of a typical established franchise chain¹⁸; ii) relative age – old enough to have an established business model and a well-defined set of required practices, yet young enough to still be expanding through the creation of new units over the entire period of observation; iii) size and use of middle managers – large enough to ensure a sufficient number of units for the study as well as large enough to use middle managers; iv) data access and quality – we were able to obtain full access to fine-grained, survival-bias-free longitudinal data that tracks all variables of interest in all units of the organization on a monthly basis over eleven years, offering a rare opportunity to subject our theory and hypotheses to an empirical test.

As in a typical franchise chain, the franchisor was mainly responsible for developing a set of required practices for doing business and facilitating its transfer to individual franchisees. Since its inception in 1980, the franchisor had been exploring and perfecting its set of required practices which was stabilized in the second half of the 1980s and remained unchanged during our entire period of observation (1991 to 2001). The duration of the franchise contract between the franchisor and a franchisee was ten years with the possibility of contract renewals with the same duration. New franchisees underwent a compulsory two-week training at the company headquarters, half of which consisted of

¹⁸ The focal franchise chain opened 2,444 units in the U.S. during our period of observation and had systemwide sales of \$1.5 billion as of the year 2000. A franchise chain that is similar in size is Baskin-Robbins. It had 2,524 units in the U.S. and systemwide sales of \$615.3 M in 2019. Another franchise chain of similar size is Anytime Fitness which had 2,200 units in the U.S. and systemwide sales of \$634 M in 2013. Just as the focal franchise chain, these chains also divide the U.S. territory into regions supervised by middle managers.

hands-on training at an existing training/pilot center. This training ensured that all franchisees had a good understanding of the franchise, especially related to their understanding of the set of required practices and how to implement them effectively in their franchise outlet. Yet, the franchisor was also aware that given franchisees are independent entrepreneurs that operate on the basis of an arm's length contract with the franchisor, they could potentially deviate from the chain's required practices – as documented by prior research (El Akremi et al., 2011; Szulanski & Jensen, 2006; Winter et al., 2012). Reflecting this concern, a senior executive we interviewed at the headquarters of the organization pointed out: *“we have a concept that is sound, but the real power of it is lies in what that individual franchisee does.”*

This was a major reason why the franchisor contracted middle managers (referred to as “area franchisees”) and tasked them with monitoring replication accuracy at the chain's units in a given region. As a senior executive at the headquarters of the franchise chain remarked in an interview: *“more control ... leads to consistency which is the greatest challenge in franchising ... we have to rely locally on the area franchisees [middle managers].”* Middle managers monitored the accuracy of replication of required practices by regularly visiting the stores of the chain in the region under their supervision and analyzing their transactions. One of the middle managers we interviewed explained: *“I tell people [franchisees] ... it is you ..., it is the image you portray, it is the product that you carry, it is utilizing the vendors that we have made arrangements with... it is utilizing those products.”*

In addition, middle managers were also responsible for expanding the franchise chain by opening new franchised units in the region under their supervision. Explaining the dual role of middle managers, a senior executive at the headquarters of the franchise chain pointed out that: *“Most of the time and attention is on area franchisees [middle managers], not directly with center franchisees [individual units]. ... area franchisees [middle managers] are focused on selling individual franchises ... as well as monitoring existing franchised outlets.”*¹⁹ One of the senior executives at the headquarters explained that

¹⁹ Individual franchisees are part of “areas” that are supervised by area franchisees. The franchise chain uses the term “area franchisee” to refer to the middle manager in charge of a given region. Scholars and

“instead of us ... trying to directly franchise out ... units across the U.S., we put in an intermediary infrastructure ... the area franchisees [middle managers] have the responsibility of selling franchises [franchised units].” Opening new units of the franchise chain in their region demands middle managers’ attention as critical decisions are involved that are fundamental to the subsequent success of the new units (Kalnins & Mayer, 2004; Salvaneschi, 1996). For instance, a middle manager we interviewed remarked: *“we do significant demographic analysis as a component of our site selection ... with the information we can collect within an area on consumers, on businesses, on so many different levels, we can really pinpoint exactly which site is closest to our critical mass of customers within that local area.”* Over our period of observation, middle managers expanded the chain organization by opening new franchised units at different rates. For instance, one middle manager opened 17 new units in a given year, while another middle manager opened 3 units in the same year. The franchisor tied middle managers’ incentives to their monitoring and expansion objectives by splitting the initial franchisee fee and ongoing franchise royalties paid by each franchisee in a given region with the middle manager in charge of that region. The percentage of the initial franchise fee and ongoing royalties that a middle manager was entitled to was the same for all middle managers and remained the same for the entire observation period.

In the focal franchise chain, the middle managers were legally independent agents who operated based on long-term (10-year) contracts with the franchisor which are automatically renewed unless either party objects. Given that they received a fixed percentage of the initial franchise fee and ongoing royalties from each franchisee in their region, the middle managers had high-powered incentives to remain in the system for the long run. As per our data, no middle manager left/joined the chain or transitioned to manage a different region during our period of observation. It is worth noting that our period of observation followed a decade of growth and consolidation of the franchise chain, a decade during which some regions were consolidated (i.e., brought under the supervision of a single high-performing middle manager) and some middle managers who were underperforming or didn’t have a long-term commitment to the chain left the system.

practitioners have used different terms to refer to the middle managers of chain organizations - we use the term “middle managers” consistently throughout this paper.

Senior executives at headquarters we interviewed pointed to that initial decade of exploration, selection, and consolidation as well as to the substantial commitment and lock-in to the system of their remaining middle managers (and, correspondingly, the substantial gains they would forfeit if they were to leave the system) as drivers of the lack of turnover during our observation period.

The high (monthly) frequency of the franchise chain data allowed us a rare insight into how required practices are replicated on an ongoing basis at the individual units of the franchise chain. Units need to adhere to required practices continuously in order to meet customers' expectations of the franchise chain's value proposition. A senior executive we interviewed at the headquarters of the franchise organization emphasized: *"customers expect to get the same type of products and services from all units around the country or their neighborhood. Omitting any of those typically causes confusions and dissatisfactions, hurting our brand overall."* Relatedly, another executive at the headquarters added: *"[if] you want to control the brand you want to control consistency...by mandating a consistent approach to service."* Furthermore, the executive pointed out in response to our interview question about the main reasons for the underperformance of some of their franchise units: *"their [franchise units'] financial performance is impeded because they're not following the [chains'] recommended approach."* Continuous monitoring has been documented by prior research to improve replication accuracy as *"... being constantly watched ... contributed to the fear ... they could be in here right now and I could be failing!"* (Bradach, 1998: 89). If units are not continuously monitored, lapses in the implementation of required practices can quickly multiply and grow out of control (Bradach, 1997, 1998; Garvin & Levesque, 2008; Kalnins & Lafontaine, 2013). Likewise, another executive at the headquarters of the franchise chain we study emphasized emphatically: *"what's critically important, in my opinion, is the constant monitoring of the system."*

The internal franchise chain data described above were supplemented with publicly available information on units' local geographic markets drawn from the United States Census Bureau's County Business Patterns database (<https://www.census.gov>) and ESRI Inc.'s annual Sourcebook of America and Sourcebook of Zip Code Demographics. The observation period extends from the year 1991, the first year for which detailed unit-level

data became available, to the year 2001, the last year for which unit-level data was made available. The sample includes all 2,444 units founded during the period of observation observed since inception until the end of the observation period or failure, i.e., until they were permanently closed down as indicated by the franchisor internal information system, yielding a final sample of 144,631 unit-month observations.

4.4.2. Measures

4.4.2.1. Dependent variable

Our dependent variable is the accuracy with which required practices of the organization are replicated (*Replication Accuracy*). The franchisor designated the provision of thirteen products and services as required products/services that all outlets of the organization should implement. They included products/services targeting the SOHO market such as mail-box rental, photocopy services, mail services, shipping, shipping supplies, office supplies, packaging materials, printing, etc. The franchisor had worked extensively to develop a set of required products/services that allows for economies of scale through nation-wide customer accounts and partnerships with suppliers such as Xerox, FedEx, and UPS. The required products and services had been documented to contribute to unit performance across a wide variety of diverse locations and were, thus, considered worth implementing in all U.S. locations of the organization. As mentioned during our interview with a top executive of the organization, the objective was that “*a number of different kinds of business services can be provided in an efficient and consistent way across different locations.*” Top management deemed the set of required products/services to be the universal “*core of the business model.*” The number and general nature of the required products/services remained the same during our observation period.

Yet, a persistent challenge the franchisor faced was that not all franchisees implemented the required set of products and services in its entirety all the time. While the franchise contract specified that the implementation of such products and services is required and included provisions that appeared to give the franchisor the right to terminate a franchise contract in the case of violations, in practice the strict implementation of required products/services prescribed by the franchise contract was notoriously difficult to enforce

through litigation (cf. Bradach, 1997). The franchisor's most potent leverage was the threat to not renew the franchise contract after it expired which was usually only a distant possibility given the long-term, multi-year duration of the franchise contract. The most effective way of ensuring that the entire set of required products/services was consistently implemented by all franchise units was having middle managers continuously monitor the accuracy of its replication. To that effect, middle managers also helped disseminate information and know-how that demonstrated the positive effects of implementing all required products/services based on data and testimonies from well-performing franchisees in their region. Nevertheless, these measures did not always work as intended as ultimately all local units were owned by independent franchisees and, thus, middle managers (or the franchisor) could not enforce replication accuracy via the exercise of hierarchical authority.

Subsequently, we operationalize *Replication Accuracy* as the extent to which a focal unit implements the set of required product/services of the franchisor in a given time period. Specifically, the measure of *Replication Accuracy* is calculated as the number of required products/services implemented by a focal unit in a given time period (month, in this case). Monthly data for *Replication Accuracy* is available for all units of the franchise system allowing us to capture all units' extent of *Replication Accuracy* in each time period over the entire eleven-year period of observation.

4.4.2.3. Independent variables

Our main independent variables are (1) *Speed of Expansion*, (2) *Irregular Rhythm of Expansion*, (3) *Failure Experience*, and (4) *Unit Operating Experience*. The franchise chain we study partitions the territory of the United States into regions managed by middle managers. Aside from monitoring that all required practices are replicated accurately at units under their supervision, a second main responsibility of middle managers is expanding the franchise chain by opening new units in their region. Fast expansion, in this case opening a larger number of franchise outlets in the focal region in a given time period, requires significant managerial attention (Hashai, Kafouros, & Buckley, 2018; Pacheco-de-Almeida, Hawk, & Yeung, 2015). Consistent with prior research (Vermeulen &

Barkema, 2002), we measured *Speed of Expansion* as the number of units a middle manager opened in his/her region in a given month.

Consistent with prior research (Vermeulen & Barkema, 2002), we measured *Irregular Rhythm of Expansion* using the kurtosis of the speed of expansion of a focal middle manager. To obtain a time-varying variable, we constructed *Irregular Rhythm of Expansion* as the kurtosis of the speed of expansion over the period starting from the start of the period of observation to the focal time period (i.e., month). Alternatively, as a robustness check, we also measured middle managers' *Irregular Rhythm of Expansion* as a time-invariant variable using the kurtosis for the entire period of observation which produced qualitatively the same results (see robustness section for details). Finally, following some prior research (Hashai et al., 2018; Laamanen & Keil, 2008), for both the time-variant and time-invariant measures, we used the standard deviation (instead of the kurtosis) of middle managers' speed of expansion which again yielded qualitatively identical results (see robustness checks section).

To measure *Failure Experience*, we followed extant literature on learning from failures (Baum & Ingram, 1998; Chuang & Baum, 2003; Kim & Miner, 2007; Madsen & Desai, 2010) and modified the measure used there based on our theory. In the literature on learning from failures, failure experience is typically measured as the cumulative number of failures experienced by a focal entity over its lifetime or within a given time period. We followed that approach yet focused only on unit failures, i.e., permanent closures of units, where the failed units had problems with replication accuracy, i.e., failed to fully implement required practices. Specifically, we counted only those unit failures where units' mean *Replication Accuracy* over their lifetime was at least one standard deviation lower than the mean *Replication Accuracy* of all units under the supervision of the focal middle manager. We measured *Failure Experience* as the total number of unit failures experienced by the middle manager up to the focal time period (month).²⁰ Since scholars have suggested that the effects of experience decay over time (Argote, Beckman, &

²⁰ For robustness, we also re-estimated our models with a measure of *Failure Experience* that does not consider the level of replication accuracy of the failed units. That is, we measured *Failure Experience* as the total number of unit failures, irrespective of failed units' replication accuracy, experienced by a focal middle manager up to the focal time period (month). The models with the above measurement yielded virtually identical results.

Epple, 1990), we also re-estimated our models with alternative measures that discount prior *Failure Experience* using common functional forms (Baum & Ingram, 1998; Kim & Miner, 2007) as well as models that consider only recent failure experience (Madsen & Desai, 2010). Our results with these alternative measures are essentially the same and are reported as robustness checks in our Robustness Checks section.

To measure *Unit Operating Experience*, we used the elapsed time since the inception of the focal unit. In particular, we measured *Unit Operating Experience* as the number of months since the opening of the focal unit divided by twelve (i.e., expressed in years).

4.4.2.4. Control variables

We controlled for the impact of factors that may be simultaneously related to a unit's accuracy of replication of required practices and our independent variables. We controlled for the possibility that units' past growth might affect the accuracy with which they replicate required practices. In particular, we measure *Unit Growth* as the average monthly revenue growth rate of each unit over the preceding three months. We also controlled for *Unit Size*, measured as the focal unit's total monthly revenue in ten thousands of U.S. dollars. Total monthly revenue figures are in real, inflation-adjusted dollars obtained using the U.S. Consumer Price Index for 1991–2001 as reported by the Bureau of Labor Statistics. *Unit Operating Experience*, measured as the age in years of the focal unit, is one of the independent variables in this study and including it in our models controlled for the possible impact of unit age on the accuracy of replication of required practices (D'Adderio, 2014). If units owned by multiunit owners exhibit differences in their implementation of required practices compared to units under single-unit ownership, multiunit ownership might be a potential confounder of the effects of our main explanatory variables. We, thus, controlled for the impact of multiunit ownership. We measured *Multiunit Owner Size* as the total number of units owned by the focal unit's owner in a given time period. The proximity of other same-chain units has been found to influence focal unit performance (Kalnins, 2003). We controlled for that impact by including a variable measured as the natural logarithm of the distance in miles to the closest same-chain unit (*Distance to Closest Same-Chain Unit*). The measure is updated for openings and closings of franchise units, i.e., it is time variant. Prior research has also documented that characteristics of the practices being replicated, in particular knowledge discreteness

(Williams, 2007) and template performance (Lawrence, 2020), can affect replication accuracy. Such characteristics of the practices being replicated are controlled for by our research design as in our analysis they do not vary across units or over time – the required practices of the franchise chain we study are the same for all units and remained the same over the entire period of observation.

Moreover, the franchisor partitions the territory of the United States into regions, akin to the territorial groupings present in virtually all large chain organizations. Each region spans a geographic area larger than the combination of a few zip codes or cities but smaller than a state. Each middle manager of the franchise chain is in charge of a specific region. The franchise organization has a total of seventy-two regions and an average of forty-one units per region with the number of units per region steadily increasing over time as new units were being opened. We controlled for *Number of Units in the Region* measured as the number of units in a given region in a given time period. According to the data provided by the franchise chain, the middle managers and the regions under their supervision did not change over our period of observation and, therefore, any stable unobserved middle manager or region differences that may be correlated with units' replication accuracy would be controlled for in the franchise unit fixed-effects specification we use to test our hypotheses. Moreover, to further address any concerns related to potential omitted variables bias, we performed instrumental variable regressions for all models which yielded identical results (see Robustness Checks section below).

We accounted for differences in local demand conditions by including a control for *Per-Capita Income* measured as the average per-capita income (in \$10,000s) in a focal unit's 5-digit zip code in a given year. We also controlled for differences in local *Population Size* measured as the population size (in 10,000s) of each unit's 5-digit zip code in a given year. The data used to construct the population size and per-capita income measures described above were drawn from ESRI Inc.'s annual Sourcebook of America and Sourcebook of Zip Code Demographics.

To further account for heterogeneity in the local conditions faced by individual units, we added additional control variables that control for local conditions at the zip code level. We describe the process for constructing these control variables below. We collected the

complete Census Bureau ZIP Code Industry data, which contains the information on local markets. We first created a variable *Number of People Employed* that measures the number of people employed in a given zip code area as a proxy for the potential customers in that zip code area. We further constructed additional controls to better account for the possible effects of differences in local competition across local markets. To do so, we used and aggregated information on direct competitors of the franchise chain based on the major SIC (or NAICS) codes the organization operates in: SIC codes Business Services (7389), Office Supplies (5112), and Photocopying Services (7334). We define a competitor as a business that operates in any of these three SIC codes²¹. For every zip code where a unit of the organization is located, we gather data on competitors as defined above from the United States Census Bureau's County Business Patterns dataset (<https://www.census.gov>). We created four variables that measure the number of competitors of different sizes in the zip code – *Number of Competitors (up to 49 employees)*, *Number of Competitors (from 50 to 99)*, *Number of Competitors (from 100 to 299 employees)*, and *Number of Competitors (more than 250 employees)* – and used their natural logarithm as control variables. Finally, to control for stable unobserved month (seasonality) and year effects, we included separate month and year fixed effects (month dummies, year dummies) in all models.

4.5. Models

To test our hypotheses, we used franchise unit fixed effects ordinary least squares panel regressions. We opted to use franchise unit fixed effects to account for unit-related time-invariant unobservable heterogeneity that could correlate with our error term and our main explanatory variables. We also controlled for time effects by including month and year fixed effects (month dummies and year dummies) in all models. Moreover, we used standard errors clustered at the middle manager level to account for a potential serial correlation of observations for franchise units under the supervision of the same middle manager. To address potential concerns that *Speed of Expansion* may be endogenous, we further also estimated all models using instrumental variables estimations (Hamilton &

²¹ Competitors are defined based on SIC codes before 1998 and NAICS codes from 1999 onward.

Nickerson, 2003; Semadeni, Withers, & Trevis Certo, 2014; Shaver, 1998) as described in our Robustness Checks section.

We ruled out using Poisson or Negative binomial models as our main models because with a unit fixed effects specification these estimators would exclude units for which the dependent variable — in this case, *Replication Accuracy* — has no within-unit variation over the period of observation (Allison & Waterman, 2002). Employing these models would lead to loss of observations which could induce sample selection issues in our estimations (Cameron & Trivedi, 2010: 623). Nonetheless, in spite of these significant limitations to the use of count models, as an additional robustness check described in our Robustness Checks section, we also re-estimated all models using Poisson models which yielded identical results (see Robustness Checks section)²².

4.6. Results

Table 4.1 reports descriptive statistics and simple pairwise correlations between the variables used to test our hypotheses. The results of pairwise correlations and the mean of variance inflation factors (mean VIF: 1.32) associated with our explanatory variables raised no significant concerns regarding multicollinearity.

Table 4.2 reports the results of fixed effects OLS panel regression estimations in five different specifications (Models 1 to 6). Model 1 reports a baseline estimation that includes only control variables. Model 2 tests the effect of middle managers' *Speed of Expansion* on *Replication Accuracy* of required practices at units under their supervision to test hypothesis 1. The coefficient of *Speed of Expansion* is negative and significant (-0.0064 , $p < 0.01$), providing empirical support for hypothesis 1 (H1). Models 3 to 5 test hypotheses 2 to 4 which posit moderators of the relationship between *Speed of Expansion* and *Replication Accuracy*. In Model 3, to test hypothesis 2 (H2), we introduce the interaction between middle managers' *Speed of Expansion* and *Irregular Rhythm of Expansion*. Consistent with H2, the coefficient of the above interaction term is positive and significant (0.0002 , $p < 0.01$). In Model 4, the coefficient of the interaction between

²² We chose the Poisson and not the Negative binomial estimator because the Negative binomial estimator does not allow the use of robust clustered standard errors in conjunction with fixed effects (Allison & Waterman, 2002).

Table 4.1. Descriptive statistics and correlations

	Mean	S.D.	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
[1] Replication Accuracy	12.0230	1.0524									
[2] Speed of Expansion	0.6758	1.4664	0.0159								
[3] Irregular Rhythm of Expansion	9.6401	13.1090	0.0460	0.0954							
[4] Failure Experience	6.1721	10.6415	0.0641	0.1199	0.3522						
[5] Unit Operating Experience	3.2209	2.2528	0.0306	-0.0797	0.1126	0.1573					
[6] Unit Size	2.9683	3.5921	0.1159	-0.0303	0.0062	0.0202	0.2362				
[7] Distance to Closest Same-Chain Unit	1.5751	1.1609	-0.0091	-0.0111	-0.0863	-0.1329	-0.0729	-0.0414			
[8] Number of Units in the Region	88.4773	86.7275	0.0572	0.3492	0.2968	0.6649	0.1084	-0.0366	-0.0913		
[9] Unit Growth	0.1851	1.6488	-0.0354	0.0478	-0.0216	-0.0219	-0.1020	-0.0281	0.0245	-0.0213	
[10] Multiunit Owner Size	1.3230	0.7770	0.0084	-0.0063	0.0349	0.0250	0.0206	0.0342	-0.0897	0.0288	-0.0082
[11] Per-Capita Income	2.3601	0.9979	0.0118	-0.0085	0.1152	0.2007	0.1772	-0.0098	-0.3441	0.1335	-0.0274
[12] Population Size	2.8705	1.4744	-0.0416	-0.0057	0.0413	0.0387	0.0694	0.0962	-0.2353	0.0111	-0.0082
[13] Number of People Employed	9.1137	1.2254	-0.0496	0.0254	0.0330	0.0263	0.0454	0.0051	-0.1906	0.0407	0.0000
[14] Number of Competitors (up to 49 employees)	2.0229	0.8089	-0.0315	0.0515	-0.0595	0.0152	-0.0615	-0.0048	-0.3530	0.0169	0.0029
[15] Number of Competitors (50 to 99 employees)	0.1337	0.3116	-0.0314	0.0125	-0.0267	-0.0193	-0.0451	-0.0031	-0.2125	-0.0188	0.0021
[16] Number of Competitors (100 to 249 employees)	0.0684	0.2234	-0.0283	0.0239	-0.0335	0.0111	-0.0375	-0.0122	-0.1259	0.0106	0.0024
[17] Number of Competitors (more than 250 employees)	0.0266	0.1404	-0.0345	-0.0077	-0.0170	-0.0205	-0.0222	-0.0015	-0.0698	-0.0324	-0.0004
	Mean	S.D.	[10]	[11]	[12]	[13]	[14]	[15]	[16]		
[10] Multiunit Owner Size	1.3230	0.7770									
[11] Per-Capita Income	2.3601	0.9979	0.0756								
[12] Population Size	2.8705	1.4744	-0.0172	-0.0800							
[13] Number of People Employed	9.1137	1.2254	-0.0060	0.0641	0.3040						
[14] Number of Competitors (up to 49 employees)	2.0229	0.8089	-0.0301	0.1570	0.3902	0.4544					
[15] Number of Competitors (50 to 99 employees)	0.1337	0.3116	-0.0343	0.0795	0.0940	0.2355	0.3665				
[16] Number of Competitors (100 to 249 employees)	0.0684	0.2234	-0.0307	0.0230	0.0722	0.1740	0.2760	0.2332			
[17] Number of Competitors (more than 250 employees)	0.0266	0.1404	-0.0134	0.0542	0.0229	0.1247	0.1745	0.1465	0.1266		

middle managers' *Speed of Expansion* and their *Failure Experience* is positive and significant (0.0003, $p < 0.01$), lending empirical support for hypothesis 3 (H3). Model 5 tests the interaction effect of *Speed of Expansion* and *Unit Operating Experience* which is positive and significant (0.0037, $p < 0.05$), supporting hypothesis 4 (H4). Finally, Model 6 reports a full model that tests all four hypotheses simultaneously. The estimated coefficients of *Speed of Expansion* and its interaction terms that test H1 – H4 are similar in terms of sign and significance to the ones reported in Models 2 to 5.

4.6.1. Robustness Checks

4.6.1.1. Instrumental variables estimations

To identify the effect of *Speed of Expansion* on *Replication Accuracy*, we conducted instrumental variable regressions, a standard approach for dealing with endogeneity concerns (Hamilton & Nickerson, 2003; Semadeni et al., 2014; Shaver, 1998). Appropriate instruments must fulfill the conditions of relevance and exogeneity (Semadeni et al., 2014), i.e., they should correlate with the endogenous variable and affect the dependent variable of interest only through their effect on the endogenous variable.

A common approach followed by previous research is to use system-level averages of the endogenous variable of interest (excluding the focal entity from the average) as an instrument for the endogenous variable (e.g., Autor, Dorn, & Hanson, 2013; Campa & Kedia, 2002; Cheng, Ioannou, & Serafeim, 2014). Accordingly, we generate our instrument for a focal middle manager's *Speed of Expansion* by calculating the average *Speed of Expansion* of all middle managers in a given time period (excluding the contribution of the focal middle manager). The rationale behind the construction of the instrument is that a focal middle manager's *Speed of Expansion* in a given period is likely to be correlated with the franchise-wide average levels of speed of expansion of middle managers in that time period. In addition, there is no reason to expect that the average speed of expansion of the middle managers in the organization (excluding the focal middle manager) will differentially predict *Replication Accuracy* at a given individual unit in the region of the focal middle manager. To instrument for the interaction terms between a middle manager's *Speed of Expansion* and other independent variables, we interacted the

instrument for the focal middle manager's *Speed of Expansion*, measured as described above, with the corresponding independent variables.

Table 4.2. Fixed effects panel regression models of replication accuracy

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Speed of Expansion		-0.0064*** (0.002)	-0.0110*** (0.003)	-0.0073*** (0.003)	-0.0162** (0.006)	-0.0210*** (0.005)
Speed of Expansion X Irregular Rhythm of Expansion			0.0002*** (0.000)			0.0002*** (0.000)
Speed of Expansion X Failure Experience				0.0003*** (0.000)		0.0003*** (0.000)
Speed of Expansion X Unit Operating Experience					0.0037** (0.002)	0.0034* (0.002)
Irregular Rhythm of Expansion		0.0001 (0.001)	-0.0000 (0.001)	0.0001 (0.001)	0.0001 (0.001)	0.0001 (0.001)
Failure Experience		0.0052*** (0.001)	0.0053*** (0.001)	0.0053*** (0.001)	0.0052*** (0.001)	0.0054*** (0.001)
Unit Operating Experience		0.0361 (0.068)	0.0361 (0.068)	0.0361 (0.068)	0.0366 (0.067)	0.0365 (0.067)
Unit Size		0.0274*** (0.005)	0.0274*** (0.005)	0.0274*** (0.005)	0.0273*** (0.005)	0.0273*** (0.005)
Number of Units in the Region	-0.0011** (0.000)	-0.0014*** (0.001)	-0.0014*** (0.000)	-0.0014*** (0.001)	-0.0017*** (0.001)	-0.0017*** (0.001)
Unit Growth	-0.0198*** (0.007)	-0.0187*** (0.006)	-0.0186*** (0.006)	-0.0186*** (0.006)	-0.0184*** (0.006)	-0.0183*** (0.006)
Multiunit Owner Size	0.0473* (0.028)	0.0485* (0.027)	0.0486* (0.027)	0.0485* (0.027)	0.0487* (0.027)	0.0488* (0.027)
Population Size	0.0002 (0.033)	-0.0034 (0.032)	-0.0032 (0.032)	-0.0032 (0.032)	-0.0035 (0.032)	-0.0032 (0.032)
Per-Capita Income	-0.0454* (0.025)	-0.0399* (0.023)	-0.0396* (0.023)	-0.0398* (0.023)	-0.0399* (0.023)	-0.0395* (0.023)
Distance to Closest Same- Chain Unit	0.0215 (0.023)	0.0142 (0.021)	0.0141 (0.021)	0.0141 (0.021)	0.0139 (0.021)	0.0138 (0.021)
Number of People Employed	0.0020 (0.004)	0.0016 (0.004)	0.0016 (0.004)	0.0016 (0.004)	0.0016 (0.004)	0.0016 (0.004)
Number of Competitors (up to 49 employees)	0.0484** (0.022)	0.0420* (0.024)	0.0421* (0.024)	0.0418* (0.024)	0.0417* (0.024)	0.0417* (0.024)
Number of Competitors (50 to 99 employees)	0.0656*** (0.023)	0.0631*** (0.022)	0.0631*** (0.022)	0.0630*** (0.022)	0.0629*** (0.022)	0.0628*** (0.022)
Number of Competitors (100 to 249 employees)	0.0100 (0.041)	0.0090 (0.040)	0.0092 (0.040)	0.0092 (0.040)	0.0088 (0.040)	0.0091 (0.040)
Number of Competitors (more than 250 employees)	-0.1060* (0.060)	-0.1125* (0.059)	-0.1128* (0.059)	-0.1126* (0.059)	-0.1122* (0.059)	-0.1126* (0.059)
Constant	11.2755*** (0.140)	11.5001*** (0.293)	11.7936*** (0.298)	11.2306*** (0.291)	11.5444*** (0.290)	11.5569*** (0.291)
Observations	144,631	144,631	144,631	144,631	144,631	144,631
Number of units	2,444	2,444	2,444	2,444	2,444	2,444
Unit FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 4.3 reports the results of first stage instrumental variables estimations. Each first stage regression model includes all control variables included in the main models reported in Table 4.2. Our instruments in the first stage regression models are positively and significantly related to the variables they instrument for. The F-statistics for the instruments in the first stage regression reject underidentification at 95%. They are greater than the required F-statistic of 10 in Staiger & Stock (1997) and the adjusted threshold F-statistic in Stock & Yogo (2005), suggesting that the instruments are not weak. The F-statistics corresponding to the test where the first stage models are compared to models without the instruments also indicate that the instruments are not weak.

Next, in the second stage models reported in Table 4.4, we use the instrumented/predicted values of *Speed of Expansion* and its interactions with *Irregular Rhythm of Expansion*, *Failure Experience*, and *Unit Operating Experience* respectively to estimate the effect of these variables on *Replication Accuracy* (see Models 11-15 in Table 4.4). All coefficient estimates on the independent variables tested by H1-H4 have the same sign and similar significance levels to the ones reported in Table 4.2. The results of our hypotheses tests are, thus, robust to accounting for the potential endogeneity of middle managers' speed of expansion via a 2SLS instrumental variables estimation.

4.6.1.2. Alternate model specifications: Poisson regressions

In spite of the limitations of count models (discussed in the “Empirical Models” subsection above), as an additional robustness test, we also tested the robustness of our results to alternative model specifications by estimating Poisson unit fixed effect regressions (Blevins, Tsang, & Spain, 2015)²³. Table 4.5 reports the results of Poisson unit fixed effect regression estimations. The estimated coefficients on our independent variables have the same signs and similar significance levels to the main results reported in Table 4.2. The results of our hypotheses tests are, thus, robust to using a count-based model specification.

²³ We do not use binomial regression models because this estimator does not allow the use of robust clustered standard errors in conjunction with fixed effects (Allison & Waterman, 2002).

Table 4.3. First stage instrumental variable regressions of replication accuracy

VARIABLES	Model 7	Model 8	Model 9	Model 10
	Dependent Variables			
	Speed of Expansion	Speed of Expansion X Irregular Rhythm of Expansion Experience	Speed of Expansion X Failure Experience	Speed of Expansion X Unit Operating Experience
Instrument	0.7638*** (0.042)	34.8668*** (2.386)	2.4788*** (0.447)	-3.0448*** (0.213)
Instrument X Irregular Rhythm of Expansion		10.2404*** (0.385)		
Instrument X Failure Experience			3.0056*** (0.073)	
Instrument X Unit Operating Experience				1.5824*** (0.091)
Irregular Rhythm of Expansion Experience	0.0179*** (0.001)	1.2814*** (0.048)	-0.0808*** (0.008)	0.0368*** (0.003)
Failure Experience	-0.0021* (0.001)	-0.5174*** (0.035)	0.0992*** (0.022)	-0.0038 (0.004)
Unit Operating Experience	-0.0081 (0.026)	-0.4041 (0.990)	0.0545 (0.201)	-0.0657 (0.086)
Unit Size	-0.0037** (0.002)	-0.0442 (0.069)	0.0215 (0.025)	0.0061 (0.006)
Number of Units in the Region	-0.0112*** (0.001)	0.0051 (0.011)	0.1275*** (0.003)	0.0456*** (0.001)
Unit Growth	0.0190*** (0.007)	0.0575 (0.044)	-0.0655*** (0.020)	-0.0068*** (0.003)
Multiunit Owner Size	0.0089 (0.011)	-0.1883 (0.302)	0.0815 (0.133)	-0.0465 (0.046)
Population Size	0.0003 (0.011)	-0.4856* (0.275)	-0.3896** (0.154)	0.0269 (0.037)
Per-Capita Income	-0.0204 (0.013)	-1.3310*** (0.483)	-0.1738 (0.166)	-0.0274 (0.046)
Distance to Closest Same-Chain Unit	-0.0245* (0.013)	0.0789 (0.315)	0.1185 (0.126)	-0.0098 (0.041)
Number of People Employed	0.0074*** (0.003)	0.2403*** (0.064)	-0.0677** (0.028)	0.0280*** (0.010)
Number of Competitors (up to 49 employees)	-0.0145 (0.012)	-0.5170 (0.337)	0.3369** (0.156)	0.0239 (0.039)
Number of Competitors (50 to 99 employees)	-0.0312* (0.018)	-0.1524 (0.424)	0.4111 (0.257)	-0.0283 (0.064)
Number of Competitors (100 to 249 employees)	0.0443** (0.022)	-0.0913 (0.509)	-0.3782 (0.347)	0.1955** (0.080)
Number of Competitors (more than 250 employees)	-0.0042 (0.036)	1.2826 (0.893)	0.2531 (0.779)	-0.0904 (0.111)
Constant	1.3258*** (0.145)	-7.3104* (3.921)	0.7176 (1.238)	1.3149*** (0.374)
Observations	144,631	144,631	144,631	144,631
Number of units	2,444	2,444	2,444	2,444
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES

Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 4.4. Second stage instrumental variable regressions of replication accuracy

VARIABLES	Model 11	Model 12	Model 13	Model 14	Model 15
Speed of Expansion	-0.1097*** (0.022)	-0.1631*** (0.032)	-0.1057*** (0.022)	-0.1313*** (0.019)	-0.1626*** (0.026)
Speed of Expansion X Irregular Rhythm of Expansion		0.0033*** (0.001)			0.0026*** (0.001)
Speed of expansion X Failure Experience			0.0032*** (0.001)		0.0026*** (0.001)
Speed of Expansion X Unit Operating Experience				0.0112*** (0.003)	0.0089** (0.004)
Irregular Rhythm of Expansion	0.0019* (0.001)	0.0005 (0.001)	0.0020* (0.001)	0.0019* (0.001)	0.0009 (0.001)
Failure Experience	0.0050* (0.003)	0.0061** (0.003)	0.0056** (0.003)	0.0050* (0.003)	0.0048* (0.003)
Unit Operating Experience	0.0352 (0.059)	0.0349 (0.059)	0.0348 (0.059)	0.0368 (0.059)	0.0406 (0.059)
Unit Size	0.0270*** (0.006)	0.0268*** (0.006)	0.0270*** (0.006)	0.0267*** (0.006)	0.0267*** (0.006)
Number of Units in the Region	-0.0025*** (0.001)	-0.0029*** (0.001)	-0.0029*** (0.001)	-0.0033*** (0.001)	-0.0033*** (0.001)
Unit Growth	-0.0167*** (0.005)	-0.0155*** (0.005)	-0.0164*** (0.005)	-0.0159*** (0.005)	-0.0139*** (0.005)
Multiunit Owner Size	0.0494* (0.025)	0.0501** (0.025)	0.0489* (0.026)	0.0500** (0.025)	0.0534** (0.026)
Population Size	-0.0034 (0.027)	-0.0013 (0.027)	-0.0018 (0.027)	-0.0036 (0.027)	-0.0030 (0.027)
Per-Capita Income	-0.0415* (0.022)	-0.0359* (0.021)	-0.0402* (0.022)	-0.0413* (0.022)	-0.0343* (0.020)
Distance to Closest Same-Chain Unit	0.0116 (0.020)	0.0103 (0.020)	0.0113 (0.020)	0.0111 (0.020)	0.0093 (0.021)
Number of People Employed	0.0024 (0.005)	0.0016 (0.005)	0.0025 (0.005)	0.0022 (0.005)	0.0020 (0.005)
Number of Competitors (up to 49 employees)	0.0405* (0.021)	0.0427** (0.021)	0.0393* (0.021)	0.0399* (0.021)	0.0413* (0.021)
Number of Competitors (50 to 99 employees)	0.0599** (0.029)	0.0598** (0.029)	0.0592** (0.029)	0.0597** (0.029)	0.0561* (0.029)
Number of Competitors (100 to 249 employees)	0.0136 (0.037)	0.0153 (0.037)	0.0144 (0.037)	0.0123 (0.037)	0.0147 (0.037)
Number of Competitors (more than 250 employees)	-0.1128* (0.062)	-0.1182* (0.062)	-0.1137* (0.062)	-0.1119* (0.062)	-0.1121* (0.062)
Constant	11.4852*** (0.250)	12.0549*** (0.246)	11.3925*** (0.248)	11.4585*** (0.247)	11.9788*** (0.242)
Observations	144,631	144,631	144,631	144,631	144,631
Number of units	2,444	2,444	2,444	2,444	2,444
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

4.6.1.3. Alternate measurements

We further checked the robustness of our results to alternative measures of our independent and dependent variables. First, we tested the robustness of our results using alternative measures of *Irregular Rhythm of Expansion*. We measured *Irregular Rhythm of Expansion* in two different ways. First, we measured *Irregular Rhythm of Expansion* as a time-invariant, rather than a time-variant, variable by using the kurtosis of *Speed of Expansion* for a given middle manager for our entire observation period (Vermeulen & Barkema, 2002). With this alternative measurement, the results are consistent with the predictions of H2, and the coefficient for the interaction of *Speed of Expansion* and *Irregular Rhythm of Expansion* remains positive and significant (0.0001, $p < 0.01$). Second, since some scholars (Hashai et al., 2018; Laamanen & Keil, 2008) have used standard deviation instead of kurtosis to measure the rhythm of specific organizational activities, we measured *Irregular Rhythm of Expansion* using the standard deviation of the speed of expansion over the period starting from the start of the period of observation to the focal time period (i.e., month). We obtain virtually identical results in terms of the sign and significance of the estimated coefficient for the interaction of *Speed of Expansion* and *Irregular Rhythm of Expansion*, i.e., positive and significant (0.0056, $p < 0.01$).

Prior research on learning from failure experience suggests that learning from failure can depreciate over time (Argote et al., 1990). As there is no theoretical basis to use a specific functional form for the decay of experience (Argote, 1999), we use commonly used functional forms to decay learning from failure experience (e.g., Baum & Ingram, 1998; Kim & Miner, 2007) and, thereby, examine the robustness of our results to alternative measures of failure experience. First, we set the discount equal to the age of a failure, which assumes a linear depreciation in the value of *Failure Experience*. Next, we set the discount equal to the age of a failure squared, which assumes that the value of past failures depreciates more rapidly than linear. Third, we set the discount equal to the square root of the age of a failure, which assumes that the depreciation of the value of past failures is slower than linear. Our results are robust to the use of these three different discounting approaches as the coefficient for the interaction between *Speed of Expansion* and *Failure Experience* is positive and significant in all three cases.

Table 4.5. Poisson regression models of replication accuracy

VARIABLES	Model 16	Model 17	Model 18	Model 19	Model 20
Speed of Expansion	-0.0005*** (0.000)	-0.0009*** (0.000)	-0.0006** (0.000)	-0.0013** (0.001)	-0.0017*** (0.000)
Speed of Expansion X Irregular Rhythm of Expansion		0.0002*** (0.000)			0.0001*** (0.000)
Speed of Expansion X Failure Experience			0.0003*** (0.000)		0.0002** (0.000)
Speed of Expansion X Unit Operating Experience				0.0003** (0.000)	0.0003* (0.000)
Irregular Rhythm of Expansion	0.0000 (0.000)	-0.0000 (0.000)	0.0000 (0.000)	0.0000 (0.000)	0.0000 (0.000)
Failure Experience	0.0003** (0.000)	0.0003** (0.000)	0.0030** (0.000)	0.0003** (0.000)	0.0030** (0.000)
Unit Operating Experience	0.0018 (0.003)	0.0016 (0.003)	0.0018 (0.003)	0.0017 (0.003)	0.0015 (0.003)
Unit Size	0.0023*** (0.000)	0.0023*** (0.000)	0.0023*** (0.000)	0.0023*** (0.000)	0.0023*** (0.000)
Number of Units in the Region	-0.0001** (0.000)	-0.0001** (0.000)	-0.0001** (0.000)	-0.0001** (0.000)	-0.0001** (0.000)
Unit Growth	-0.0016*** (0.001)	-0.0016*** (0.001)	-0.0016*** (0.001)	-0.0016*** (0.001)	-0.0016*** (0.001)
Multiunit Owner Size	0.0043* (0.002)	0.0043* (0.002)	0.0043* (0.002)	0.0043* (0.002)	0.0043* (0.002)
Population Size	-0.0005 (0.003)	-0.0005 (0.003)	-0.0005 (0.003)	-0.0005 (0.003)	-0.0005 (0.003)
Per-Capita Income	-0.0032 (0.002)	-0.0031 (0.002)	-0.0032 (0.002)	-0.0032 (0.002)	-0.0031 (0.002)
Distance to Closest Same-Chain Unit	0.0013 (0.002)	0.0013 (0.002)	0.0013 (0.002)	0.0013 (0.002)	0.0013 (0.002)
Number of People Employed	0.0001 (0.000)	0.0001 (0.000)	0.0001 (0.000)	0.0001 (0.000)	0.0001 (0.000)
Number of Competitors (up to 49 employees)	0.0034* (0.002)	0.0034* (0.002)	0.0034* (0.002)	0.0034* (0.002)	0.0034* (0.002)
Number of Competitors (50 to 99 employees)	0.0050*** (0.002)	0.0050*** (0.002)	0.0050*** (0.002)	0.0050*** (0.002)	0.0050*** (0.002)
Number of Competitors (100 to 249 employees)	0.0007 (0.003)	0.0007 (0.003)	0.0007 (0.003)	0.0007 (0.003)	0.0007 (0.003)
Number of Competitors (more than 250 employees)	-0.0091* (0.005)	-0.0091* (0.005)	-0.0091* (0.005)	-0.0091* (0.005)	-0.0091* (0.005)
Observations	144,620	144,620	144,620	144,620	144,620
Number of units	2,433	2,433	2,433	2,433	2,433
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Note: The variables Irregular Rhythm of Expansion and Failure Experience were divided by 10 for ease of presentation. The results should be interpreted accordingly. Eleven observations were dropped by the estimation procedure due to eleven units having only one observation.

Additionally, as organizations might learn more from recent failures than from more distant ones (Madsen & Desai, 2010), we examined how middle managers' recent *Failure*

Experience affects the *Replication Accuracy* of units in their portfolio. We re-estimated our models on the interaction effect of *Failure Experience* using recent time windows (past 24, 30, and 36 months) for failure experience. Our results are robust to using these alternative measures and consistent for all of the above time windows.

Next, we examined whether the effect of the interaction term between *Speed of Expansion* and *Failure Experience* may be affected by a high correlation between *Failure Experience* and *Number of Units in the Region* by using different measures of *Failure Experience*. First, we computed a *Failure Dummy* variable, which takes a value of 1 if the *Failure Experience* of a middle manager at a given time is greater than zero, and 0 otherwise. Second, we computed *Ratio of Failures* by dividing the *Failure Experience* of a middle manager by the total *Number of Units in the Region* in each given period. We re-estimated the models using *Failure Dummy* and *Ratio of Failures* respectively instead of *Failure Experience*. Our results are robust to this alternative measurement of *Failure Experience*. In line with H3, the coefficients on the interaction terms between *Speed of Expansion* and *Failure Dummy* (0.0029, $p < 0.01$) and between *Speed of Expansion* and *Ratio of Failures* are positive and significant (0.0592, $p < 0.01$).

Furthermore, we examined the robustness of our results to measuring *Per-Capita Income*, *Population Size*, *Number of People Employed*, *Number of Competitors (up to 49 employees)*, *Number of Competitors (from 50 to 99)*, *Number of Competitors (from 100 to 299 employees)*, and *Number of Competitors (more than 250 employees)* at the metropolitan statistical area (MSA) or county level instead of the zip code area level. Estimating our models with those alternative measures at the MSA or county level produced essentially the same results in terms of sign, magnitude, and significance of the estimated coefficients on our independent variables.

Finally, we tested the robustness of our results to an alternative measure of our dependent variable (and an alternative empirical model specification) by using a dummy variable as our measure of *Replication Accuracy* and estimating fixed effects logistic regressions. To do so, we generated a new dummy dependent variable that takes a value of 1 if the focal franchise unit accurately replicates all required practices in a given time period, and 0

otherwise. We re-estimated Models 1–5 with this alternative dependent variable using fixed effects logistic regression estimations (Hoetker, 2007) and the same independent and control variables as those reported in Table 4.2 and obtained qualitatively identical results. As a final robustness check, we transformed our dependent, independent, and control variables from unit-monthly to unit-quarterly observations and re-estimated Models 1-5 in Table 4.2. The results obtained were qualitatively the same and quantitatively nearly identical. In sum, the results of our hypotheses tests are robust to all of the above additional robustness checks, lending further empirical support to our findings.

4.7. Discussion

Ensuring that required practices are replicated accurately by their geographically dispersed units is a major challenge and concern for multiunit chain organizations (Bradach, 1998; Winter & Szulanski, 2001; Winter et al., 2012). This paper examines and finds attention and experiential learning mechanisms operating at the middle management level to be significant determinants of replication accuracy. We draw on the attention-based view of the firm (Ocasio, 1997, 2011) to develop theory on how middle managers' allocation of attention to their expansion versus their monitoring role affects the accuracy of replication of required practices at units under their supervision. We theorize that competing demands on middle managers' attention create a "speed-accuracy tradeoff" such that, *ceteris paribus*, when middle managers' speed of expansion increases, replication accuracy at units under their supervision decreases. We further argue that the capacity to switch attention focus and better balance the tradeoff—what (Ocasio, 2011) calls executive attention—will be regulated by, middle managers' past rhythm of expansion experience (Kunisch et al., 2017; Weick & Sutcliffe, 2006), past failure experience (Dahlin et al., 2018), and the operating experience of the focal unit under the managers' purview (Darr et al., 1995; Desai, 2008). Using unique data that tracks middle managers' speed of expansion and replication accuracy at the units of a large U.S.-based non-food franchise chain over eleven years, we test and find empirical support for our hypotheses.

This paper makes three contributions to the literature. First, we contribute to the literature on replication (Winter & Szulanski, 2001; Winter et al., 2012), and specifically the limited work on the determinants of replication accuracy (D'Adderio, 2014; Lawrence, 2020; Williams, 2007; Winter & Szulanski, 2001), by identifying novel determinants of

replication accuracy. While prior work has identified the presence of a hierarchical manager (Winter & Szulanski, 2001), unit age (D'Adderio, 2014), knowledge discreteness (Williams, 2007), and template performance (Lawrence, 2020) as determinants of replication accuracy, we examine and find that middle managers' speed of expansion, their past expansion and failure experience, as well as the operating experience of units under their supervision are significant determinants of replication accuracy. We identify and clarify the role of middle managers' attention allocation and experiential learning as key drivers of the accuracy with which required practices are replicated in multiunit chain organizations.

Second, we also contribute to the attention-based view of the firm (Ocasio, 1997, 2011). Although the importance of executive attention and attentional stability (vigilance) have been documented in prior research (Ocasio, 2011), it is rarely acknowledged that they may have countervailing implications for organizational behaviour. As Ocasio and colleagues (2020: 8) note, these mechanisms are somewhat contradictory to each other in the sense that organizational members who vigilantly attend to particular knowledge domains or experience may find it difficult to flexibly switch their focus of attention to others, or vice versa. Yet, research in this area has yet to investigate the relationship between the two. Our study is a first step that points to important contingencies which moderate this relationship – in particular, the role of experiential learning in the form of learning from the rhythm of expansion experience, failure experience and focal unit operating experience. Further work is needed to understand the relevant contingencies and boundary conditions and, more generally, the impact of attention stability and executive attention on overall attention focus and subsequent organizational behavior and performance.

Third, we contribute towards a better understanding of the effect of speed in organizations. While the theory of the growth of the firm (Penrose 1959) and research on the costs of rapid expansion/scaling (Chandler, 1990; Pierce & Aguinis, 2013; Sterman et al., 2007) and time-compression diseconomies (Dierickx & Cool, 1989; Hawk & Pacheco-de-Almeida, 2018) have documented the existence of a tradeoff organizations face between speed and other desired outcomes, this paper is the first to examine and find a relationship between middle managers' speed of expansion and the accuracy of replication of required

practices at units under their supervision as well as to clarify the attention and experiential learning mechanisms that govern this relationship.

Practically, our research raises implications for middle managers and multiunit chain organizations. For middle managers, our research suggests that they should make a particular effort to learn from their prior expansion and failure history as well as build strong ties and trust with the units under their supervision. For multiunit chain organizations, our research confirms that the mere presence of middle managers who monitor does not consistently mitigate the problem of inaccurate replication of required practices at individual local units. The headquarters of chain organizations need to examine how their middle managers focus on and allocate attention to their expansion and monitoring roles respectively as well as learn more about the role of individual units' learning from operating experience. Investments in deliberate learning and transfer of accumulated experience and best practices in that regard can enable the middle management of chain organizations better dynamically balance competing demands on scarce attention and, thus, help multiunit chain organizations ameliorate the tradeoff between speed of expansion and replication accuracy.

4.7.1. Limitations and Future Research

This study has limitations future research could address. First, the empirical setting for our study is a single U.S.-based franchise organization. Not all multiunit chains use franchising or use franchising exclusively. Some chains possess only company-owned units or a combination of company-owned and franchised units (Kalnins, 2004; Kalnins & Mayer, 2004; Sorenson & Sørensen, 2001; Yin & Zajac, 2004). While our setting provides an appropriate context to test our hypotheses, future research could examine the generalizability of our findings across a diverse set of organizations and sectors. Second, the generalizability of our results could be potentially influenced by national differences. Future studies can examine whether and how, for instance, cultural differences in managerial attentional patterns and decision-making affect the way managers allocate attention to their expansion and monitoring roles. In that regard, future studies could examine how different dimensions of national culture (Dorfman, Javidan, Hanges, Dastmalchian, & House, 2012; Hofstede, 1994) and values (Inglehart, Basanez, Diez-Medrano, Halman, & Luijkx, 2000) affect the impact of speed of expansion on monitoring

outcomes as well as more broadly the impact of values and cultural dimensions on how managers allocate attention among their expansion and monitoring roles. Thus, replication of this study in different cultural settings would help test the generalizability of our theory and findings. Moreover, future research could extend our knowledge by examining the relationship between the speed of expansion and replication accuracy in the context of MNCs. The regional centers and regional headquarters of multinational corporations occupy an intermediate layer in the hierarchy of MNCs that can be seen as also facing an ongoing tension between expansion and monitoring goals (see, e.g., Belderbos, Du, & Goerzen, 2017; Desai, 2009), creating competing demands on regional managers' scarce attention. Finally, we examine the case where middle managers allocate attention between two key roles (expansion and monitoring). Future work could also examine the generalizability of our findings to settings where middle managers may need to allocate attention among a possibly larger number of roles.

Our study suggests several other ways in which future research could advance our understanding. While expanding fast may provide middle managers with salient achievements that quickly affect the top line and valuation of their organization, the accurate replication of required practices at the lower levels of the organization can be expected to have significant longer-term benefits. Future research can explore whether and how additional contingencies affect the way middle managers in organizations undergoing expansion allocate attention and learn to balance the tradeoff between their expansion and monitoring roles. Moreover, the literature on middle management in strategic management has elaborated various ways middle managers can become involved in strategy implementation and even formulation (Wooldridge et al., 2008). While we focus on the high-level distinction between the expansion and monitoring roles of middle management in multiunit chain organizations, future research could explore finer-grained distinctions and subroles within these two roles. Further research is also needed to examine the extent to which organizations may be better able to cope with the speed-accuracy tradeoff they face by having dedicated units and management in charge of monitoring and expansion respectively – though at some higher level in the hierarchy they would still need to ensure integration and have mechanisms and managers that allocate attentional resources between the two roles and have to learn about both roles.

In addition, research on replication would benefit from further theoretical advances in understanding the costs and benefits resulting from the speed-accuracy tradeoff in organizations that grow by replication. Such theory would help us more comprehensively answer questions of fundamental theoretical and managerial significance such as: How fast is too fast or too slow and, thus, what is the “right” speed for a given organization and manager at a given time? How does one best balance the costs of expanding too fast with the costs of expanding too slow? In what way and to what extent is the tradeoff between speed of expansion and accuracy of replication of required practices contingent on the nature of an organizations’ business model (e.g., “brick and mortar” vs. “digital business”)? Future research could also explore the role of middle managers in expanding social and hybrid enterprises (Battilana & Lee, 2014; Chliova & Ringov, 2017) where the social or hybrid nature of the objectives and goals of the organization may place different, additional roles and demands on middle managers’ attention.

4.7.2. Conclusion

This research provides theory and evidence that attention and experiential learning mechanisms can help explain the fundamental and pervasive problem of inaccurate replication of required practices in multiunit chain organizations pursuing a strategy of growth by replication. The dual role – expansion and monitoring – that middle management is typically tasked with in multiunit chain organizations results in competing demands on their limited attention creating a speed-accuracy tradeoff. Thus, *ceteris paribus*, when middle managers’ speed of expansion increases, the accuracy of replication of required practices at units under their supervision decreases. Yet, learning from experience, in particular learning from prior expansion experience, prior failure experience, and unit operating experience, enables managers to better balance the speed-accuracy tradeoff they face.

4.8. References

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5.

Conclusion

This chapter contains a discussion of the theoretical contributions, managerial implications, limitations, and future research opportunities of chapters 2, 3, and 4.

5.1. Discussion

Although exploiting knowledge is fundamental to realizing competitive advantage (Argote & Ingram, 2000; Zander & Kogut, 1995), it has been a fundamental and persistent challenge for firms (Grant, 1996; Kogut & Zander, 1992). Previous studies have identified that the appropriation and effective replication of knowledge are pertinent to the exploitation of knowledge within the firm (Grant, 1996), and that firms use different strategies to improve the appropriability (Arrow, 1962; Teece, 1986, 1987) and replicability (Szulanski, 1996; Winter & Szulanski, 2001) of their knowledge (Winter, 1995). The three essays in this Ph.D. dissertation focus on the specific deterrents to knowledge exploitation that have implications for knowledge appropriation and replication within the firm and propose novel strategies to deal with them. While the connecting point of the three essays is to understand the strategies to exploit knowledge effectively, the essays in this dissertation build on different streams of literature and analytical frameworks. The first essay builds on the literature on the fragmentation of Intellectual Property (IP) rights (Heller & Eisenberg, 1998; Ziedonis, 2004) and technology acquisitions (Ahuja & Katila, 2001), and the framework on appropriability (Teece, 1986; Williamson, 1991) to theorize that firms mitigate the challenges to the appropriability of their innovation efforts in fragmented markets for technology by engaging in technology acquisitions. The second essay builds mainly on the literature on knowledge worker mobility (Agarwal et al., 2009; Almeida & Kogut, 1999) and R&D dynamics (Kor & Mahoney, 2005; Mudambi & Swift, 2014), and the framework on appropriability (B. A. Campbell et al., 2012b; Teece, 1986) to theorize that firms adjust their R&D investments in response to the appropriability threats posed by anticipated knowledge worker mobility. The third essay builds on the literature on replication of organizational practices (Winter & Szulanski, 2001) and organizational learning (Argote, 1999; Argote & Miron-Spektor, 2011) and uses attention-based view (Ocasio, 1997, 2011) as the framework to theorize that the speed of expansion of a middle manager affects replication accuracy at the units under her supervision. To test the proposed hypotheses, the three essays rely on quantitative methodology and different datasets.

5.1.1. Theoretical contributions

This Ph.D. dissertation makes several contributions to the strategy literature. First, the dissertation contributes to the literature on knowledge exploitation (Grant, 1996; Kogut & Zander, 1992), and specifically the work on appropriability (Arrow, 1962; Teece, 1986, 1987). Although previous studies have examined how firms acquire and retain valuable complementary assets to exploit their knowledge effectively (Teece, 1986), the primary focus of these studies has been on complementary manufacturing and distribution assets that improve the appropriability of firm knowledge when new inventions are introduced to the market (e.g., Gans, Hsu, & Stern, 2002; Tripsas, 1997). The first two essays of this dissertation use an extension of Teece' framework of appropriability and propose strategies that firms use to mitigate the appropriability challenges to knowledge exploitation. Building on Heller & Eisenberg (1998) and Ziedonis (2004), the first essay of this dissertation focuses on another important complementary asset — IP rights — and suggests that fragmented ownership of IP rights in an industry affects the profits realized from knowledge exploitation. While previous studies have paid attention to patent filing strategies to deal with appropriability challenges posed by the industry fragmentation of IP rights (Ceccagnoli, 2009; Ziedonis, 2004), the first essay proposes a novel strategy in the form of technology acquisitions to mitigate such threats. In doing so, the first essay also contributes to the literature on the determinants of technology acquisitions (Ahuja & Katila, 2001; Schweizer, 2005; Valentini, 2012; Valentini & Di Guardo, 2012) as this essay identifies fragmented ownership of IP rights at the industry level as a driver of firms' use of technology acquisitions. Building on the literature on knowledge worker mobility (Agarwal, Audretsch, & Sarkar, 2007; Campbell, Ganco, Franco, & Agarwal, 2012), the second essay of this dissertation suggests that another critical asset for the appropriation of firm knowledge are its knowledge workers. While previous studies have paid attention to the impact of the threat of losing knowledge workers on firm innovation outcomes (Conti, 2014; Keum, 2020), the second essay of this dissertation proposes that firms adjust their R&D strategy by reducing the volatility of their R&D expenses to mitigate the appropriability threats induced by knowledge worker mobility. In doing so, the second essay also contributes to the literature on the determinants of R&D volatility (Kor & Mahoney, 2005; Mudambi & Swift, 2014) by identifying the threat of losing knowledge workers as an underexamined determinant of firm R&D dynamics.

Second, the dissertation contributes to the literature on the use of replication as a means of knowledge exploitation (Winter & Szulanski, 2001; Winter et al., 2012) by identifying novel determinants of replication accuracy. While previous studies have identified the presence of a hierarchical manager (Winter & Szulanski, 2001), unit age (D’Adderio, 2014), knowledge discreteness (Williams, 2007), and template performance (Lawrence, 2020) as determinants of replication accuracy, the third essay of this dissertation proposes that the middle managers’ speed of expansion, their past expansion, and failure experience, as well as the operating experience of units under their supervision, are significant determinants of replication accuracy. In doing so, the third essay also contributes to the understanding of the effect of speed in firms (Chandler, 1990; Dierickx & Cool, 1989; Hawk & Pacheco-de-Almeida, 2018; Pierce & Aguinis, 2013; Sterman et al., 2007) as it documents the existence of a tradeoff that firms face between their speed of expansion and other desired outcomes.

5.1.2 Managerial implications

The findings in this dissertation also have managerial implications for firms that seek to exploit their existing knowledge. It is essential for managers of firms operating in high technology sectors that the distribution of IP rights in their industry and departures of their knowledge workers could affect profiting from knowledge exploitation. The findings call attention to the fact that managers engage in strategic decisions to accumulate complementary IP rights and retain knowledge workers to improve the appropriability of firms’ knowledge. Understanding the contingencies that can make the threats to appropriability of knowledge more or less severe can be crucial for managers when strategizing. Additionally, another important aspect that is considered in this dissertation is how managers achieve accurate replication to exploit their knowledge effectively. From the perspective of the replicating firms, this dissertation suggests that competing demands on middle managers’ attention create a “speed-accuracy tradeoff”. The findings confirm that the mere presence of middle managers who monitor does not consistently mitigate the problem of inaccurate replication and that middle managers could alleviate this problem by making efforts to learn from their experiences when exploiting firm knowledge using replication as a strategy.

5.1.3. Limitations

While this dissertation deepens our understanding of how firms exploit their knowledge effectively, it has limitations future research could address. First, the generalizability of the theory and findings needs further examination. While the empirical settings used in the essays of this dissertation provide appropriate contexts to test the proposed hypotheses, future research could examine the generalizability of our findings across a diverse set of sectors and firms. Moreover, since the generalizability of the findings could be affected by various national or institutional level characteristics (Hofstede, 1994; Ingram & Silverman, 2002), there is a need to replicate the findings of this dissertation in different geographies. For example, building on the third essay of this dissertation, future studies could examine how cultural dimensions such as collectivism, long-term orientation, or uncertainty avoidance (Hofstede, 1994) affect managerial allocation of attention between their expansion and monitoring roles. Second, the essays in this dissertation primarily focus on single strategies that firms use to improve appropriability (Teece, 1986) or replication performance (Winter et al., 2012) when exploiting their knowledge (Grant, 1996). Future research could examine how firms combine different strategies, simultaneously or sequentially, to exploit their knowledge effectively. For instance, future research could address whether firms that apply for IP rights aggressively also engage in more technology acquisitions as the industry fragmentation of IP rights increases, or how firms combine, sequence, and/or prioritize the two mechanisms differently at different levels of fragmentation. In the first essay of this dissertation, while we have made an initial step towards exploring this question by performing supplementary analysis, future studies could take this issue as their core concern, and examine these questions in detail.

5.1.4. Directions for future research

This dissertation suggests several other ways in which future research could advance strategy literature. First, the findings of this dissertation suggest directions for future research to improve our understanding of firm innovation and growth (Penrose, 1959; Schumpeter, 1934). Strategy scholars have examined how firms seek to innovate and grow by exploiting their existing knowledge (Levinthal & March, 1993). However, it has been recognized that innovative firms and high growth face substantial barriers in achieving

desired performance (Pe'er, Vertinsky, & Keil, 2016; Rosenbusch, Brinckmann, & Bausch, 2011). Innovate firms face substantial challenges that can destroy value, such as resistance in adoption of new processes within the firm (Ram & Jung, 1991) and of products in the marketplace (Rogers, 2003), over-commitment of resources (Li & Atuahene-Gima, 2001), and problems in appropriating value from innovation (Schumpeter, 1934). Similarly, growing rapidly is challenging, and growing firms face issues in the form of adjustment costs (Garnsey, 1998), substantial over-commitment of resources (Pe'er et al., 2016), and deficits in managerial capacity (Penrose, 1959). While the essays in this dissertation focus on the strategies that firms use to improve the appropriability and replicability of existing knowledge, future research could improve our understanding of other barriers to knowledge exploitation that are identified by the extant literature on growth and innovation.

Second, this dissertation suggests opportunities for research for the literature on scaling up (DeSantola & Gulati, 2017; Garg et al., 2019) which bears a natural genealogical relationship to foundational theory of the growth of the firm (Penrose, 1959). While the scaling literature has emphasized the managerial constraints that rapidly scaling firms face, it should also allow for managerial agency (Hitt, Ireland, Camp, & Sexton, 2001; Shane & Venkataraman, 2000). Future research could examine how managers allocate their attention to various deterrents of knowledge exploitation during the firm growth phase. For instance, the third essay of this dissertation furthers our understanding in this direction by showing that competing claims on middle managers' attention in rapidly scaling replicating multiunit chains creates a "speed-accuracy tradeoff". Future research could explore various tradeoffs which result from interdependencies across activities and across organizational levels created by competing claims on managers' attention when firms exploit their existing knowledge to scale up.

Third, we call for a deeper conversation between knowledge exploitation (Grant 1996, Kogut & Zander 1992) and managerial dynamic capabilities (Teece, 2007) literatures. Such integration would help us more comprehensively answer questions of fundamental theoretical and managerial significance, such as: Why there is heterogeneity in managerial responses to the threats to the appropriability of their knowledge exploitation efforts? Why are some managers more effective at sensing the threats to appropriability of their

knowledge exploitation efforts than others? It would also help us understand how managers in charge of expansion can improve their learning from past experiences of failure and success, e.g., learn how to better deal with the challenges pertaining to overconfidence (Moore & Healy, 2008) or superstitious learning (Levitt & March, 1988; Zollo, 2009), as well as learn to evaluate better and manage the attention demands and salience of their different tasks, objectives, and roles.

Fourth, we call for future research on how managerial incentives shape effective exploitation of knowledge. While exploiting firm knowledge relieves managers of short-term performance pressures (Lavery, 1996), exploitation without paying attention to appropriability and replicability of knowledge could destroy value in the long-term. As immediate exploitation of knowledge may provide managers with very salient achievements that quickly affect the top line and valuation of their firm, creating incentives that promote the use of strategies to improve appropriability and replicability of knowledge is essential for the firm as a whole. Future research could explore additional contingencies that affect managerial attention to strategies to improve appropriability (Teece, 1986) and replicability (Winter & Szulanski, 2001) of firm knowledge.

Overall, there is a need for a more comprehensive theory that embraces not only knowledge creation but also knowledge exploitation. The research on knowledge exploitation would benefit from further theoretical advances in understanding the deterrents to knowledge exploitation and how firms respond to them to exploit their knowledge effectively. For instance, future research could examine how firms' absorptive capacity (Cohen & Levinthal, 1990) has implications for knowledge exploitation. It is important to understand how the challenges to knowledge exploitation shape firm strategy.

5.2. Conclusion

This dissertation focuses on fundamental and persistent challenges to knowledge exploitation and the strategies firms use to overcome them. The first essay provides theory and evidence that firms mitigate the challenges to the appropriability of their innovation efforts in fragmented markets for technology by engaging in technology acquisitions. The second essay provides theory and evidence that firms reduce their R&D volatility in

response to the appropriability threats posed by the anticipated loss of knowledge workers. The third essay provides theory and evidence that a middle managers' speed of expansion reduces replication accuracy at the units under her supervision. The three essays also explore additional contingencies that affect the relationships mentioned above.

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