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Three Essays on the Mobility of Human Capital and Knowledge Transfer

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To my father, Eun Sik Kim who raised me with great love and motivated me unwearyingly

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ABSTRACT

Both economics and strategic management literature illuminate the impacts of human capital and knowledge on the growth of regional economies and firms. Despite their different characteristics as factors of production, human capital and knowledge often move (or stay) together, as knowledge is often embedded in the human brain. In addition, human capital and knowledge share certain characteristics; a region or firm cannot be completely free from the risk of unintended leakage because human capital can move deliberately in the labor market, at their own will, and knowledge can spill over through various channels against the knolwedge holder's will. Therefore, it is in the best interests of firms and regions to retain (or foster) human capital and knowledge. The three papers constituting this thesis address the antecedents of knowledge spillovers and mobility decision by talented indivduals including the costs of transportation between two regions and the competition between two firms, as well as the attractiveness of a firm as an employer.

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INTRODUCTION

1.1. The Overview of the Thesis

This Ph.D. thesis is consisted of three papers sharing common conerns on how loci of human capital and knowledge moves acorss the boundaries of firms and regions, and how such flows affect competitive advantages of firms and regions.[1] Those papers are mostly based on and contribute to two different streams of literature in economics and management: 1) (strategic) human capital[2] (Coff & Kryscynski, 2011; Wright, Coff, & Moliterno, 2014; Becker, 1962) and 2) knowledge and technological innovation (Romer, 1986, 1990; Lucas, 1998; Nelson, 1993). So, the entire thesis is entitled as "Three Essays on the Mobility of Human Capital and Knowledge Transfer."

Both human capital and knowledge are constrained imperfectly by the boundaries of firms and regions, including different types of barriers such contractual and legal agreements[3] as well as geographical distances and relational ties.[4] The labor market in reality is full of frictions those which induce search costs and matching costs (Pissadrides, 2011). However, both human capital and knowledge are not perfectly restrained and therefore can move and spread across such boundaries, against the policies developed and induced by firms and regional governments to retain them (Coff, 1997). The Resource-Based View (Barney, 1986) and the Endogenous Growth Theory (Romer, 1986; Lucas, 1998) together imply that heterogeneous factor endowments including human capital and knowledge lead to heterogeneous outcomes (e.g.,

[1] Related to the competitive advantage, the third and fourth chapters of this thesis indirectly inquire. They limitedly focus on gaining or losing of human capital and knowledge, which are the endowment contributing to regional and firm competitive advantages.
[2] Throughout the thesis, I use interchangeably the terms 'human capital' and 'persons possessing the human capital' because of their inalienability.
3 Examples: non-competing agreement (Marx & Fleming, 2009; Starr, Prescott, Bishara, 2016), non-solicitation agreement (Dormans, 2013), and intellectual property rights (Gans, Hsu, & Stern, 2009).
[4] Examples: localized knowledge spillovers (Arora, Belenzen, & Lee, 2018), structural holes (Burt, 1992).

technological innovation, financial performance, and economic growth). This thesis investigates the antecedents and/or aftermaths of region/firm-level heterogeneity in human capital mobility and knowledge transfer. Understanding of the factors that impact individuals' mobility decisions and knowledge transmission could deepen our understanding of the source of heterogenous growth among firms and regions.

This thesis consists of three papers sharing a single leitmotif: how the inter-firm/region mobility and knowledge transfer of individuals increase (or decrease) in response to changes in the costs of transportation or information (Giroud, 2013; Charnoz, Lelarge, & Trevien, 2018). Apart from the other types of factor endowments, both human capital and knowledge are the types of endowments which cannot be completely restrained within a firm or region. As firms and regions compete for talents and knowledge, understanding and identification of the factors that impact outflows of human capital and knowledge may have some implications for business managers and government policy makers. The three researches outlined in this thesis all inquire into research questions prompted by gaps in our understanding of the mobility of human capital, the transfer of knowledge, and how gaining and losing them impact the competitive advantages of firms and regions (Porter, 1990; Almedia & Kogut, 1999; Coff, 1997). However, these papers differ in their levels of analysis: regional-level, firm-level, and individual-level.

Regarding the regional level, the first paper, "The Impacts of Transportation Costs on Inventor Mobiltiy, Knowledge Spillovers, and Regional Competitive Competitiveness," focuses on how human capital and knowledge flow between a pair of regions, particularly if the regions are discrete in terms of quality. The New Economic Geography tradition (Krugman, 1991; Fujita & Thisse, 2013) makes inquiries regarding the uneven characteristics across regions. The phenomena of agglomeration, dispersion, and transportation costs are their favorite topics of discussion (Redding & Turner, 2015; Donaldson, 2018). However, the impact of transportation costs on the inequality between two heterogenous regions has not yet been discussed. Lowering inter-regional transportation costs changes the industry dynamics in the connected regions, thus motivating individuals to change their locations interregionally (Catalini, Fons-Rosen, & Gaulé, 2019; Tamura, 2017; Giroud, 2013). This paper mainly finds that, when an airline connection lowers the cost of transportation between a technologically advanced core region and a technologically lagged periphery region, 1) the agglomeration of human capital is accelerated, 2) innovative activities increases only in the core and decreases in periphery regions, 3) knowledge transfer between the core and periphery regions decreases in both directions, and 4) patents quality increase all regions regardles sof their dyad types, but some of them are insignificant.

Regarding the firm-level, the second paper, "Strategic Alliances and Inventor Mobility: Evidence from the U.S. Pharmaceutical Industry," focuses on the dyads of alliance partners. In a strategic alliance for the purpose of learning and R&D, two firms may have one of two antinomic strategic goals with regard to human capital and knowledge: 1) creating value by building a good, sustained relationship between two firms or 2) misappropriating value by poaching its partner's human capital and taking existing knowledge rather than creating new knowledge (Hamel, 1991; Das & Teng, 2000; Lavie, 2007; Hess & Rothaermel, 2011). These two goals might not be pursued simultaneously because employee poaching is often perceived as an opportunistic behavior, likely causing the alliance itself to be discontinued or making the poached firm less collaborative (de Rond & Bouchikhi, 2004). In terms of information, a learning alliance enables a firm to know more about its partner's knowledge base and human capital, thus lowering mobility barriers between the two firms as the poacher is more informed about the potential target indiviuals to poach and the poached individual (Campbell, Kryscynski,

& Olson, 2017). This paper finds that the stronger competitive orientation of a firm increases its poaching of corporate scientists[5] from its partner in a learning alliance. Once firms gain a better understanding of each other's human capital and knowledge, a firm that was more during the pre-alliance phase against its future alliance partner will behave more opportunistically during the alliance and post-alliance phases. This effect can be moderated if the poacher has different channels of learning from its alliance partner other than employee poaching and the alliance itself or technological similarity with the alliance partner.

Regarding the individual level, the third paper, "Stakeholder Orientation as a Quality Signal in the Labor Market: Evidence from Post-M&A Retention of Newly Acquired Human Capital," focuses on the retention of individual corporate scientists whose employer changed through M&A. For the newly acquired human capital, the cognitive cost of mobility is lowered because they have suffered from a sudden change in their social and organizational identifications subsequent to M&A and less attachments to the acquiror as new employer (Ullrich & van Dick, 2007). Such a psychological shock impacts those employees evenly. Before M&A, the corporate scientists had only abstract information about their (upcoming) employer. Once M&A were announced, these scientists suddenly needed to assess the quality of their new employer using the information they were given, but the information was insufficient and incomplete. Also, the newly acquired human capital did not join the new employer at their own will, which decreases bias from self-selection. That the treatment is even and self-selection bias is eliminated makes newly acquired human captial as ideal sample to test the idea how the signal from the (upcoming) acquiror affects the decisions of the newly acquired human capital if stayin g in the acquired firm. The empirical analysis indicated that a high-quality acquiror would retain

[5] Throughout the thesis, I will use the term, scientist, corporate scientist, and inventor interchangeably.

the newly acquired human capital for a longer period; such an effect is stronger if the newly acquired human capital is also of high quality.

The three papers outlined in this thesis commonly use patent data from the United States Patent and Trademark Office. Patent data provides information regarding each patent's technological categories, assignees (patenting organizations), inventors, dates of application, and grant. Patent data also allows for the identification the inter-regional/firm human capital mobility and knowledge transfer as it disambiguates identities of individual inventors. In this thesis, each paper integrates a different portion of data into the main dataset relating to human capital mobility and knowledge transfer. For example, the first paper uses airline data from the U.S. Department of Transportation (Giroud, 2013), the second paper uses alliance and product market competition data from the U.S. pharmaceutical industry (Cui, Yang & Vertinsky, 2018), and the third paper uses M&A and stakeholder orientation datasets.

Table 1.1. provides a bird's-eye view of these three papers. All three papers shares Strategic Human Capital as a theoretical background. However, each paper presented a unique combination of theories and inventor/knowledge-related data derived from patent data. Each region and firm tried to retain and attrac human capital as a container of existing knowledge and as a source of knowledge creation. The geographical setting of those papers were all located in the United States because USPTO data was used for them. However, all three papers differed in their empirical models. The first paper utilized a difference-in-differences model based on the Ordinary Least Squares (OLS) with dyad and year fixed effects, which allowed for claiming causality. The second paper used a negative binomial distribution with fixed effects due to the overdispersion of the dependent variable. The third paper utilized the Cox Proportional Hazard model for continuous survival analysis. Both the second and third papers do not make causality

calims because of the limitations in their econmetric models and identification strategies. However, the dependent variables of the second and third papers were chronologically sequential to the independent variables, and multiple robustness checks were conducted for each paper. Therefore, the results of all three papers were either causal or, at least, robust.

Insert Table 1.1. about here

1.2.THE CONTRIBUTIONS AND LIMITATIONS OF THIS THESIS

This thesis inspected what happen to the loci of human capital and knowledge once labor market barriers are lowed in terms of their geospatial locations and affiliations (Campbell *et al.*, 2017). The findings of the three papers demonstrate that firms/regions of higher quality or motivation end up pulling more and better human capital and subseqeuntly knowledge assocaited with human capital, at least in the short run. Such findings have implications for several different streams of literature in economics and management. First, following recent trends in labor economics and management (Moretti & Wilson, 2017; Akcigit, Baslandze, & Stantcheva, 2016; Campbell *et al.*, 2017), these papers inquired as to how individual human capital directly and indirectly reacts to changes in the following mobility costs: 1) transportation cost, 2) information cost, and 3) cognitive cost of leaving current employer. Second, these papers also emphasized the role of knowledge as a source of competitive advantage among firms and regions. Since knowledge is tightly linked to competitive advantage in strategic management and economics (Grant, 1996; Romer, 1990; Porter, 1990). Third, these papers, taken together, can deepen our understanding of microfoundations of economic growth and firm performance because human capital mobility affects changes in firm/region-level knowledge creation and transfer (Felin, Foss, & Ployhart, 2015; Duranton & Puga, 2004). The three papers commonly inquire the drivers of the loci of human capital and knowledge, which serves as the micro-level mechanism of the macro-level performances like regional and firm-level competitive advantage.[6]

However, this thesis has limitations. For example, these papers lack a view of what happens to the individual human capital of those who decide to move (or not move) across boundaries. Although the third paper addresses individual-level issues, it examines the antecedents of human capital mobility rather than the consequences of human capital mobility. As Groysberg, Lee, and Nanda (2008) have explicated, the individuals may experience some expected or unexpected downturns in productivity immediately after mobility. For instance, Moretti (2019) compared the productivity of individual human capital before and after mobility from a periphery region to a core region. All of the three papers outlined in this thesis could be complemented by further individual-level analyses.

[6] But only the first paper tests both the micro-level and the macro-level. The second and third papers examine the micro-level mobility of individual inventors, based on the assumption that mobility of human capital is associated with mobility of knowledge and such mobilities end up enhancing the competitive advantage to the destination firm (and halting the competitive advantage of the origin firm). However, knowing the micro-level mechanisms in relation to the macro-level outcomes also contributes to the microfoundations literature (Felin *et al.*, 2015).

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Table 1.1. Summaries of Three Papers

	Paper #1	Paper #2	Paper #3
Theory	Strategic Human Capital New Economic Geography	Strategic Human Capital Competitive Strategy Cooperative Strategy	Strategic Human Capital Instrumental Stakeholder Theory
Level of Analysis	Region (dyad)	Firm (dyad)	Individual
Setting	United States (all industry), 1991 ~ 2015	U.S. Pharma, 1986 ~ 2008	U.S. M&As (all industry but finance)
Data	Patentsview / T-100 (U.S. Gov.)	Patentsview / Alliance & Competition in the U.S. Pharma	Patentsview / SDC Platinum / KLD / ASSET4
Observation	A Pair of Regions– Year (directional dyad)	Alliance – Year (directional dyad)	M&A – Inventor
Dep. Var.	# of Mobility per year	Post-alliance Inventor Mobility (5yr) (B → A)	Duration between M&A and Departure (Inventors)
Ind. Var.	Airline Connection Airline Connection * Core-Periphery Airline Connection * Periphery-Core	Pre-alliance Competitive Aggressiveness (A → B)	Stakeholder Orientation of the Acquiror - Main: KLD, Robustness: ASSET4
Causality	Yes (*diff-in-diffs)*	No (chronologically sequencing, but no causal)	No (chronologically sequencing, but no causal)
Type of Costs	Transportation / Information	Information	Psychological / Information
Regression	OLS with fixed effects	Negative binomial	Survival analysis (Cox Hazard)

THE IMPACTS OF TRANSPORTATION COSTS ON INVENTOR MOBILITY, KNOWLEDGE SPILLOVERS, AND REGIONAL COMPETITIVENESS ADVANTAGE

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THE IMPACTS OF TRANSPORTATION COSTS ON INVENTOR MOBILITY, KNOWLEDGE SPILLOVERS, AND REGIONAL COMPETITIVENESS ADVANTAGE

ABSTRACT

The agglomeration or dispersion of human capital and knowledge, which lie at the intersection of economic growth and economic geography, are widely viewed as key factors underlying sustainable economic prosperity of regions and nations. We explore the microfoundations of these processes by examining the mobility of human capital and the flows of knowledge that accompany such mobility. In particular, we analyze the impact of new airline routes on the mobility of inventors between pairs of regions that we classify as either “core” or “periphery” on the basis of their patenting activity. We also examine aggregate outcomes in terms of changes in patenting and citation activities in these pairs. Our results demonstrate that, given lower transportation costs, the forces of agglomeration that make human capital gravitate toward the core outweigh the forces of dispersion that pull human capital toward the periphery. This effect persists regardless of whether inter-regional mobility takes the form of inter- or intra-firm mobility. We also find that inter-regional knowledge flows (measured in terms of patent citations) decreases in both directions (i.e., from core to peripheral regions and vice versa). In terms of patenting activities, the numbers of patents and of patenting firms increase in the core and decrease in the periphery. Lastly, patent quality increases at both ends of core-periphery dyads.

1. INTRODUCTION

Human capital and knowledge flows are at the center of political and scholarly discussions on economic growth. For example, in 2010, President Barack Obama used his State of the Union speech to highlight “Tampa, Florida, where workers will soon break ground on a new high-speed railroad funded by the Recovery Act. … There are projects like that all across this country that will create jobs and help move our nation's goods, services, and information” (Obama, 2010). The idea behind such political pronouncements is that reducing the costs of transportation will lead to economic development in those geographical areas that are connected by a new railroad, a new highway, or a new airline route, and that this is true regardless of their pre-connection status or factor endowments. Some research in economics supports this view, as it suggests that reductions in the costs of human capital mobility and in the costs of transferring knowledge across geographical distances improve general welfare (Donaldson & Hornbeck, 2016; Dittmar, 2011; Tang, 2014; Bernard, Moxnes, & Saito, 2019).

However, the geographical distribution of welfare gains and losses is uneven, and depends on the distribution of factor endowments across regions and the economic forces set in motion by changes in costs of transportation. This paper follows the New Economic Geography literature, which often labels the more prosperous regions as “core” and the less-prosperous regions as “periphery” (Krugman, 1991). Audretsch and Feldman (1996) find that the distribution of innovative activities is more skewed than the distribution of production activities, but we do not know of if how a change in transportation cost affects the loci of human capital and knowledge which are the sources of regional competitive advantage. Where transportation reduces the costs from distance, but the New Economic Geography literature suggests that forces of agglomeration and forces of dispersion may be initiated by new infrastructure investments that shortens travel time and costs (Fujita & Thisse, 2013; Behrens, Caignè, Ottaviano, and Thisse, 2006; Krugman, 1991).[7] Nevertheless, the effects on welfare across such regions is an issue that is poorly understood despite the expanding literature on the link between infrastructure, including transportation, and economic growth (Ottaviano, 2008; Banerjee, Duflo, & Qian, 2012; Glaeser & Kohlhase, 2004).

[7] In addition to scenarios in which nothing changes, there are four possible scenarios for a given dyad of a core and a periphery: 1) the core flourishes and the periphery loses, 2) the periphery flourishes and the core loses, 3) both the core and the periphery flourish, and 4) both the core and the periphery decline.

We particularly focus on flows of human capital and knowledge because they play important roles in regional competitive advantage and economic growth (Romer, 1986, 1990; Lucas, 1988; Porter, 1990). Such flows are influenced by pecuniary and non-pecuniary incentives. For example, recent research examines the interregional mobility of particularly productive inventors ("star scientists") in response to differences in tax rates (Moretti & Wilson, 2017; Ackigit *et al.*, 2016). Inventor mobility is also influenced by labor-market frictions and information asymmetries (Campbell, Kryscynski, & Olson, 2017; Derenoncourt, 2019; Starr, Ganco, & Campbell, 2018; Di Lorenzo & Almeida, 2017). A third important friction can be found in transportation costs. However, the impact of transportation costs on inventor mobility and knowledge flows between heterogeneous regions remains unexplored.[8] As Redding and Turner (2015: 1341) observe, the literature on the economic impact of transportation costs either "considers the role of transportation costs between cities and is mainly interested in the movement of goods" or "considers the role of transportation costs within cities and is mainly interested in the movement of people." In general, we lack an understanding of how transportation costs, in the presence of regional heterogeneity, influence inflows and outflows of human capital and knowledge, and of the aggregate implications of inventor mobility in terms of changing patterns of innovating activities across regions, which subsequently impacts the economics growth of regions (Romer, 1990).

To gain insight into these issues, we analyze the impact of a new airline route on the mobility of inventors and examine the aggregate outcomes in terms of changes in patenting and citation activities in core-periphery pairs (i.e., knowledge flows). New airline routes reduce transportation and information costs and, therefore, affect industry dynamics and labor markets at both ends of those routes (Tamura, 2017; Giroud, 2013; Charonz, Lelarge, & Trivien, 2018). Several highly interdependent mechanisms and variables are involved here. As the sorting literature (Eeckhout *et al.*, 2014; Gaubert, 2018) implies, heterogeneous human capital and firms are paired within heterogenous regions, but mobility across regional labor markets may be impaired by various frictions (Campbell *et al.*, 2017). We examine whether and how such spatial sorting of human capital is influenced by shocks to transportation costs (Eeckhout *et al.*, 2014;

[8] A partial exception is Tamura (2017). However, Tamura (2017) considers how geographical patterns of patent citations are influenced by shocks to transportation costs rather than mobility per se. Moreover, Tamura (2017) does not directly tackle the issue of the core-periphery relationship between regions.

Mori & Nishikimi, 2002).[9] And subsequently, we also examine how such spatial sorting affects regional innovative activities like patenting and citation received. However, the argument is not that inventor mobility is a direct consequence of lower transportation costs, but rather that lower transportation costs entail changes in the costs and benefits of doing business in the focal region, which affects inventors' interest in that region.[10] A change in transportation cost indirectly impacts the loci of human capital and knowledge, as well as the regional competitive advantage through various channels.

Reduced transportation costs are often associated with an increase in geographical proximity between two regions, which entails more interactions between the connected regions (Boschma, 2005). However, the precise patterns of inventor mobility and knowledge transfers set in motion by a shock to transportation costs are hard to predict *a priori*. A change in transportation costs influences mobility across regions for several reasons and in several ways. First, according to the New Economic Geography literature, people agglomerate in the core regions because they offer more opportunities to do businesses, a better quality of life, and access to human capital (Acemoglu, 1996; Florida, 2008). In this context, the more connected the core is, the more attractive it becomes because of the network effect (Fujita & Thisse, 2013; Glaeser & Kohlhase, 2004). Second, a decrease in inter-regional transportation costs increases the proximity between the regions, so that the firms in each area become be more likely to compete with each other. As the periphery's firms tend to be less competitive than those in the core, the periphery loses businesses and, thus, loses human capital to the core (Flückiger, Hornung, Larch, Ludwig & Mees, 2019; Chauvin, 2017; Borjas & Doran, 2012). Third, if transportation costs fall, inter-regional business trips become cheaper (Catalini *et al.*, 2019). This means that an inventor working in a peripheral region may be able to live in the more attractive core region without losing social and business relations in the peripheral region (Behrens *et al.*, 2006; Duranton & Puga, 2004).[11] Fourth, on the other hand, the same New Economic Geography literature suggests that the periphery may gain the core's inventors because the higher costs of

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[9] In this paper, "transportation costs" does not simply mean the fees paid to use modes of transportation. It also includes the length of time spent on transitions as well as various psychological factors.

[10] Thus, our paper is similar to Michaels (2008), which shows that a new highway affects the local labor market: "By increasing trade, the highways raised the relative demand for skilled manufacturing workers in skill-abundant counties and reduced it elsewhere" (Michaels, 2008: 683).

[11] A periphery firm may use distant inventors as external consultants and pay their travel costs to enable them to regularly visit the firm instead of hiring them and redeploying them inter-regionally. This becomes cheaper than in the pre-connection period.

living and doing business in the congested core region may disperse the core's human capital to the periphery. This human capital then serves existing customers in the core through business trips. Fifth, lower transportation costs may mean lower costs of accessing knowledge held in other regions (whether core or periphery) as well as lower costs of information acquisition and monitoring (Bernstein *et al.,* 2016; Tamura, 2017; Bernstein *et al.,* 2016). In particular, the lowered cost of information and monitoring enables the periphery to gain access to the core's knowledge at a lower cost (Bernard *et al.,* 2019; Hjort & Poulsen, 2019), which enables it to prosper and become more attractive to the core's human capital. In addition, we need to consider the firm-level decision to continue or close a business in a specific region given a new cost structure (Bernard *et al.*, 2019; Giroud & Mueller, 2015; Boeh & Beamish, 2012). These five mechanisms provide mixed predictions for the flows of human capital and knowledge given lower transportation costs because the agglomeration forces benefiting the core and the dispersion forces benefiting the periphery coexist, and we do not know which is stronger (Fujita & Thisse, 2013).

Our approach is related to a few earlier papers on the inter-regional influence of transportation costs on individuals' spatial mobility and knowledge flows. Scholars have used reductions in transportation costs as a proxy for increases in geographical proximity between two firms or individuals. For instance, Heuermann and Schmieder (2018) examine changes in the geospatial distribution of long-distance commuting patterns resulting from the expansion of a German high-speed rail network. Baum-Snow *et al.* (2017) found that, in China, the newer and denser configurations of railroad and highway networks changed the country's economic outcomes (in GDP) by allowing for sprawling regional populations and industrial activities. Giroud (2013), Charnoz, Lelarge, and Trevien (2018), Levine, Lin, Peng and Xi (2019), and Bernstein *et al.* (2016) use airline connections or high-speed railways as instruments for increasing monitoring efficiency in principal-agent relationships (e.g., venture capital-startup relationships, headquarters-subsidiary relationships). They propose that such connections enable more business trips, so that monitoring distant plants (Giroud, 2013), banking branches (Levine *et al.*, 2019), or startups (Bernstein *et al.*, 2016) becomes easier. Catalini *et al.* (2019) also view airlines as a tool for short-term business trips that can increase interactions among academic scholars and expand their types of research. Sohn, Seamans, and Sands (2018) argue that exposure to airmail and airline networks drives peripheral regions to start inventing in fields related to aviation technologies. However, none of these papers investigate whether transportation costs affect the inter-regional mobility of individuals. They also fail to examine innovation patterns in both regions after the introduction of transportation infrastructure.

To explore these issues, we analyze the effects of a shock to transportation costs on patterns of inventor's mobility and knowledge flow, which impact the regional competitive advantage through technological innovation. In specific, we test the impact of transportation costs on the inter-regional mobility of inventors and on patent citations received of the focal regions' patents. In addition, we analyze the consequences of those flows of inventors and knowledge for the regions at both ends of the dyads in terms of such variables as the number of unique firms patenting and the number of patent applications. They show how a macro-level change, a change in transportation cost, impacts the micro-level variables like flows of inventor and knowledge, which subsequently impacts the macro-level outcomes like the number of patents, patenting firms, and citation received. Such a bird-eye view scheme meets the approach taken by the microfoundations literature in economic geography and management (Duranton & Puga, 2004; Acemoglu, 1996; Felin, Foss, & Ployhart, 2015). In sum, this paper takes microfoundational approach to the regional innovative performance by investigating the mechanims of how a change in macro-level affects macro-level outcomes through the micro-level channels. Figure 2.1. visualize the mechanisms that this paper investgates.[12]

Insert Figure 2.1. about here

Empirically, we use a patent dataset to identify the locations and affiliations of inventors in the contiguous United States from 1991 to 2015. The same dataset is used to measure the number of citations received of those patents as a proxy of the flow of knowledge, while the number of patent applications is used as a proxy of regional innovative productivity.

To interpret a newly established airline connection between two previously unconnected core/peripheral regions as a shock to transportation costs that has implications for mobility patterns (Giroud, 2013), we need a robust definition of "region." By "regions," we mean U.S. metropolitan statistical areas (MSAs), which are large cities (or a number of cities) and the areas

[12] The diagram is originated from the Coleman's bathtub model of social change (Coleman, 1994).

on which those cities have substantial business and economic influences. This justifies an assumption that people tend to keep living in an MSA unless there is an exogenous shock.

We utilize a generalized difference-in-difference framework to identify the relevant effects. The results show that the outmigration ratio of inventors (Moretti & Wilson, 2017) from a core region to its paired peripheral region decreases following a decline in transportation costs between those regions, while the outmigration ratio from a periphery to its paired core increases (Moretti & Wilson, 2017).[13] The airline connection regardless of the type of the regional dyads has negative, significant impact on the outmigration ratios.[14] These results hold if we limit our dependent variable to inter-regional mobility, which encompasses inter-firm mobility and intra-firm mobility. Our following patent and citation analyses find some interesting results. First, the proxies of the focal region's patenting activities like the number of firms patenting, the number of firms start patenting, and the number of patents applied are positive in the core region and negative in the peripheral region. This aligns with the findings from the inventor outmigration ratio, as the periphery loses inventors, its patenting activities diminish in the periphery regions and the opposite is true in the core regions. These results hold in the connected dyads regardless of its type. Second, the knowledge outflow from the core to the periphery increases while that from the periphery to the core decreases. The airline connection regardless of their dyad types has positive impact on the knowledge outflow from the focal region. These results imply that the lowered cost access to the core's knowledge and loss of human capital drive the inventors in the periphery to refer and depend more on the core's knowledge. Third, the new patent's quality, proxied by the number of citations received, increases in both directions and all new connection. However, some of the coefficients are insignificant. Lastly, the interregional collaboration in patenting decreases in all dyad types (core-periphery, periphery-core, all), but only periphery-core dyads are significant.

2.1. Empirical Setting and Data

This section provides basic information on our datasets on the geolocations and technological classes of patents (including inventors and their affiliations), and on airline connections. We use a unique dataset that integrates the geographical data of patent inventors with the corporate-level aggregated data of those inventors' affiliations and airline connection data.

[13] These ratios are defined as the ratio of 1) estimated inventor mobility from the focal region to another region to 2) the estimated inventor population in the focal region.

[14] This includes all three types of dyads if they are connected by airline: core-periphery, periphery-core, and neither.

U.S. Patent Dataset

We utilize U.S. patent data to identify the inter-regional mobility of inventors both within and across firms and other types of organizations. Specifically, we use the PatentsView dataset, which consists of patent data provided by the United States Patents and Trademark Office (USPTO). Notably, the USPTO's own dataset does not provide sufficient information about the individual inventors and their patent history because the USPTO does not require inventors or their affiliated organizations to provide unique identifying information. This means that, for instance, several "John Smiths" may be registered as applicants, and the dataset does not offer a good way of distinguishing them from one another. However, patent applications include the names of inventors and their affiliations as well as other information, such as their addresses, and citations of previous patents and other documents (e.g., articles in scientific journals). Thus, through PatentsView, the USPTO provides the outcomes of a probabilistic algorithmic estimation rather than an exact pairing of a unique inventor and his or her patents (Monath & McCallum, 2015). Therefore, further analysis is needed to determine whether an inventor associated with a patent is the same person as an inventor with a similar name associated with another patent. In other words, disambiguation is necessary. The accuracy of disambiguation is often a critical issue in research using patent datasets (Hall, Jaffe, & Trajtenberg, 2001; Trajtenberg, Shiff, & Melamed, 2006; Li *et al.*, 2014; Ge *et al.*, 2016).

In detail, the PatentsView platform adopts a "discriminative hierarchical coreference" algorithm to disambiguate data on inventors and their affiliations (Monath & McCallum, 2015). Although there are other datasets that disambiguate data on inventors and/or their affiliations using similar but different algorithms (Li *et al.*, 2014; Ventura, Nugent, & Fuchs, 2015; Morrison, Riccaboni, & Pammolli, 2017), we rely on PatentsView for several reasons. First, it is officially from the USPTO. Second, it disambiguates both inventors and affiliations. Third, it is linked to geolocations. More specifically, it provides coordinates (latitude and longitude) for the inventors and affiliations in each patent. We use geolocation data to track the whereabouts of inventors across time. From this dataset, we know the identities of inventors, the identities of affiliations, the citing-citation relationship for each patent, the year of patent application, and the geolocations of each inventor-patent and affiliation-patent based on information included in their applications.

Defining Core and Peripheral Regions in the U.S. Using Patent Data

In line with the literature, we treat the MSA as the relevant geographical unit. An MSA is a group of counties that are consolidated in terms of business activities, such that workplaces can generally be reached by car. Each inventor-patent and affiliation-patent pair is linked to geolocation data (latitudes and longitudes). In the U.S., most of these pairs are in one of the MSAs. We classified each MSA as a core region, peripheral region, or other region.[15, 16] As we are interested in mobility in the context of the uneven distribution of human capital and knowledge across regions, we define the technologically advanced regions as the core and the technologically lagging regions as the periphery. The uneven distribution of knowledge and human capital persists over time, as individuals tend to remain in a specific region for decades. Most job mobility is not associated with residential relocation even though job changes increase the likelihood of such relocation. In other words, inter-firm mobility is mostly localized (Clark & Withers, 1999; Breschi & Lissoni, 2001); and we expect interregional mobility between two regions is stable until an exogenous shock impacts them.

We use the accumulated number of patent-inventor pairs in a specific region as a measure of that region's stock of knowledge.[17] A patent-inventor pair belongs to a region if the address information for a patent's inventor is within the geographical boundaries of the region. Fortunately, the PatentsView database provides the geolocation data (latitude and longitude) for each patent-inventor pair, so that we can identify the geographical presence of each patent and its inventor in a specific year.

Our dataset covers more peripheral regions than core regions because the basic core-periphery model (Krugman, 1991; Fujita & Thisse, 2013) assumes a narrow core and a broad periphery, which is also true in reality. However, as we do not have absolute definitions of "core" and "periphery," we use multiple definitions for defining the core. Thus, for the core, we apply a threshold of the top 5% in terms of accumulated patents. If an MSA is within the top 5% among the 362 MSAs in terms of the number of patent applications in a specific year (i.e., the top 18), then the region is counted as a core region. In addition, Kerr (2008) deliberately picked 18 MSAs as the top MSAs in terms of technological innovation. If a region is coded as top 5% is

[15] Therefore, our sample has pairs of core-periphery, pairs of periphery-core, and the others.
[16] Some of the extant literature views intra-regional affairs as encompassing both the core and the periphery in the same geographical region in which the core is the urban area and the periphery surrounds it. However, as our focus is on the national level, we classify sub-national regions into core and periphery.
[17] For example, a patent with 10 inventors may have 10 different patent-inventor pairs.

not persistent across time, but if a region is coded as top 18 regions according to Kerr (2008) is persistent throughout our research. For the periphery, we apply a threshold of the bottom 75% throughout our analyses. The types of regions (core, periphery, and other[18]) are not defined by their regional GDP or population. So, a less dense area in terms of population or urbanization can be a core, by definition.

Estimating Inventor Mobility Using U.S. Patent Data

The main variable of interest is the outmigration ratio of the focal region's inventors in a dyadic relationship with another region (Moretti & Wilson, 2017). In this ratio, estimated inventor mobility (measured as mobility events) from the focal region to its paired region in a given year is divided by the estimated size of the inventor population in the focal region in the same year. This ratio helps to determine whether a region gains or loses human capital each year. To estimate this ratio, we need to assign regions to active inventors each year between their first year of patenting and their latest year of patenting based on their appearances in patent dataset.

We use geolocation data for patent-inventor pairs to track the inter-regional and inter-firm mobility of inventors.[19] Inventor mobility may be the result of an inventor's decision to leave a region or firm in favor of another region or firm (inter-firm mobility). Alternatively, the mobility event may be the result of the inventor's employer relocating the inventor geographically (intra-firm mobility). We aggregate those two subsets of inter-regional mobility to examine the impact of lower transportation costs on inter-regional inventor mobility. We excluded the all patent-inventor pairs those which do not have affiliation / assignee information from our sample. For instance, a sample inventor might have some patents for inventions developed outside of his or her employment contract—those patents are not counted in the sample.

To track the flow of inventors across firms and regions, we estimate the locations of inventors for each year using PatentsView. We use application dates and geolocation data for inventors and assignees from 1976 through 2017 to estimate the MSAs and affiliation of the inventors from 1991 to 2015.[20,21] We use each inventor's patent history to track his or her history

[18] We have three types of regions: core (top 5%), periphery (bottom 75%), and other (20%). In addition, our unit of analysis is the directed dyad-year, so that we have a combination of core-periphery (3.75% of all observations), periphery-core (3.75%), and neither (92.5%).

[19] The reality is complicated. For example, some Silicon Valley executives commute to California from Texas due to financial and taxation issues. This is made possible by low transportation costs (Business Insider, 2018).

[20] PatentsView updates its inventor disambiguation irregularly. We use the version dated May 28, 2018.

[21] Our dataset includes U.S. patent data applications from 1976 through 2017.

of employment and geolocation.[22] An inventor may not be affiliated with an organization (e.g., corporation, non-profit organization, or the government)[23] because he or she is self-employed or the respective invention was developed outside of the employer's supervision and without the employer's support.

Patenting is not a frequent event for most inventors in the patent dataset, and most inventors do not patent each year. This is a common issue in mobility research. To address it, researchers typically impute the focal inventor's geolocations and affiliations for the missing years based on algorithms that include certain assumptions (e.g., Di Lorenzo & Almeida, 2017; Akcigit *et al.*, 2016). Similarly, we assume, first, that an inventor is actually located at the affiliation and geolocation mentioned in the patent application in the year of that application. The addresses of inventors and assignees often differ. For example, a patent with a European assignee may have an assignee address in a European country, while the inventor's address is in the U.S. because the intellectual property rights belong to the European headquarters, but the actual R&D was carried out at the European corporation's U.S. laboratory.

Second, we assume that inventors stayed in the geolocation and affiliations if neither changed between two consecutive patents by the focal inventor. If a change in geolocation or affiliation occurs, then the change is a mobility event that is assumed to have occurred in the middle of the two patents' application years [(the application year for patent 1 + the application year for patent 2)/2]. If the gap between the two years is an even number, we round up the year. This assumption enables us to calculate the number of inventors who stay in a region in a given year. As we do not have data on when the inventors started their careers, we assume that their careers started in the year of their first patent application and ended in the year of their last or latest patent application.

Third, as mentioned by Hoisl (2007) and Ge *et al.* (2016), the assignee is not always the inventor's employer. This can occur if two or more assignees file a patent or if the R&D was performed under a contract that required the resulting patent to be assigned to a client. Our

[22] Despite recent criticism of the use of patent data to identify mobility history (Ge, Huang, and Png, 2016), we use patent data because 1) recent developments in disambiguation algorithms decrease the incidence of both type I errors of linking an inventor to the wrong patent and type II errors of failing to link an inventor to his or her own patent (Monath and McCallum, 2015), and 2) the patent dataset we use enables us to simultaneously track both knowledge transmission and inventor mobility.

[23] The USPTO uses the term "assignee" to represent the beneficiary organization of a patent. However, the USPTO also allows individuals to register as assignees, so that not every assignee is the organization to which an inventor belongs. We use the term "affiliation" to refer to the organization to which individual inventors belong. Thus, our use of "affiliation" differs from the USPTO's "assignee."

dataset does not have a direct way to eliminate this source of error. However, cases involving both two or more assignees for a patent and contract R&D are rare. Therefore, we ignore this low-frequency event (see Hoisl, 2007: 624).[24]

Fourth, an inventor may whimsically move across affiliations within a short period of time. This may also be caused by the outsourcing of patent-related research or having more than two assignees for a patent. We adopt the normalization technique employed by Hoisl (2007: 624-625). If an inventor patents with a specific affiliation but his or her preceding and subsequent patents have a different affiliation, we consider it as an irregularity caused by misclassification (Ge *et al.*, 2016).

Lastly, an inventor may have more than two geolocations or assignees in a given year. We assume that the most frequently appearing region or assignee in a given year is the geolocation or the affiliation for that inventor in that year. If there are more than two assignee names with the same frequencies, we choose the oldest one. If there are more than two assignees for a given patent (so that we cannot determine the representative affiliation for the inventor-year), we choose the assignees with which the inventor patents in the previous and/or the latter years as the affiliation of the inventor for that year.

Based on the above algorithms, we tracked the geolocations and affiliations of each inventor during the period from his or her first patent to his or her most recent patent.[25] PatentsView offers coordinates information (latitude and longitude) and the names of the affiliations that the inventors reported in the patent application. With disambiguated inventor identity, we can track the presence of individual inventors over time. We are interested in inter-regional mobility rather than intra-regional mobility. We use a crosswalk file with county names and MSA names that is accessible on the NBER website. We rely on the MSA classification for the year 2011, which includes 373 MSAs. In the empirical analyses, we use only 362 MSAs located in the 48 states and the District of Columbia (i.e., the contiguous United States). Therefore, MSAs in Alaska, Hawaii, and the U.S. territories are excluded. We transformed the coordinates information for each pair of inventor-patent into county-level addresses using

[24] Ge *et al.* (2016: 239) find that the "[a]ccuracy of patent mobility is not significantly related to frequency of patenting."
[25] This estimation algorithm requires more than two patents for an inventor in order to track an inventor's retention and mobility. Therefore, we excluded every inventor who had only one patent in the focal period.

Google Maps API. This enables us to identify the MSA in which an inventor-patent pair is located.

A firm may apply for patents using different names because, for example, it is pursuing an intellectual property rights strategy in which doing so makes sense or because it has many subsidiaries with different names. Some firms use the same name whenever a patent application is submitted by any entity under its ownership. This can occur because the USPTO regulations do not require the identification of the ultimate owner of a patent's assignee. Consequently, we need to aggregate and cleanse the assignee names in order to determine the exact affiliation information for each inventor. If we do not do so, we cannot precisely identify inter-firm mobility when an inventor's two consecutive patents have different assignees. PatentsView offers disambiguated assignee identification numbers based on the information on assignee names, locations, and citation networks. However, PatentsView's disambiguation algorithm is limited to correcting typos, which means that firms with different names but sharing the same ultimate owner and working as business units of that ultimate owner would not have the same assignee identification number. This motivates us to aggregate the assignees with different identification numbers based on their ultimate owners.

Each firm is eventually assigned either GVKEY (Global Company Key), which is a company identifier widely used (Hall *et al.*, 2001) or affiliation names. Accordingly, we first used a dataset that matches patents to their assignees' PERMNO[26] using a text-matching algorithm and manual corrections (Hall *et al.*, 2001; Kogan, Papanikolaou, Seru, and Stoffman, 2017).[27] This dataset allows us to determine whether a mobility event across two different assignees is actually a mobility event between two affiliations that do not share an ultimate owner (i.e., firm). Each inventor is given an affiliation, which is an equivalence of each ultimate owner, with a PERMNO provided by Kogan *et al.* (2017) or an identification number assigned to every assignee by PatentsView. Based on those numbers, we aggregated each PatentsView assignee to the GVKEY level. If two assignees have the same GVKEY, they share the same affiliation identity. If not, we compare their assignee names and the assignee identification

[26] In the CRSP database, PERMNO is a unique company identifier of public firms. A PERMNO number is assigned to every U.S. firm that goes public. It offers an advantage when tracking the history of a firm because it does not change over time, while other comparable company identifiers (e.g., CUSIP) change over time. CRSP also offers a crosswalk file to match PERMNO to GVKEY.
[27] Given the purpose of their dataset construction, Kogan *et al.* (2017) did not link non-public firms and non-US firms to their patents. However, many assignees located in the U.S. have foreign ultimate owners. We match some foreign companies with GVKEYs (which are similar to PERMNO) to their U.S. patents to improve our dataset.

numbers provided by PatentsView to determine whether they are in the same firm. If two such affiliations are different, then we classify the event as an instance of inter-firm mobility.

Based on the above estimations, we can derive the estimated inventor population and the number of actively patenting affiliations in a specific region. We divide inventor mobility across regions (both inter-firm and intra-firm) by the number of inventors who stay in the focal region. Thus, we have three variables of inventor mobility: 1) aggregated (inter-firm + intra-firm), 2) only inter-firm mobility, and 3) only intra-firm mobility.

In sum, we observe and analyze two types of inventor mobility: inter-firm and inter-regional. Inter-firm mobility occurs when an inventor applies for two chronologically consecutive patents using different affiliations that do not share the ultimate owners. For this, we use the PERNO and PatentsView's assignee identification numbers. Inter-regional mobility occurs when two chronologically consecutive patents of an inventor have different geolocations in different regions (MSAs). We use a multiple imputation algorithm to estimate an inventor's geolocations and affiliations during the years in which that inventor has no patent history. Consequently, we track the locations of unique inventors throughout their tenure in the PatentsView database.

Estimating Knowledge Transfers Using U.S. Patent Data

Knowledge transfers can happen as either unintended spillovers of knowledge or intended flows of knowledge. It is difficult to disentangle intended knowledge flows from unintended knowledge flows in our dataset. For instance, a firm may intentionally monitor and learn from another firm in another region, or a firm's employee may overhear an interesting idea during a business trip. Moreover, two firms may be in a licensing, alliance, or joint venture relationship focused on sharing and developing innovations. Therefore, we ignore the issue of intentionality and assume that the citing-cited network is a result of unintended knowledge spillovers.[28]

In line with the literature (Jaffe, Trajtenberg, & Henderson, 1993; Thompson & Fox-Kean, 2006), we use the citing-cited relationship between two patents as a measure of knowledge flow between two affiliations and two regions. PatentsView provides information on the citing-cited relationship between patents for patents granted after 1976. Regardless of the technological fields of the citing and cited patents, if an affiliation/region cites another affiliation's/region's

[28] We also include self-citations if they are cross-regional because a decline in transportation costs would also affect the intra-firm knowledge flows.

patent, knowledge has flowed between the two affiliations or regions. The greater the citation intensity between one affiliation/region and another affiliation/region, the more knowledge flows between them. We operationalize such knowledge flows in two variables. The first is the logged ratio of a) the number of citations from the paired region's patent applications to the patents applied in a given year in the focal region to b) the accumulated number of patent applications in the focal region. This measures the extent to which the existing knowledge become available to the paired region's inventors after the introduction of an airline connection. It serves as a proxy of how much easier it is to transmit knowledge between the two regions after an airline connection. The second variable is the log of the number of citations received by the focal region's patent applications in a given year from the patents in all regions, including that of the focal region. This serves as a proxy for patent quality.

Examining Airline Connections using DoT Data (Including Airport Geolocations)

We use airline connection between two regions as a proxy for a reduction in transportation costs. Our definition of transportation costs includes the airline fares as well as other costs, like the time used and opportunity costs for travelling as well as the fatigues from jetlag. We assume that the Americans will avoid travelling if doing so is costly and we assume that the transportation costs increase in a linear fashion as the travelling time increases. We also assume that other forms of transportation may compete with airlines in the inter-city transportation market if the two cities are within 500 kilometers of each other. This assumption is based on anecdotal evidence from the Japanese transportation market in which high-speed rail competes with airlines for travel between 500 and 1,000 kilometers. The more distant, the more advantage the airline enjoys.

We use airline data from the U.S. Department of Transportation (DoT) from 1990 to 2017 to estimate changes in transportation costs (Giroud, 2013; Bernstein *et al.*, 2016). The data were acquired from the T-100 Domestic Segment Database.[29] This database is compiled from Form 41, which all airlines operating in the United States must file. Misreporting on Form 41 is subject to fines. Therefore, the airlines have a strong incentive to report the information thoroughly. The form requires airlines to report flight frequencies, distances, focal airports, destination airports,

[29] Other papers using U.S. domestic airline data also use ER-586 Service Segment data, which cover airline routes prior to 1990. However, we do not use that data because the core-periphery status of the regions is determined by the number of patents accumulated during the 10-year (or longer) period prior to the focal year and our patent dataset starts from 1976.

and other information about airline routes each month. The T-100 database includes all airline connections during the sample years. We extracted data on the airline routes that met our criteria. Two regions (i.e., 2 of the 362 MSAs in our dataset) are considered connected if any two airports in those regions are connected by at least four flights per month in a specific year. A route has two directions—if the routes in either of the two directions meet this criterion, we consider it a connection. However, if the airports are closer than 500 kilometers, we exclude them from consideration, as there are likely to be cheaper alternative transportation routes in these cases, such as driving or taking a train. Apart from the T-100, we used several other sources, including Google Maps API, to identify the geolocations and addresses of each airport. We coded the MSAs of each airport using that data.

2.2.Empirical Methodology

In this section, we describe the methodology we use to address and answer our three main research questions: 1) What is the impact of a change in transportation costs on the inter-regional mobility of inventors? 2) How does a change in transportation costs influence the flow of knowledge? 3) What are the impacts of inventor mobility and knowledge flows associated with lower transportation costs on the focal region's innovative outcomes (i.e., the number of patenting firms and the quality of patents)? We detail our empirical research strategies, including our econometric models, and we discuss how we address endogeneity concerns.

Econometric Specification

We use a difference-in-differences framework at the pair of regions by year level (Athey & Imbens, 2006).[30] Our difference-in-differences model helps to compare the impact of an airline connection on the pairs of regions ("treatment" group) to pairs of unconnected regions ("control" group). As airline connections occur in different dyads at different times (Goodman-Bacon,

[30] Our unit of analysis is the directed dyad-year. The dyads of every possible combination of sample MSAs have two directions—in one dyad, one region is designated as the focal region while it is designated as the destination in the other direction.

2018; Betsey & Wolfers, 2006), we use the generalized difference-in-differences model suggested by Athey and Imbens (2006) and Bertrand and Mullainathan (2003).

For each of our research questions, we estimate the following OLS models, which compare treated and control groups:

$$Y_{odt} = \beta_1 * TREATED_{odt} + \beta_2 * CONTROL_{odt} + Year\_FE + DYAD\_FE + \varepsilon_{odt.} \quad (1)$$

$$Y_{odt} = \beta_1 * TREATED\_CP_{odt} + \beta_2 * CONTROL_{odt} + Year\_FE + DYAD\_FE + \varepsilon_{odt.} \quad (2)$$

$$Y_{odt} = \beta_1 * TREATED\_PC_{odt} + \beta_2 * CONTROL_{odt} + Year\_FE + DYAD\_FE + \varepsilon_{odt.} \quad (3)$$

The Ys are the dependent variables. These are measured in several ways: 1) the log ratio of estimated inventor mobility from a focal region to a destination region to the estimated number of inventors staying in the focal region (Moretti & Wilson, 2017) (see Table 2.3.); 2) the log ratio of estimated inter-firm inventor mobility from a focal region to a destination region to the estimated number of inventors staying in the focal region (Moretti & Wilson, 2017) (see Table 2.4.); 3) the log ratio of estimated intra-firm inventor mobility from a focal region to a destination region to the estimated number of inventors staying in the focal region (Moretti & Wilson, 2017) (see Table 2.5.); 4) the logged number of firms patenting in the focal region (see Table 2.6.), 5) the logged number of firms who had no patent in the focal region before the given year (see Table 2.7.), 6) the logged number of patent applications in the focal region (see Table 2.8.); 7) the logged number of citations of the focal region's patents from the paired regions (see Table 2.9.); 8) the log of the average number of citations received per patent (see Table 2.10.).

In the specifications, *o* indexes the focal region (MSA), *d* indexes the destination region (MSA), and t indexes the year. *CONNECTION_DUMMY*, TREATED_CP, TREATED_PC, TREATED_Kerr_P, and TREATED_C_Kerr are the independent variables. First, *CONNECTION_DUMMY* is a binary variable, which assumes a value of 1 if the focal region is connected by airline with the paired region regardless if the focal region is core, periphery, or neither. Second, *TREATED_CP*, is a binary variable, which assumes a value of 1 if the focal region is a core region and the other region is a peripheral region, and they are connected by an airline route in the same year. Otherwise, it assumes a value of 0. Third, *TREATED_PC* is also an independent variable but its direction differs. It has a value of 1 if the focal region is a peripheral region and the destination is a core region, and the two are connected by an airline in a given year. Otherwise, its value is 0. Fourth, *TREATED_KERR_P* is 1 if the focal region is a core according to Kerr (2008) whereas the paired region is a periphery. Otherwise, it assumes a value of 0. Fifth, *TREATED_P_KERR* is that the focal region is a periphery whereas the paired region is a core according to Kerr (2008). Otherwise, it assumes a value of 0. The key coefficient of interest is $\beta 1$.

Identification Strategy

Our main goal is to identify the impact of transportation costs on inventor mobility and knowledge flows across regions. In line with the literature (Giroud, 2013; Bernstein *et al.,* 2016; Campante & Yanagizawa-Drott, 2017; Catalini *et al.,* 2019), we exploit airline connections between two regions, and we interpret them as quasi-natural experiments. Our identification strategy is based on the notion in previous research that lower transportation costs induce more business travel and higher flows of information/knowledge between two regions (Catalini *et al.,* 2019; Bernstein *et al.,* 2016).

Airline connections are initiated by airlines and/or regional stakeholders, such as politicians and business people, based on calculations of commercial feasibility, socio-economic factors, competitive conditions, and cost conditions, as well as aviation-related aspects, including technological capabilities and airport capacities. Decisions to initiate airline connections are not random. Endogeneity issues may emerge because the opening of airline routes may reflect a response to calls by the business community or large firms for better infrastructure. To test for such endogeneity, we examined whether inter-regional economic activities, like inventor mobility and knowledge spillovers, changed after the introduction of the airline connection, but we could not find a significant trend before the connection. In addition, we use dyad fixed effects to control for time-invariant factors, such as the geographical distance of the dyads. For each pair of regions, there are two dyads.

As we discussed above, we focus on four subsets of the sample. The first type of dyad is a group including every pair of regions connected. This includes the following three types of dyads of regions. The second is the core-periphery group of dyads in which the focal region is a core region and the destination region is a peripheral region. The third is the group of periphery-core dyads in which the focal region is a peripheral region and the destination region is a core region. The last is the group of dyads consisting of at least one non-core or non-peripheral region. Therefore, its dyads are neither core-periphery nor periphery-core. When we estimate the impact of transportation costs on the core-periphery dyads, we use the other dyads as the control group.

To capture the unobservable factors, we control for two-way fixed effects of dyad fixed effects and year fixed effects.[31] In addition, as the standard errors might be correlated over time within a panel, we clustered the standard errors by the symmetric dyads to show robustness in heteroscedasticity, as Bertrand, Duflo, and Mullainathan (2004) recommend.

2.3. Results

Table 2.1. shows the summary for our sample dyads consisting of a focal dyad and a destination dyad; and Table 2.2. shows the correlations between the main variables. As our sample has 362

[31] For dyad fixed effects, we use directed dyads. For clustering, we use symmetric dyads in which we assume the invariant characteristics exist regardless of dyads' directions.

MSAs and as each MSA is paired with another MSA, we have 130,682 dyads [362 x 361] with 26 years of observations (1990 to 2015). The dyads are all directed, so that a dyad pair of region A and region B is different from a dyad pair of region B and region A. In total, we have 3,397,732 dyad-year observations. 71,406 dyad-year observations are connected by airlines.

We apply two types of treatment conditions. The first is when the focal region in the dyad (*focal*) is a core region and the paired region (*dest*) is a peripheral region, with the regions connected by an airline after 1990. The second is the opposite: the focal region is a periphery and the paired region is a core region, with the regions connected by an airline after 1990.[32] Relatively few dyads satisfy the treatment conditions. Specifically, we have 6,428 treated dyad-year observations for core-periphery dyads and for periphery-core dyads.

Inventor mobility is also skewed. Only 166,244 dyad-year observations exhibit more than one inventor moving between two regions. The maximum number of inter-regional mobility events per dyad-year is 379. Accordingly, we log all dependent variables in the dyad-level analysis, including three variables related to inventor mobility. First, we estimate the log ratio of inventors moving from one region to another region (including inter-regional mobility within and across firms) to the entire number of inventors in the focal region (*ln_interregion*). Second, we estimate the log ratio of inventors moving from a region to another firm in another region to the entire inventor population in the focal region (*ln_interinter*). Third, we estimate the log ratio of inventors moving from a region to another region without changing their employer (*ln_interintra*). For inventor mobility, as we divide the estimated number of inventors moves from the focal region to another region by the estimated number of inventors in the focal region,

[32] Please see section 2.1. to find the definition of "airline connection."

we add 1 to the numerator and 2 to the denominator. We logged all other dependent variables (listed Section 2.2.).

Insert Table 2.1. about here

Insert Table 2.2. about here

Table 2.3. shows the results of the regression analyses of the impact of transportation costs on inter-regional inventor mobility. The models include two-way fixed effects: year and directed dyad. As the two directed dyads covering the same regions may have common characteristics, like the absolute distance between them, we clustered the standard errors at the symmetric dyad level. The coefficient of the treatment variable CONNECTION_DUMMY is -0.0539 [p-value < 0.001]. This implies that connection itself decreases the outmigration. The coefficient of the treatment variable *TREATED_CP* is -0.151 [p-value < 0.001]. The coefficient of the treatment variable *TREATED_KERR_P* is -0.0717 [p-value < 0.001]. This indicates that a core region loses fewer inventors if it is newly connected to a periphery. However, these results themselves support neither agglomeration nor dispersion as it only sees what happens to the core region's inventors. So, taking a look on the periphery region's inventors, we find that the treatment variable *TREATED_PC*, has a coefficient of +0.158 [p-value < 0.001], and the treatment variable has a coefficient of *TREATED_P_KERR* +0.259 [p-value < 0.001]. These indicate a periphery loses more inventors to the core with which it is connected. So, the core gains inventors while the periphery loses them when those two regions are connected.

Basically, these findings support the idea of agglomeration rather than dispersion by showing that the treated cores lose fewer inventors than the control groups, while the treated peripheries lose more inventors. After the establishment of a connection, the periphery inventors are more likely to leave their regions. The core regions benefit because they not only retain their human capital but also attract human capital from the paired periphery. But these results are insufficient to understand the mechanisms of the agglomeration. So, in the Table 2.4. and Table 2.5., we divided the connections into two subsets: inter-firm and intra-firm.

Insert Table 2.3. about here

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Tables 2.4. and 2.5 provide insights into the nature of inventor mobility by dividing mobility into two types: inter-firm and intra-firm. Based on their name similarity and ownership structure, we bundle patent assignees into groups sharing the same ultimate owners. For example, an inventor may move from a regional Samsung Electronics office to a Samsung Display office in another region. This is coded as intra-firm mobility because the mobility event might be the result of a reallocation or redeployment of human capital by the corporate headquarters (Giroud & Mueller, 2015; Sakhartov & Folta, 2014).

In Table 2.4, we investigate the impact of transportation costs on inventor mobility across regions and across firms at the same time. The results of this test show how individuals react to the lower transportation costs regardless of their employers' decisions. In this table, *CONNECTION_DUMMY* has a coefficient of -0.0534 [p-value < 0.001]. This indicates the connection with any region decreases inventor outflow from the focal region. *TREATED_CP* has a coefficient of -0.119 [p-value < 0.001]. *TREATED_KERR_P* has a coefficient of -0.0389 [p-value < 0.05]. *TREATED_PC* has a coefficient of -0.158 [p-value < 0.001]. *TREATED_P_KERR* has a coefficient of 0.259 [p-value < 0.001]. These results suggest that, aligning with Table 2.3., the agglomeration force is stronger than the dispersion force.

Because the interregional mobility may be a result of decision made by firm or decision made by individual inventors. In this Table 2.4., we focus on mobility as a result the individual inventor's decision. Individuals tend to stay in the core and leave the periphery when the transportation cost is lowered. The business and employment conditions get better after airline connection in the core or get worsened in the periphery so that the core's inventors stay and the periphery's inventors leave to the core, independently from the corporate decision.

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Insert Table 2.4. about here

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In Table 2.5., we investigate the impact of transportation costs on inventor mobility across regions but within a firm. A firm may strategically reallocate an inventor between its two existing facilities across regions or expand its operation in the new region in response to a change in transportation cost.

We find that the coefficient of the variable *CONNECTION_DUMMY* is -0.0547 [p-value < 0.001]. This too implies that connection halts mobility of inventors across regions. The coefficient of the variable *TREATED_CP* is -0.143 [p-value < 0.001]. The coefficient of the variable *TREATED_KERR_P* is -0.0492 [p-value < 0.01]. These results indicate that the inventors less move to the connected periphery from the core region. On the other hand, the coefficients of *TREATED_PC* and *TREATED_P_KERR* are +0.151 [p-value < 0.001] and +0.248 [p-value < 0.001], respectively.

These may mean that: 1) firms that had R&D facilities in both the core and peripheral regions prior to an airline connection concentrate their inventors in the core region, 2) firms that had an R&D facility in the core and no presence in the periphery prior to an airline connection are less likely to disperse their R&D activities to new facilities, or 3) firms that had an R&D facility in the periphery and no presence in the core prior to an airline connection so that those firms have no inventor to relocate from periphery to core. These results align with the commonly held idea that advanced regions (e.g., cities) attract highly skilled workers and/or their employers (Moretti, 2012, 2019; Florida, 2008).

Insert Table 2.5. about here

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The findings in Table 2.3., 2.4., and 2.5. suggest that firms in a peripheral region lose their inventors to firms in the core, which is reminiscent of the "straw effect" mechanism: "[i]mproved … transport infrastructure between a developed location enjoying a market size advantage and a less developed one can decrease the attractiveness of the latter" (Ottaviano, 2008: 19). Also, these results suggest that an airline connection benefits firms in the core regions by making it easier for them to retain their inventors. Moreover, the peripheral regions lose inventors to their labor market competitors in the core.

Table 2.6. demonstrates the impact of transportation costs on the logged number of firms patenting in the region. This provides insights into corporate behaviors given a decline in transportation costs. The number of actively patenting firms in a specific region is considered a proxy for a region's innovative foundations (Wu, 2008). The results show increases in the number of firms patenting in both the core regions and the peripheral regions. The coefficient of

CONNECTION_DUMMY variable is +0.0803 [p-value < 0.001]. This result indicates that the lower transportation cost positive impact on the patenting activities in the focal region. The coefficients of *TREATED_CP* variable is +0.0673 [p-value < 0.001] and of TREATED_KERR_P variable is +0.00148 [p-value > 0.05]. On the other hand, the coefficients of TREATED_PC variable is -0.0934 [p-value < 0.001] and TREATED_P_KERR is -0.195 [p-value < 0.001].

Insert Table 2.6. about here

Table 2.7. demonstrates the impact of transportation costs on the logged number of firms start patenting in the focal region. This dependent variable is different from that in Table 2.6. to the extent that the number of firms start patenting implies how lowered transportation costs promotes innovative activities and in the focal region. The coefficient of *CONNECTION_DUMMY* is +0.0544 [p-value < 0.001]. This implies that airline connections itself promote innovative activities in the focal region. The coefficients of *TREATED_CP* is +0.0791 [p-value < 0.001] and of *TREATED_KERR_P* is -0.00282 [p-value > 0.05]. They have opposite signs, but the latter is insignificant. The core region may have more innovative activities as a result of lower transportation cost. The coefficients of *TREATED_PC* is -0.0850 [p-value < 0.001] and of *TREATED_P_KERR* is -0.179 [p-value < 0.001]. These findings suggest that airline connection with a core region demotivates the actors in the periphery to start patenting or the periphery loses its essential endowments for innovation to the core so that the periphery becomes less innovative.

Insert Table 2.7. about here

Table 2.8. displays the impact of transportation costs on the logged number of patent applications in a given region. The number of patents applied is another proxy of innovative activities in the specific region. The coefficient of *CONNECTION_DUMMY* is +0.0500 [p-value < 0.001]. This indicates that patenting activities is promoted if the transportation cost is lowered regardless of the type of the regions in the dyad. The coefficients of *TREATED_CP* variable is +0.118 [p-value < 0.001] and of *TREATED_KERR_P* variable is +0.0164 [p-value < 0.05]. Despite that one of the coefficients is insignificant, these results imply that the innovative activities are promoted as a consequence of lower transportation cost in the core regions, if they are connected with periphery regions. The coefficients of *TREATED_PC* variable is -0.173 [p-value < 0.001] and of *TREATED_P_KERR variable* is -0.286 [p-value < 0.001]. These results suggest that the periphery regions have less active in terms of technological innovation when they are connected with the core regions. In sum, the findings in this Table 2.8. align with the above findings in support of agglomeration. In other words, the periphery, which loses inventors, eventually exhibits less innovation, while the core gains inventors and exhibits more innovation.

Insert Table 2.8. about here

In Table 2.9., we examine the log of the number of citations received by the focal region's patents from the paired region's patents. This measures how lower transportation costs change the flow of knowledge between two regions. In this study, we only include citing-cited relationships between the two regions in the dyads. This is a proxy of the knowledge flow from the cited region to the citing region. So, in this framework, the focal region is where refers the knowledge of the paired region. For example, if a patent application submitted in the paired destination region in 2008 cites a 1991 patent from the focal region, then we count it as one citation received by the focal region in 2008 (the year in which knowledge was transmitted from the focal region to the destination). The coefficient of *CONNECTION_DUMMY* is +0.0931 [p-value < 0.001]. This result displays that the focal region, regardless of its dyad type, receives more citations from the paired region. It may be because the monitoring cost of the firms and inventions in the paired region is lowered as the transportation cost is lowered (Bernstein *et al.*, 2016) and/or because the social network had emerged as a consequence of increased inventor mobility across regions (Agrawal, Cockburn, & McHale, 2006). The coefficients of *TREATED_CP* is -0.837 [p-value < 0.05] and -0.110 [p-value < 0.05]. The literature suggests that the citations increased via the newly emerged social network between the two regions (Agrawal *et al.,* 2006). And Oettl and Agrawal (2008), in international business context, the firm losing an inventor also receives knowledge from the firm gaining the inventor despite the knowledge transfer in the opposite direction is larger. In other words, the core region which gains inventors from the periphery region will receives more knowledge from (citing more of) the periphery's patents. However, this does not match to our empirical finding. On the other hand, the coefficients of *TREATED_PC* is -0.149 [p-value < 0.05] and of TREATED_P_KERR is -0.318 [p-value < 0.001]. This partially also does not meet the prediction from the above.

Insert Table 2.9. about here

In Table 2.10., we examine the log of the number of citations received by the patents of the regions in a given year. It is a proxy of the focal region's patent quality. The coefficients of *CONNECTION_DUMMY* is +0.821 [p-value < 0.001]. The lowered transportation cost induce benefits the connected regions by increasing the quality of patents. The coefficients of *TREATED_CP* is +0.154 [p-value > 0.05] and of *TREATED_KERR_P* is +0.473 [p-value < 0.01]. These findings partially support, as only one of them is significant, the positive impact of lower transportation cost on the patent's quality. The coefficients of *TREATED_PC* is +0.0306 [p-value > 0.05] and of *TREATED_P_KERR* is +0.0447 [p-value > 0.05]. While the coefficients are not significant, these coefficients imply that connection with a core may benefit the periphery in terms of its patent's quality subsequent to its connection.

Insert Table 2.10. about here

2.4.Conclusions

The tension between the forces of agglomeration and the forces of dispersion is at the center of new economic geography. However, how such forces affect the loci of human capital and knowledge, which are key sources of economic growth, is poorly understood. In particular, the literature has not examined how changes in transportation costs impact inventor mobility and knowledge across regions. We examine the role of transportation costs in influencing forces of agglomeration and dispersion in a context of regions with inequal endowments. If agglomeration is linked to lower transportation costs, then the advanced regions labeled as core regions will enjoy more inflows of human capital and knowledge from the lagged regions labeled as periphery regions by the introduction of a new inter-regional airline connection. The opposite is true if lower transportation costs drive dispersion.

We tested the relationship between transportation costs and agglomeration/dispersion in a single setting: airline connections across regions. The opening of airline routes between two regions increases the interactions between those regions' firms and individuals. However, that increase does not allow us to predict which region will benefit from the connection. Both may benefit, one may benefit, or both may suffer. To investigate this issue, we used a setting in which two discretely developed regions were connected by an airline. We tested whether the advanced core gained more than the lagged periphery and whether innovations (measured in terms of patent citations received and the number of patent applications) increased in both regions.

This paper makes its main contribution to economic geography (Krugman, 1991; Redding & Turner, 2015; Fujita & Thisse, 2013; Carlino & Kerr, 2015; Jaffe *et al.*, 1993). This paper displays the microfoundations of agglomeration by explicating how lowering transportation cost leads to the agglomeration of inventor and innovative activities. In principle, our findings support the view that the agglomeration mechanism outweighs the dispersion mechanism. After an airline connection is introduced, the outmigration of inventors to the paired region (a periphery if the focal region is a core) is reduced in the core and increased in the periphery. Moreover, the innovative activities increase in the core and decrease in the periphery. However, the finding that agglomeration is associated with lower transportation does not justify a lack of investments in infrastructure.

This paper also contributes to the human capital literature focused on geographical mobility in strategic management (Marx, Strumsky, & Fleming, 2009; Ganco, Ziedonis, & Agarwal, 2015; Campbell *et al.*, 2017) and economics (Borjas & Doran, 2012; Moser, Voena, &

Waldinger, 2016; Moretti & Wilson, 2017; Akcigit *et al.*, 2016). This stream of literature examines the barriers to and consequences of inventor mobility. Our research views geographical distance and transportation costs as barriers in the labor market that prevent inventors from engaging in inter-regional mobility. As such, it complements the extant literature, which focuses on tax rates (Moretti & Wilson, 2017; Akcigit *et al.*, 2016), law enforcement (Marx *et al.*, 2009), employer specific reasons (Hoisl, 2007; Di Lorenzo & Almeida, 2017), and information asymmetries (Starr, Frake, & Agarwal, 2017).

Future research should investigate how the collaboration patterns and outcomes change between the pre-connection and the post-connection periods (Catalini *et al.*, 2019), and how individual inventors with heterogenous characteristics are spatially sorted (Gaubert, 2018; Moretti & Wilson, 2017). Another issue that should be taken into account is the possibility that shocks to transportation costs may affect firms' locations, which may have implications for production activities, the products that are offered, and competitive dynamics[33]—all of which may influence hiring patterns and, thereby, inventor mobility.

[33] Thus, Chauvin (2017) finds that a new inter-regional road makes firms in the regions move closer. She also investigates how the opening or upgrading of inter-regional roads enhances competition.

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FIGURE 2.1. The Microfoundations of Regional Competitive Advantage

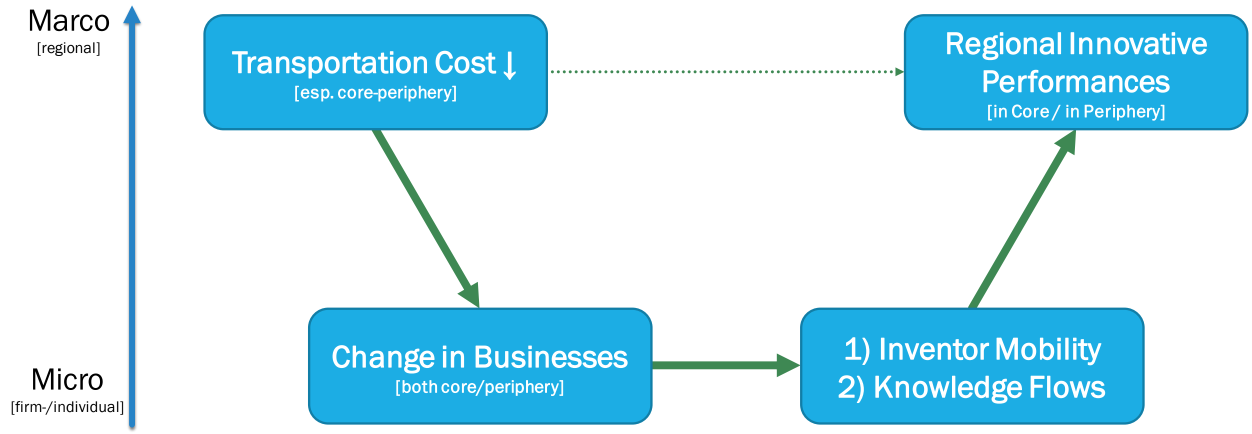

TABLE 2.1. SUMMARY STATISTICS

Variables	Observations	Mean	Std. Dev.	Min	Max
Connection	3,397,732	0.021016	0.143437	0	1
Core → Periphery	3,397,732	0.001892	0.043454	0	1
Periphery → Core	3,397,732	0.001892	0.043454	0	1
Outmigration Ratio (full)	3,397,732	-4.41479	1.62507	-9.8024	0.693147
Outmigration Ratio (inter-firm)	3,397,732	-4.43266	1.639752	-9.8024	0.693147
Outmigration Ratio (intra-firm)	3,397,732	-4.43366	1.642084	-9.8024	0.693147
Firms Patenting (focal MSA)	3,397,732	2.529536	1.442543	0	7.150702
Firms Start Patenting (focal MSA)	3,397,732	1.823643	1.288423	0	6.278522
Number of Patents (focal MSA)	3,397,732	4.916692	1.748095	0	10.66844
Number of Citations (from paired MSA)	3,397,732	0.605143	1.085616	0	10.2848
Patent Quality	3,397,732	-2.3417	2.991229	-10.6684	5.284894
Co-Invention	3,397,732	0.123643	0.449009	0	8.483843

TABLE 2.2. CORRELATIONS

	Variables	1	2	3	4	5	6	7	8	9
1	Outmigration Ratio (full)	1								
2	Outmigration Ratio (inter-firm)	0.9975	1							
3	Outmigration Ratio (intra-firm)	0.9975	0.9955	1						
4	Firms Patenting (focal MSA)	-0.9068	-0.9115	-0.912	1					
5	Firms Start Patenting (focal MSA)	-0.8625	-0.8676	-0.8682	0.9647	1				
6	Number of Patents (focal MSA)	-0.9835	-0.9877	-0.9876	0.9125	0.8688	1			
7	Number of Citations (from paired MSA)	-0.4504	-0.4713	-0.4719	0.5052	0.497	0.5108	1		
8	Patent Quality	-0.0925	-0.1016	-0.102	0.1582	0.168	0.1188	0.6982	1	
9	Co-Invention	-0.2335	-0.2647	-0.2597	0.309	0.3072	0.3129	0.6075	0.2615	1

TABLE 2.3. Number of Inventors Leaving the Focal Region (inter-/intra-firm mobility)

	(1)	(2)	(3)	(4)	(5)
	ln_interregion	ln_interregion	ln_interregion	ln_interregion	ln_interregion
CONNECTION_DUMMY	-0.0539***				
	(-5.43)				
TREATED_CP		-0.151***			
		(-10.54)			
TREATED_KERR_P			-0.0717***		
			(-4.66)		
TREATED_PC				0.158***	
				(7.09)	
TREATED_P_KERR					0.259***
					(9.36)
_cons	-4.414***	-4.415***	-4.415***	-4.415***	-4.415***
	(-21167.43)	(-162599.35)	(-191232.90)	(-105117.19)	(-106229.02)
N	3397732	3397732	3397732	3397732	3397732
adj. R^2	0.955	0.955	0.955	0.955	0.955

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE: standard errors clustered by directed dyad in parantheses

TABLE 2.4. Number of Inventors Leaving the Focal Region(inter-firm mobility)

	(1)	(2)	(3)	(4)	(5)
	ln_interinter	ln_interinter	ln_interinter	ln_interinter	ln_interinter
CONNECTION_DUMMY	-0.0534***				
	(-5.40)				
TREATED_CP		-0.119***			
		(-8.03)			
TREATED_KERR_P			-0.0389*		
			(-2.34)		
TREATED_PC				0.158***	
				(7.50)	
TREATED_P_KERR					0.259***
					(9.91)
_cons	-4.432***	-4.432***	-4.433***	-4.433***	-4.433***
	(-21347.00)	(-157984.79)	(-178075.06)	(-111471.74)	(-112942.80)
N	3397732	3397732	3397732	3397732	3397732
adj. R^2	0.958	0.958	0.958	0.958	0.958

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
NOTE: standard errors clustered by directed dyad in parantheses

TABLE 2.5. Number of Inventors Leaving the Focal Region (intra-firm mobility)

	(1)	(2)	(3)	(4)	(5)
	ln_interintra	ln_interintra	ln_interintra	ln_interintra	ln_interintra
CONNECTION_DUMMY	-0.0547***				
	(-5.55)				
TREATED_CP		-0.143***			
		(-10.23)			
TREATED_KERR_P			-0.0492**		
			(-3.05)		
TREATED_PC				0.151***	
				(7.19)	
TREATED_P_KERR					0.248***
					(9.51)
_cons	-4.433***	-4.433***	-4.434***	-4.434***	-4.434***
	(-21387.27)	(-168191.41)	(-183428.42)	(-111531.23)	(-113394.21)
N	3397732	3397732	3397732	3397732	3397732
adj. R^2	0.958	0.958	0.958	0.958	0.958

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
NOTE: standard errors clustered by directed dyad in parantheses

TABLE 2.6. Number of Firms Patenting in the Focal Region

	(1) ln_firmspatenting _inthemsa	(2) ln_firmspatenting _inthemsa	(3) ln_firmspatenting _inthemsa	(4) ln_firmspatenting _inthemsa	(5) ln_firmspatenting _inthemsa
CONNECTION_DUMMY	0.0803^{***}				
	(6.78)				
TREATED_CP		0.0673^{***}			
		(4.71)			
TREATED_KERR_P			0.00148		
			(0.09)		
TREATED_PC				-0.0934^{***}	
				(-3.60)	
TREATED_P_KERR					-0.195^{***}
					(-5.02)
_cons	2.528^{***}	2.529^{***}	2.530^{***}	2.530^{***}	2.530^{***}
	(10153.74)	(93644.66)	(100129.22)	(51572.18)	(43444.44)
N	3397732	3397732	3397732	3397732	3397732
adj. R^2	0.939	0.939	0.939	0.939	0.939

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
NOTE: standard errors clustered by directed dyad in parantheses

TABLE 2.7. Number of Firms Start Patenting in the Focal Region

	(1)	(2)	(3)	(4)	(5)
	ln_firmsstartpatenting_inthemsa	ln_firmsstartpatenting_inthemsa	ln_firmsstartpatenting_inthemsa	ln_firmsstartpatenting_inthemsa	ln_firmsstartpatenting_inthemsa
CONNECTION_DUMMY	0.0544^{***}				
	(4.90)				
TREATED_CP		0.0791^{***}			
		(5.65)			
TREATED_KERR_P			-0.00282		
			(-0.15)		
TREATED_PC				-0.0850^{***}	
				(-3.61)	
TREATED_P_KERR					-0.179^{***}
					(-5.23)
_cons	1.822^{***}	1.823^{***}	1.824^{***}	1.824^{***}	1.824^{***}
	(7805.67)	(68785.43)	(64585.59)	(40939.13)	(35622.16)
N	3397732	3397732	3397732	3397732	3397732
adj. R^2	0.890	0.890	0.890	0.890	0.890

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
NOTE: standard errors clustered by directed dyad in parantheses

TABLE 2.8. Number of Patents Applied in the Focal Region

	(1)	(2)	(3)	(4)	(5)
	ln_number_patents_permsa_from	ln_number_patents_permsa_from	ln_number_patents_permsa_from	ln_number_patents_permsa_from	ln_number_patents_permsa_from
connection_dummy	0.0500***				
	(4.59)				
treated_c5p75		0.118***			
		(7.28)			
treated_kerr_p75			0.0164		
			(0.78)		
treated_p75c5				-0.173***	
				(-7.67)	
treated_p75_kerr					-0.286***
					(-9.91)
_cons	4.916***	4.916***	4.917***	4.917***	4.917***
	(21484.83)	(160230.18)	(156484.89)	(115463.59)	(113422.19)
N	3397732	3397732	3397732	3397732	3397732
adj. R^2	0.962	0.962	0.962	0.962	0.962

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE: standard errors clustered by directed dyad in parantheses

TABLE 2.9. Knowledge Flow from the Focal MSA to the Paired MSA

	(1)	(2)	(3)	(4)	(5)
	ln_within_dyad_citiations_received	ln_within_dyad_citiations_received	ln_within_dyad_citiations_received	ln_within_dyad_citiations_received	ln_within_dyad_citiations_received
CONNECTION_DUMMY	0.0931^{***}				
	(7.52)				
TREATED_CP		-0.00837			
		(-0.13)			
TREATED_KERR_P			-0.110		
			(-1.34)		
TREATED_PC				-0.149^{*}	
				(-2.44)	
TREATED_P_KERR					-0.318^{***}
					(-4.17)
_cons	0.603^{***}	0.605^{***}	0.605^{***}	0.605^{***}	0.606^{***}
	(2318.97)	(4865.66)	(4942.52)	(5251.98)	(5296.28)
N	3397732	3397732	3397732	3397732	3397732
adj. R^2	0.759	0.759	0.759	0.759	0.759

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE: standard errors clustered by directed dyad in parantheses

TABLE 2.10. Patent's Quality in the Focal Region

	(1) ln_patent_quality	(2) ln_patent_quality	(3) ln_patent_quality	(4) ln_patent_quality	(5) ln_patent_quality
CONNECTION_DUMMY	0.821***				
	(11.91)				
TREATED_CP		0.154			
		(1.49)			
TREATED_KERR_P			0.473**		
			(2.85)		
TREATED_PC				0.0306	
				(0.59)	
TREATED_P_KERR					0.0447
					(0.37)
_cons	-2.359***	-2.342***	-2.342***	-2.342***	-2.342***
	(-1629.03)	(-12018.53)	(-9435.50)	(-23853.81)	(-12841.50)
N	3397732	3397732	3397732	3397732	3397732
adj. R^2	0.426	0.426	0.426	0.426	0.426

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE: standard errors clustered by directed dyad in parantheses

STRATEIC ALLIANCES AND INVENTOR MOBILITY: EVIDENCE FROM THE U.S. PHARMACEUTICAL INDUSTRY

April 10, 2020

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&

Victor Cui

ABSTRACT

Attention on the same domain (e.g. industry, technology) often leads intensive competition between the firms; and such an attention also increases the likelihood of alliance formation, too. Particularly, in learning alliances, those ‘competitors turned collaborators’ often have a tension between to collaborate more to create new knowledge and compete within the alliance to misappropriate each other’s knowledge. While sustaining collaboration with good faith and trust would help to generate more technological innovation, poaching of the partner’s corporate scientists is often a result of such an effort of knowledge misappropriation. While the non-poaching mobiltiy is held stable, within-alliance compeittion increases poaching as the returns from learning-by-hiring exceeds those from the learning allaince. Integrating datasets of R&D alliances, corporate scientist mobility, and product market competition in the U.S. pharmaceutical industry from 1985 to 2008, we found that a firm’s competitive aggressiveness toward its alliance partner in the pre-alliance period positively affected the number of corporate scientists it poaches from its partner during the post-alliance period. This main effect is negatively moderated by the geographical and technological proximities between the paired partner firms and positively moderated by the firm specificity of the partner’s knowledge base.

INTRODUCTION

To sustain their competitive advantage through continuous innovation, firms attempt to learn and acquire knowledge from external sources.[34] There are various channels of acquiring external knowledge, such as licensing, alliances, reverse engineering, localized knowledge spillovers, poaching corporate scientists from the competitors, espionage, and consulting (Glitz & Meyerssen, 2017; Laursen & Salter, 2006; Chesbrough, 2003; Arora, Belenzon & Lee, 2018). Previous literature has generally examined the individual learning channels one by one separately based on a notion that a firm does not use multiple learning channels simultaneously; however, in reality, firms use multiple learning channels simultaneously and congruently; and eventually a tension exists between them, too. From the viewpoint of the interplay between competition and cooperation[35] (Hoffmann, Lavie, Reuer, & Shipilov, 2018), this paper explicates how firms juggle multiple learning channels simultaneously. This paper particularly focuses on two channels which are difficult to be compatible: learning alliance and learning-by-hiring (Hess & Rothaermel, 2011). The firms' learning-by-hiring strategy is affected by their pre-allaince relationship (i.e. competitive aggressiveness) with their alliance partners; and the alliance strategy is affected by multiple learning channels, including learning-by-hiring, contingent to the partners in the learning alliance. We therefore refer interplay as the key construct of this paper.

The ***learning alliance*** literature often addresses the learning race between alliance partners, while not every learning alliance is a learning race. Learning race is a competition within the boundary of an alliance (Hamel, 1991; Yang *et al.*, 2015). Such a race is often opportunistic despite that the primary motivation of the alliance firms is to pursue technological

[34] Throughout this paper, *learning* refers to a firm's learning from external sources, rather than its *learning-by-doing* within the firm itself.

[35] Hoffman *et al.* (2018: 3035) defined interplay as 1) "how competition and cooperation interrelate" and 2) "their interaction in driving outcomes such as corporate behavior and performance".

innovation by collaborating (Hamel, 1991; Das & Teng, 2000; Khanna, Gulati, & Nohria, 1998; Lavie, 2007). In the technologically intensive industries, firms incorporate the joint-R&D together based on the premise that each firm has specific knowledge that complements its partner's knowledge (Hess & Rothaermel, 2011). In most cases, the offical goal of learning alliance is to create and/or appropriate new knowledge together so that the partners shake their hands; but under the table, the alliance partners would also compete to misappropriate the partner's knowledge.

Ironically, the risk of such misappropriation of a firm's knowledge increases when the partners collaborate intensively (Oxley & Sampson, 2004). The increased interaction within a collaboration agreement inevitably exposes focal firm's existing knowledge bases including who knows what, beyond the collaboration agreement to the partner. So, a firm's learning alliance for a new knowledge is always accompanied by the risks of leakage of its own existing knowledge to its partner (Yang, Zheong & Zaheer, 2015; Hamel, 1991; Kumar, 2011).[36] Such a leakage may be actualized by unintetional knowledge spillovers but also actualized by employee poaching.

Creating value from creating new knowledge (e.g. innovation) and appropriating value from misappropriating the existing partner's knowledge are barely compatible. Under a tension between value creation and value appropriation, a firm may choose a strong and sustainable collaboration to create and appropriate new knowledge more; or the same firm may choose misappropriate the partner's existing knowledge in exchange of losing the partner's trust. Emergence of distrust between partners would not only damage the performance in the current alliance but also lowers the likelihood of subsequent alliance formation with the same partner.

[36] The knowledge at risk of misappropriation includes both the knowledge co-created in the alliance and the knowledge the focal firm accumulated prior to the alliance formation.

The *learning-by-hiring* literature has asserted that the inter-firm mobility of human capital enables a transfer of knowledge from the origin firm to the destination of a mobile employee, thereby motivating firms to attract the competitors' human capital (Yang *et al.*, 2015). In learning alliances, more intensive collaboration decreases the information asymmetry between a firm's employees and the partner firm. So, the partner firms get to know better of the true quality of each other's employees (Oxley & Sampson, 2004; Brymer, Molloy, & Gilbert, 2013; Song *et al.*, 2003).[37] In R&D allainces, more efficient infomration motivates interfirm mobility, both poaching and non-poaching[38], of corporate scientists between alliance partners (Campbell, Kryscynski, & Olson, 2017).

Hiring a corporate scientist from the alliance partner enables the focal firm to acquire human capital and thus knowledge, while the partner firm loses them.[39] The literature has reported that poaching dampens within-alliance trust it is a breach of gentlemen's agreement (de Rond & Bouchikhi, 2004). So, firms in a learning alliance face to choose either 1) be more cooperative in the learning alliance to build sustainable relationship and value creation from a new knowledge or 2) be more competitive in the learning race to misappropriate the partner's existing knowledge inside the corporate scientist's brain. Poaching as an opportunistic behavior is followed by distrust between alliance partners so that an alliance firm with lower trust has more incentive to poach from its alliance partner. Each alliance firm has different incentives to poach its partner's corporate scientist.

[37] Higher information efficiency reveals each corporate scientist's capacity and roles in the past R&D projects; but higher information efficiency also reveals the true type of the partner firm as an employer. The latter also can motivate the corporate scientists to walk out the focal firm's door and join the partner firm without a strong intention of the partner firm to poach.

[38] Not every inter-firm mobility of employee is poaching. We refer a kind of inter-firm mobility which is intentionally triggered by the destination firm as poaching (Gardner, 2005). Non-poaching mobility which is initiated by the mobile worker does considerably not damage the inter-firm relationship between the firms involved.

[39] The extant research has reported the positive consequences of employee poaching, such as 1) an increase in knowledge transfer from the poached firm to the poaching firm (Correidora & Rosenkopf, 2010; Oettl & Agrawal, 2008) and 2) an increased likelihood of alliance formation between the poaching and poached firms (Wagner & Goossen, 2018).

The intensity of the learning race is affected by the competition between the alliance partners. Since the situations and factor endowments each firm having are heterogenous, each firm's incentives to be collaborative or cooperative in a specific alliance are heterogenous, too (Cui, Yang, & Vertinsky, 2018; Dussauge, Garrette, & Mitchell, 2000). The extant researches present that heterogeneity in their choices in learning alliance among the firm come from their different learning capacities (Hamel, 1991; Lavie, 2007), but they overlook the role of competitiveness in learning race despite it's a 'competition'. How a firm's competitiveness in the product market might influence its misappropriation of knowledge from its partner (de Rond & Bouchikhi, 2004; Khanna *et al.,* 1998).

This paper sheds light on pre-alliance competition with regard to firms' competition for knowledge (and human capital) during and after an alliance. The interplay between competition and cooperation in a learning alliance affects if and how a firm hires its partner's corporate scientists. In the context of learning, hiring the partner's employees to gain knowledge is opportunistic behavior and thus incurs the risk of losing the partner's trust and lessen the likelihood of further cooperation (Cui *et al.,* 2018; Krishnan, Martin, & Noorderhaven, 2006; Kilduff, 2019; Yu, Subramaniam, & Cannella, 2009; Yang *et al.,* 2015; Hamel, 1991).

To investigate the interplay between learning alliance and learning-by-hiring, we integrated product market competition data and corporate scientist mobility data, relating to alliance firms in the U.S. pharmaceutical industry, from 1985 to 2008. We defined corporate scientists as scientists who were affiliated to our sample firms during the sample period. A corporate scientist's affiliation was estimated using the patent dataset provided by PatentsView. We found that post-alliance poaching was positively affected by the pre-alliance competitive aggressiveness of the poacher on the poached. We also tested the moderators like geographical and technological proximities between the alliance firms as channels of learning alternative to poaching or alliance, as well as the specificity of the poached firm's knowledge.

The findings of our empirical research demonstrated that such heterogeneity in the competitive aggressiveness of a firm toward its partner positively affected its learning through its poaching of corporate scientists. We also considered how the technological and geographical proximities between two firms moderated the main effect. They both proved to have positive moderating effects. Lastly, we found that the specificity of the partner firm's knowledge negatively moderated the main effect.

3.1. THEORY AND HYPOTHESES

Knowledge is a main source of competitive advantage and a firm is an institution that creates, acquires, and retains such knowledge (Grant, 1996; Kogut & Zander, 1992); hence, acquiring external knowledge is crucial for corporate survival and sustainment. Recent literature has implied that organizational learning is shaped and nuanced by both competition and cooperation simultaneously (Hoffmann *et al.*, 2018; Yang *et al.*, 2015; Hamel, 1991). Firms often form alliances in order to learn from their partners' knowledge which is external to them; for example, two archrivals in the automobile industry, General Motors (GM) and Toyota Motor Corporation (hereafter, Toyota), formed an alliance to facilitate a joint venture (JV) in California. It was named NUMMI[40] and lasted from 1984 to 2010. Both GM and Toyota intended to learn from their partner; GM sought knowledge of Toyota's highly efficient manufacturing system, and Toyota wanted to learn how to adapt its production system to the U.S. market (Womack, Jones, & Roos, 1991; Gomes-Casseres, 2009). Such a learning alliance as a form of cooperation is associated with activities involving the participating firms' employees.

[40] New United Motor Manufacturing, Inc.

A learning alliance is formed to create and share knowledge, but such learning benefits come with the risk that each alliance firm's proprietary knowledge would be misappropriated by its partner (Khanna *et al.*, 1998; Gimeno, 1999; Yu *et al.*, 2009). The alliance firms often have interests in the same or overlapping domains, such as product markets, technological areas, or geographical locations, like GM and Toyota. Those competing firms are sometimes preferred partners to form an alliance with, despite (or because of) their ongoing competition in the respective domains. With no overlap in their areas of interest, firms would have far less incentive to collaborate.

Each firm in a learning alliance aims to appropriate knowledge from the alliance partner's knowledge base, unless there is an explicit or implicit penalty exceeding the benefits to be gained from knowledge (mis)appropriation. From the organizational learning perspective, an alliance is not simply a form of cooperation, but an arena of competing (mis)appropriation of the partners' knowledge; however, most of this scarce knowledge is protected and/or tacit, and is embedded in human capital. Often, the poaching of corporate scientists represents an effective and immediate mechanism for appropriating knowledge from elsewhere; but the poaching also undermines trust (Krishnan *et al.*, 2006). Indeed, a learning alliance as a means of cooperation is associated with risks of competitive poaching, and poaching is associated with the risk of distrust between the partners. Such relationships shape and determine a firm's decision about whether to poach or not. Employee poaching, particularly by an alliance partner, is one of the channels for acquiring external knowledge, and poaching between alliance partners constitutes opportunistic behavior that negatively affects the sustainability of the alliance relationship between the partners (Song *et al.*, 2003; Yang *et al.*, 2015).

In the context of a knowledge-based view, employees and their human capital are crucial for their employers' competitive advantage, because knowledge is mostly created by the employees and stored in their brains. Poaching from competitors benefits the focal firm, not only by acquiring the competitor's knowledge, but also by deteriorating the competitor's resource base (Somaya, Williamson, & Lorinkova, 2008; Foss, 1996; Coff & Kryscynski, 2011). We proposed poaching of corporate scientists as a channel for misappropriating an alliance partner's knowledge. Despite non-poaching mobiltiy also leaks the origin firm's knoweldge, we assume that it does not damage the partners' relationship as much as the poaching.

How much a firm engages in learning-by-hiring varies between firms and even between the alliance partners. According to the alliance literature, firms in an alliance have different learning outcomes, because of their different learning capacity (Hamel, 1991; Yang *et al.*, 2015). The heterogeneity in their learning outcomes can also emerge from differences in their motivation for alliance formation and capabilities from the pre-alliance period. Some firms are willing to risk losing a partner's trust by poaching the partner's employees, while others are not. Based on the interplay between competition and cooperation (Hoffmann *et al.*, 2018), we identified the asymmetric level of competition between alliance partners as the antecedent of such heterogeneity in a learning race.

How a firm competes with its alliance partner prior to the alliance affects how the firm behaves opportunistically, during and after the alliance. The literature reports the role of competitive aggressiveness as an outcome of strategic choices of the firms (Yang *et al.*, 2015; Cui *et al.*, 2018; Connelly, Lee, Tihanyi, Certo, & Johnson, 2019). However, this paper particularly focuses on the role of competitive aggressiveness as an antecedent of the competition between alliance partners for the human capital. Simply, we view that the competitive aggressiveness before their alliance formation impacts how they compete within the boundary of a learning alliance. In our research, a firm's attempts to misappropriate its partner's knowledge, facilitated by the number of corporate scientists poached, was partially dependent on the focal firm's competitive aggressiveness toward the partner firm[41].

Competitive Aggressiveness in the Product Market and Inter-Firm Mobility

In our model, the employee mobility which is not a poaching or not of corporate scientists are presumed as not impactful on the trust between the partners (or evenitually the outcomes) of the learning alliance. A certain number of corporate scientist mobiltiy exists, between alliance partners, as non-poaching mobility. However, what we are interested in is the increase of mobility between alliance partners as a conseuqent of learning-by-hiring at the risk of losing trust wihtin the alliance. A firm's pre-alliance competitive aggressiveness against its partner increases the number of corporate scientist mobility as the poaching is added to the non-poaching mobility between the ordinary partners. Increase of mobitliy is higher when a firm had been belligerent against is future alliance partner and stable regardless of the pre-alliance competition.

Also, learning alliances are inevitably learning races too, but the levels of competition within an alliacne is heterogenous across alliances. Alliance partners are asymmetric in their aggressiveness toward each other. How frequently a firm offends against its alliance partners in the product market, before the alliance formation, is a good indicator of such competitive

[41] Of course, there are barriers to prevent or deter poaching behavior. Since it erodes the competitive advantage of the poached firm and enhances that of the poaching firm, multiple legal and non-legal measures are taken to prevent mobility between industry rivals (Reuer & Ariño, 2007), However, none of them are perfect; for example, non-compete agreements (NCAs) prevent mobility within a peer group, often an industry, but do not prohibit mobility between firms that are technologically similar but in different industries (Marx, Strumsky, & Fleming, 2009; Starr, Ganco, & Campbell, 2018), and only a few states now maintain or enforce NCAs (Gardner *et al.,* 2010). On the other hand, the literature has presumed that a "gentlemen's agreement" exists among groups of firms, by which firms avoid poaching from their alliance partners. A case reported by de Rond and Bouchikhi (2004) demonstrated that an alliance between two pharmaceutical firms continued, despite the poaching of a star scientist who was participating in a collaborative R&D project. Poaching behavior may dampen the inter-firm relationship, but does not always destroy the alliance between the poached and poaching firms. Not every R&D alliance contract forbids "alliance parties to actively approach each other's employees for employment" (Dormans, 2013: 94), but some do.

aggressiveness (Cui *et al.,* 2018; Yu *et al.*, 2015). The learning race between two partners inevitably comes along with competitive aggressiveness, because we can presume that the incumbent under attack in the product market has more knowledge and human capital relative to the product domain under attack. Firms are also asymmetric in their motivation to learn from partners, and such firms are heterogenous in their development, fields, and areas of learning from their partners (Hamel, 1991). This is partially due to their absorptive capacity or receptivity, but we focused on the differences in their intention or eagerness to learn from their partners.

The alliance literature has demonstrated that, the more aggressive a firm is, the more likely it is to capture high value and resources from an alliance (Lavie, 2007), because the higher competitive aggressiveness often results in opportunistic behavior and misappropriation of the knowledge created from the alliance, or the knowledge of the partner itself. Additionally, greater competitive aggressiveness means that the focal firm enters new knowledge domains in which its partner is already established, so the focal firm is more eager to learn from its alliance partner than the other way around. We used a firm's competitive aggressiveness towards its partner before their alliance as an indicator of its eagerness to learn from its partner. In the literature, greater competition between alliance partners has often been shown to increase opportunistic behavior; thus, higher competitive aggressiveness is often equated with higher misappropriation of value from the alliance (Yu *et al.,* 2015). While previous research has mainly focused on such resources as partner's proprietary technology, we argued that high-value corporate scientists who invent or carry such knowledge are also strategically important resources.

Poaching of corporate scientists from an alliance partner can be an efficient and effective way of learning if the competitive aggressiveness toward the partner is sufficiently high to risk the aftermath of poaching as an opportunistic behavior. An alliance also reduces barriers hurdling employee poaching, such as information asymmetry and causal ambiguity (Oxley & Sampson, 2004; Campbell *et al.*, 2017), so that the focal firm can easily poach the right personnel with lower cost. A firm that aggressively attacks its alliance partner desires or needs to poach the partner's corporate scientists in order to misappropriate the partner's knowledge; thus, the higher a firm's pre-alliance competitive aggressiveness towards its alliance partner, the more corporate scientists it will poach.

H1: The competitive aggressiveness of a firm towards its partner positively influences the number of active corporate scientists that the firm hires from its partner.

The Moderators

Firm have alternative channels to learn from its alliance partner other than learning-by-hiring and learnig alliance. In the presence of such alternatives, a focal firm's relative gains from poaching its partner's employees would become a less attractive option so that the focal firm chooses learning in alternative channel than learning-by-hiring. Such alternaive channels moderate the main effect of the competitive aggressiveness of inventor mobility by providing alternative learning channles which can partially replace poaching of corporate scientists.

To such extent, the main effect of competitive aggressivness on poaching is often shaped by the technological and geographical synergies between the poacher and the poached firms (Song *et al.,* 2003; Fallick *et al.,* 2006; Almeida & Kogut, 1999). This does not affect non-poaching mobiltiy. In addition, how general the partner's knowledge also affect the focal firm's decision to learn.

Technological similarity.

We predicted that the technological similarity between two firms' knowledge bases during the pre-alliance period would affect how much a firm need, and is able to, misappropriate its alliance partner's knowledge by poaching. First, we expected that, if the two firms already had similar knowledge bases, the focal firm would be less likely to poach its partner's scientists, because the focal firm would already know what the partner knew. Second, if the two firms were technologically similar, then the focal firm would have a higher relative capacity to absorb its partner's knowledge (Lane & Lubatkin, 1998; Volberda, Foss, & Lyles, 2010). Third, being technologically similar means that two firms are sharing their domains of interest so that they have more corporate scientists of interest to poach, too. In such a case, a firm could more efficiently misappropriate the same knowledge with less poaching or through other channels of knowledge misappropriation; hence, technological similarity would negatively moderate our main effect.

H2: Technological similarity between allies negatively moderates the relationship between the competitive aggressiveness of a firm and the number of active corporate scientists hired by the firm.

Geographical overlap.

Mobiliity induced by poaching would be decreased if two firms are geographically close to each other because they can expect to learn via unintentional knowledge spillovers and non-poaching mobility. Geographical proximity between two firms increase the baseline, non-poaching mobility between the firms, itself. We focus on only mobility induced by poaching. In particular, the economic geography literature has asserted that knowledge is localized, so that geographical proximity facilitates easier learning (Jaffe *et al.*, 1993; Arora *et al.*, 2018). Firms that are geographically close to each other will have alternative means of learning, such as through knowledge spillover, rather than poaching. The localized knowledge is transmitted through various channels—friendship networks, face-to-face communication, and business meetings

(Jaffe *et al.*, 1993). If the corporate scientists who embody the firms' knowledge collocate in the same region, the focal firm has other channels through which to obtain its partner firm's knowledge; thus, geographical proximity should negatively moderate our main effect.

H3: Geographical collocation between allies negatively moderates the relationship between the competitive aggressiveness of a firm and the number of active corporate scientists hired by the firm.

Specificity of the partner firm's knowledge base.

The focal firm's behavior toward its alliance partner is also dependent on the characteristics of the partner firm's knowledge: its specificity. Sometimes higher firm-specificity of knowledge is a result of the firm's isolation in terms of knowledge. But, in a leanring alliance where the partner is interested in the focal firm's knoweldge, we can interpret this as a high-level of tacitness of the knowledge, which is difficult to transfer without learning-by-hiring. So, we can assume high complementarities between the poached firm and the poaching firm. In other words, if the partner's knowledge is firm-specific, its knowledge is contained within it and barely overlaps with the knowledge bases of other firms, so the partner firm's knowledge is difficult for outside firms to interpret and understand. High specificity of firms' knowledge may make such firms less attractive as alliance partners, because of the difficulties in understanding their knowledge and the lack of overlap in the areas of interest; however, since our sample alliances were all learning alliances, we presumed that the firms in such learning alliances had rationales for accepting the costs of decoding and understanding such firm-specific knowledge. The focal firm's need to poach the partner's corporate scientists increases as the partner firm's specific knowledge increases; thus, the partner firm's specific knowledge should positively moderate our main effect.

H4: Knowledge specificity of the partner positively moderates the relationship between the competitive aggressiveness of a firm and the number of active corporate n hired by the firm.

3.2. METHODS

Sample

Our sample included a set of focal firms and their partners engaged in learning alliances. So, the firms have rationales to construct alliance relationship despite of their previous relationships including competitive aggressiveness. Specifically, our sample covers learning alliances in the U.S. pharmaceutical industry from 1985 to 2008. Only the technological alliances are included, which are usually aimed at capability building and knowledge creation (Hamel, 1991; Hoffmann *et al.*, 2018; Khanna *et al.*, 1998). In the pharmaceutical and biotechnology industries, which are highly knowledge-intensive, learning alliances often occur in the form of R&D collaboration (Lane & Lubatkin, 1998).

Knowledge is the key driver for value creation and value appropriation in the pharmaceutical industry, so firms collaborate and compete to create, acquire, and protect their own knowledge. In addition, the knowledge outcomes of R&D activities are usually reported to the government in the form of patents and drug authorizations and, in developed countries, such knowledge is registered, managed, and effectively protected according to intellectual property laws. In the pharmaceutical industry, because of its highly protected intellectual property rights, innovative R&D results are mostly patented, rather than kept confidential (Krieger, Li, & Papanikolaou, 2018; Moser, 2013; Cohen, Nelson, & Walsh, 2000).

To extract those employees having knowledge particuarly related to ‘technological’ alliance, we picked corporate scientists, those who have patents, in the pharmaceutical industry.

Despite its limitations of tracking their career and reflecting the true contributions of knowledge production in each phases of the research and development projects (Ge *et al.*, 2016; Bergek & Bruzelius, 2010), we use patent dataset as it has advantages reporting the necessary information of indivduals containing human capital and knowledge.

We assume the mobility of non-inventors is not due to the learning alliance as the interaction in individual-level during the learning alliance only increases those who are involved in R&D projects. Particularly, our sample includes inventors who had patented more than 2 patents from 1976 to 2017, and was granted at least one patent in the sample firms during the 5 year windows before and after a sample alliance. This includes both star and non-star inventors as the majority of inventors in this area had patented more than twice. Our sample includes inventors who had patented more than 2 patents from 1976 to 2017, and was granted at least one patent in the sample firms during the 5 year windows before and after a sample alliance. This includes both star and non-star inventors.[42]

We selected a set of firms with alliances in the pharmaceutical industry more than twice during our sample period. The data was formatted in a 'focal firm–partner firm–alliance deal' format. Two firms might be involved in two different R&D alliances in the same year. Since the competitive aggressiveness of a focal firm toward a partner firm is asymmetric, with competitive aggressiveness also coming from the opposite direction, the same two firms in an alliance could have two dynamics (firm A–firm B or firm B–firm A). A firm could be the focal firm in one relationship and or the partner in another observation within an alliance. Because we were interested in a dyadic relationship, alliances involving more than three firms were split into a pair of firms. Those pairs included all possible combinations of the alliance firms. The sample

[42] We basically comply the commonly used thresholds of 'star'-ness: top 1~5%.

included both firms specialized in this industry and firms that were diversified but also doing pharmaceutical business.

We excluded dynamics in which neither alliance firm had a global key (GVKEY), because we added some firm-level control variables from Compustat, in which the GVKEY was used as a common identifier. We also excluded dynamics in which the partners merged, or a partner acquired the majority share of another partner, in the year of the alliance's formation, because the firms the same ultimate owner, regardless of whether it was known at the time of the alliance's formation, and the dependent variable of interest was the post-alliance mobility of corporate scientists. Our final sample comprised 1,641 focal firm–partner alliance pairs, from alliances existing in the pharmaceutical industry from 1985 to 2008, inclusive. The number of unique firms in the sample was 141[43].

We compiled the data regarding alliances in the pharmaceutical industry from multiple sources: SDC Platinum, MedTrack, and ReCap (Cui *et al.*, 2018). From this data, we selected data regarding 1) the year of alliance establishment, 2) each partner's name in an alliance, and 3) the characteristics of each alliance (i.e. joint venture, the purpose of the alliance). Following Lavie and Rosenkopf (2006), the data was cross-validated using several sources, such as LexisNexis News and corporate websites. Such verification increased the accuracy of our dataset by eliminating those alliances that were announced, but not confirmed by follow-up announcements.

[43] Because our subject of interest was inter-firm competition and cooperation, we excluded data for two firms with the same ultimate owner from our sample. Technically, alliances can occur between companies that have the same ultimate owner (e.g., to create synergy, Janssen, a division of Johnson & Johnson, launched a collaborative project with McNeil, another division of Johnson & Johnson); however, such cooperation between two firms sharing the same ultimate owner is a result of the ultimate owner's internal coordination, based on its corporate strategy, rather than an outcome of the competition between them. Such intra-firm alliances were not of interest to us. Furthermore, like Johnson & Johnson, there are many multi-divisional firms with various subsidiary names, where the ownership of a firm can be transferred through spin-offs, mergers, and acquisitions without any change in corporate name. For this project, we manually identified the ultimate owner of each alliance firm, and only the alliances between firms with two separate ultimate owners were included in our sample.

To investigate how firms competed in the pharmaceutical market, we collected data concerning FDA-approved drugs from the National Drug Code Directory. In particular, the Approved Drug Products with Therapeutic Equivalence Evaluations (the "Orange Book") of the FDA provided information regarding all the approved drugs, including generic products, with the producer's name, the market introduction date, and the classifications of each drug.

We integrated the alliance dataset and drug dataset with the mobility data for corporate scientists using patent data. To estimate the mobility of corporate scientists before and after the years of alliance formation, we used the PatentsView dataset from the United States Patent and Trademark Office (USPTO). Since we were interested in alliances in the U.S. pharmaceutical industry, the corporate scientist data we used was limited to scientists located in the United States. The PatentsView dataset provided the disambiguated names and geolocations of corporate scientists and assignees, the years of applications and grants, and the technological classes of each patent. We excluded patents with a corporate scientist–geolocation pair outside the US, because we focused on the U.S. pharmaceutical industry.

Dependent Variable:

Inter-Firm Mobility of Corporate Scientists.

Our dependent variable was the number of corporate scientists' moves from a focal firm to its alliance partner during the post-alliance period. Technically, post-alliance period, in this paper, refers to a period from year = + 1 to year = + 5, where year = 0 was the year of announcement of each alliance; and pre-alliance window is between year = 0 and y = -4. Each patent detailed the names of corporate scientists and assignees, and this data enabled us to match each individual corporate scientist to a firm.

To estimate the number of corporate scientists moving from one firm to another, we needed to estimate the timing of each corporate scientist's move. Their mobility was tracked based on their identification on the patent documents. For each year, we estimated each corporate scientist's affiliation and geolocation. Following the literature, we assumed that, in the year of the patent application, a corporate scientist was at a firm, in a certain geolocation, as indicated on the patent application document. We could not track a corporate scientist's affiliation and location before or after their appearance in the patent dataset, because patenting is a rare experience for the majority of corporate scientists and most of them do not patent every year. For two consecutive patents by the same corporate scientist, we took the chronological midpoint between those patents as the year in which a move might have happened.[44] If the affiliation/geolocation was the same across two patents, we interpreted it as an absence of mobility in terms of affiliation/geolocation. Before the mobility year, a corporate scientist was as assumed to be working or residing at firm A or location A; after the mobility year, the corporate scientist was assumed to be working or residing at firm B or location B,[45] respectively. In principle, we followed the extant literature in tracking corporate scientists' history (Hoisl, 2007; di Lorenzo & Almeida, 2017).

The mobility research based on patent data has recently been criticized by Ge, Huang, and Png (2016), due to several cases of misclassification that seemed difficult to perfectly eliminate. We took their criticism seriously; however, this paper used patent data to track the corporate scientists' affiliations and locations, because we improved the method of tracking careers using patent data. Ge *et al.*, (2016) claimed that a corporate scientist may be misclassified

[44] We used each patent's application year to estimate mobility, because it takes several years for the approval of a patent and the specific applicant (corporate scientist) may have already left the firm when the patent was granted.
[45] If the last digit of the midpoint was 0.5, we rounded down the number for two patents in 2013 and 2017, the midpoint would be ROUNDDOWN((2013 + 2016) /2) = 2014 in Microsoft Excel.

with an incorrect affiliation in cases of collaborative R&D, like learning alliances (p. 240-241). A patent application may have more than two assignees, and there was nothing to indicate to which assignee a corporate scientist on a patent was affiliated; moreover, it was common for an innovative outcome of an alliance to be patented under the names of the alliance firms. We carefully considered the firms with more than two assignees (if those assignees were under a single ultimate owner, then having more than two assignees was unproblematic). First, if a corporate scientist repeatedly patented at a firm, and this was discontinued on patents with more than two assignees, then it is considered to be an indication of immobility. Second, since patenting is pursued by the firm with the intellectual property right for a technological innovation, the respective corporate scientist (and the corporate scientist's employer) on the patent might be in a temporary contractual relationship with the assignee on the application document. To reduce misclassification due to a temporary relationship, we estimated each corporate scientist's affiliation history for each year. If a corporate scientist had more than two affiliations in a specific year, or a patent with a different affiliation was chronologically placed between patents with one affiliation, we normalized them by ignoring the irregularity and adopted the more frequent one as the affiliation for the corporate scientist/year (Hoisl, 2007; Palomeras & Melero, 2010). Third, mergers and acquisitions can also generate misclassification because, as discussed above, the past assignee's name can continuously be used after a transfer of ownership, because the assignee's name does not have to reflect the ownership structure of the firm. We considered the Mergers and Acquisitions (M&A) and spin-off data from SDC Platinum and Crunchbase by matching each assignee's name to the ownership for each year. Fourth, a firm may change its patenting policy based on its intellectual property rights (IPR) strategy, but this is difficult to verify in the world of corporate R&D in the pharmaceutical industry because, as discussed in above, the pharmaceutical firms are mandated and incentivized to patent all the patentable results they achieve. At least, the institutional setting of the pharmaceutical industry discourages them from changing their patenting policy arbitrarily. Fifth, personal inventions not tied to an assignee were considered to indicate the departure of an assignee, which is not true. We excluded all the patents without assignee names to avoid such an error. Lastly, since the algorithm to disambiguate individuals' identities was incomplete, a corporate scientist could be linked incorrectly to an employer, or a corporate scientist could be falsely mistaken for another scientist[46]; however, the accuracy of disambiguation improved as new techniques, like machine learning, were adopted. Compared to that of the Harvard Patent Corporate Scientist Database (Li, Lai, D'Amour, Doolin, Sun, Torvik, Yu, & Fleming, 2014), which Ge *et al.*, (2016) used as a benchmark, the disambiguation algorithm used by PatentsView is significantly improved. (Bailey, 2015; Monath & McCallum, 2015; Morrison, Riccaboni, & Pammolli, (2017), so we believed that using a patent dataset was reasonable in this setting.

The three datasets and Compustat for the firm-level financial information did not have common identifiers so, after we bundled assignees into business groups sharing an ultimate owner, we merged the datasets, using the text similarity of the names of the ultimate owners. For the string matching, we used a user-written *matchit* command in STATA 15[47] (Raffo, 2015), and we manually checked the validity of the matching after the string-matching procedures.

Independent Variable

Competitive aggressiveness.

[46] This source of misclassification could not be eliminated due to the nature of the patent data, since the USPTO does not ask inventors to provide any unique identifier (http://www.patentsview.org/community/methods-and-sources), and the USPTO continuously updates the algorithm based on the newer data.
[47] This allowed fuzz-matching based on the text strings for the company names.

Following the previous literature (Cui *et al.,* 2018; Yu *et al.*, 2009; Yang *et al.,* 2015), we measured the level of attack in the product market that a firm undertakes against its alliance partner using competitive aggressiveness. This construct included both the intensity and diversity of a firm's attack on its alliance partner. To capture both dimensions, we calculated the average of the three different dimensions of competitive aggressiveness: First, the number of competitive actions that a firm made against its future alliance partner during the period of five years preceding the alliance, up to the year before the alliance. Second, to measure the breadth of such competitive actions, we counted the number of different therapeutic areas which the focal firm entered when its future alliance partner was an established player during the same time window. Third, to measure the intensity of such competitive actions, we counted the number of 'destructive competitive actions' by the firm against its future alliance partner. We used the average of those three dimensions as a proxy for competitive advantage.

Moderators

Technological similarity.

Technological similarity between two firms captured how much they differed in terms of the technological domain. We calculated the vector similarity between two firms' portfolios in terms of technological classes according to the Cooperative Patent Classes. We used the five-year moving window of patent portfolios to measure the distribution of the firms' patents across different technological classes. If their portfolios overlapped, then the partners were technologically similar (Cui, Ding, & Yanadori, 2019; Jaffe, 1986; Oxley & Sampson, 2004; Yang *et al.,* 2010).

Geographical collocation.

Geographical collocation was measured by the number of states in which both of two partners made patent applications each year. We used a corporate scientist's geolocation, instead of the assignee's, based on the premise that knowledge and human capital are embodied by the corporate scientists, and sometimes a corporate scientist might be geographically distant from his or her employer (Oxley & Sampson, 2004). This variable reflected how much the partners competed for human capital. Since mobility barriers involve costs (Campbell *et al.*, 2017), corporate scientists were assumed to be less mobile than the hypothetically efficient labor market. In particular, geographical distance creates a huge barrier (Moretti & Wilson, 2017). As Fallick *et al.*, (2006) and Almeida and Kogut (1999) demonstrated, employee mobility is geographically bounded, and most of the mobility occurs within a regional boundary; so, if two partners' R&D activities were collaborative, it would be more likely for each partner to poach its partner's corporate scientist(s).

Firm specificity of the partner's knowledge.

The specificity of a firm's knowledge was measured by its number of self-citations in the patent applications in a certain year, divided by the number of all citations it made in the same year (Wang, He, & Mahoney, 2009). This captured how much a corporate scientist's knowledge was localized by the employer. A corporate scientist is poached because his or her knowledge and skills will benefit the new employer and generate similar or better outcomes (Groysberg, Lee, & Nanda, 2008); however, if the knowledge of a corporate scientist is highly firm-specific, then it is less likely to generate the expected outcomes following mobility.

Control Variables

Pre-alliance mobility.

We controlled the number of moves from a firm to its partner during the pre-alliance period. The pre-alliance period refers to a period between year = -4 to year = 0. This variable controlled how the dynamic relationships between two firms affected the mobility between them. The estimation method for pre-alliance mobility was the same as that for post-alliance mobility.

Focal firm's quality of patents.

We used the five-year moving average of the citations received by the focal firm's patents in order to control for high-quality outputs attracting the potential employees, regardless of the explanatory variable and the moderators.

Focal firm's number of patent applications.

We controlled the five-year moving average for the number of patent applied by the focal firm. This variable captured the level of patent activity of the focal firm, which could also be understood as a signal of quality to the potential employees.

Focal firm's return on assets (ROA).

The focal firm's ROA was understood as a financial buffer, based on which a firm could bear the additional cost of hiring.

Focal firm's R&D intensity.

The focal firm's R&D intensity, which was the R&D expenditure divided by sales, was controlled because it reflected how greatly a firm was oriented toward technological innovation. This positively correlated with the focal firm's attractiveness and its demand for human capital.

Repeated alliances dummy.

This variable was 1 if the pair of firms had ever been in alliance relationship prior to a certain alliance; otherwise is was 0. Firms' repeated relationships are often understood in terms of the higher information efficiency and trust between them.

Multi-party dummy.

Each observation of our sample considered two firms; however, there were alliances involving more than two firms. Since trust is sometimes based on network embeddedness (e.g. the number of common ties, network distance), the bi-lateral relationship could be affected by the presence of a third party in the alliance relationship.

Alliance Scope dummy.

An alliance can be classified as R&D, marketing, manufacturing, or all of these. As we focus on learning alliance, the main scope of our sample alliances are R&D but an alliance may cover multiple scopes simultaneously. The type of alliance determines the level of information efficiency between two firms. Cui *et al.*, (2018) found that a wider alliance scope mitigates the risk of opportunistic behavior by increasing alliance firms' mutual dependence. If an alliance is for R&D purposes, the motivation of the firms involved in the alliance are clear and straightforward: learning. We coded 1 if an alliance was limited for R&D and had no other motivation; otherwise, we coded 0.

Joint venture dummy.

A joint venture often aims to have an organizational structure that is independent from either alliance partner; this is often associated with the collocation of corporate scientists from each partner firm, so the likelihood of knowledge misappropriation increases. This variable was 1 if an alliance resulted in the formation of a JV; and otherwise, it was 0.

M&A after Alliance dummy.

The alliances often result in M&A subsequently. Once M&A occurs, the acquiror may decide whether to merge the target or to keep the target as an independent entity. Even the target is remained as an independent entity, the target's employees can be redeployed to the acquiror. So, we control the alliances of which the partners ended up in M&A within five-year duration posterior to the alliance formation. We coded 1 if there's a post-alliance M&A in which the post-M&A shareholding exceeds 50%, otherwise, 0.

Non-Solicitation dummy.

Alliance partners generally rely on gentlemen's agreement, which is neither explicit nor codified, to prevent employee poaching by the collaborative partner. Losing partner's trust by breaching the gentlemen's agreement and thus delving the alliance performance are the costs induced by employee poaching (de Rond & Bouchikhi, 2004). To keep scarce knowledge, alliance partners may insert a non-solicitation clause in the alliance contract. It prevents partner firms to actively allege its partner's employees involved in the collaborative projects (Dormans, 2013; Oxley & Wada, 2009). The publicly listed firms are required by SEC to disclose the contracts which are expected to have material subsequent impacts to the firm. So, for many firms, alliances have material and substantial impacts on partners' performances. We coded 1 if the alliance contract explicitly contains such a non-solicitation clause; otherwise, 0.

USA headquarters dummies.

Although we used alliances in the US, the data included firms which were not headquartered in the United States. Those foreign firms would act and be perceived, differently from US firms because their hiring is often a result of internationalization and the main R&D lab of them would exist in their home regions. This variable was 1 if the firm's headquarters were in the US; otherwise, it was 0. We use this variable for both the focal and partner firm. Our sample corporate scientists would have heterogenous preferences on the nationalities of the pharmaceutical firms so that would more from an American firm to another American firm or from a foreign firm to another foreign firm, we also control an interaction term, 1, if both firms were US firms; otherwise 0.

Model.

Our unit of analysis was focal firm–partner firm alliance. Our dependent variable was the number of moves of corporate scientists between a focal firm and partner firm in the post-alliance period, and this was over-dispersed, so we tested our hypotheses by using negative binomial models with fixed effects. To capture unobserved time-variant trends and unobserved traits in the dyadic relationship between a focal firm and its partner, we used both year fixed effects and dyad fixed effects.

3.3. RESULTS

Table 1 reports summary and descriptive statistics for all the variables in our model.

Insert Table 3.1. about here

Table 2 shows the results from the negative binomial models with fixed effects. Model 1 included the baseline model with control variables and fixed effects only, while Models 2–5 included separate models for the main effect and interaction models with moderators. Model 6 was the full model, including all the variables of interest. To test the multicollinearity, we used the variance inflation factor (VIF) and coldiag2 code in STATA 15. None of the mean VIFs exceeded 7, whereas the cut–off line was 10. The result from *coldiag2* was also 20.32, which was below the threshold of 30. For the robustness check, we tested the same models using negative binomial with random effects, and the results were consistent and significant (see Table 3).

In Model 2 of Table 2, we tested Hypothesis 1 by examining the impact of competitive aggressiveness on the mobility of corporate scientists. The results suggested a positive association between the pre-alliance competitive aggressiveness of the focal firm toward its alliance partner and the number of corporate scientists' moves from the partner to the focal firm during the post-alliance period (coefficient = 0.162, p-value = 0.022). Hypothesis 1 was supported.

In Model 3 of Table 2, we tested Hypothesis 2 by using the interaction term between the competitive aggressiveness of the focal firm toward its partner firm prior to the alliance formation, and the technological similarity between two firms. This interaction term moderated how the main effect (Hypothesis 1) was mitigated, because higher technological similarity between two firms diminished the necessity for a firm to misappropriate its partner's knowledge and human capital, and risk inter-firm distrust. The results showed that the technological similarity between two firms negatively moderated the relationship between pre-alliance competitive aggressiveness and the post-alliance mobility of corporate scientists (coefficient = -0. 4262701, p-value < 0.001). Hypothesis 2 was supported.

In Model 4 of Table 2, we introduced the interaction term of competitive aggressiveness and the geographical overlap between the two firms. If two firms and their corporate scientists geographically overlapped, there were alternative channels of learning apart from employee poaching, like knowledge spillover; hence, we predicted a negative moderation effect for the interaction term. The results showed that, when regions overlapped, the impact of pre-alliance competitive aggressiveness on the post-alliance mobility of corporate scientists was dampened. This supported Hypothesis 3 (coefficient = -0.8996581, p-value = -0.004).

In Model 5 of Table 2, we introduced the interaction term of the focal firm's competitive aggressiveness and the firm-specificity of the partner firm's knowledge base. If the partner firm's knowledge was siloed and not transferred elsewhere through another channel, learning-by-hiring might be the more rational option to choose. Unlike the other two moderators, capturing the relationship of the focal firm and the partner firm, this moderator reflected the attributes of the partner firm. The results supported Hypothesis 4 (coefficient = 1.647762, p-value 0.015).

Model 6 of Table 2 was the full model, including all the independent variables, interaction terms, and control variables. The results still held in this full model.

Insert Table 3.2. about here

We ran a Hausman test to confirm whether the fixed-effects models were preferable over random-effects models to test our hypotheses. The results of the Hausman test suggested the use of fixed-effects models (in STATA, the *hausman* command returned Prob>chi2 = 0.0000); however, for the robustness check, we also ran the negative binomial with random-effects models and the results were consistent with those of the fixed-effects models (see Table 3).

Insert Table 3.3. about here

3.4. DISCUSSION

This paper has reviewed a range of strategic management literature concerning the interplay between competition and cooperation (Hoffmann *et al.,* 2018). To the best of our knowledge, the previous literature did not take an integrative approach to learning-by-hiring and learning alliances in the context of the interplay between competition and cooperation.[48] In the context of the learning alliances and learning-by-hiring literature, we considered how alliance firms compete to win in the learning race within an alliance (Yang *et al.*, 2015; Khanna *et al.*, 1998; Hamel, 1991; Song *et al.*, 2003; Das & Teng, 2000). Particularly, in this paper, firms conceptually incorporated multiple channels of learning, and we highlighted the learning alliance as a cooperative learning channel and employee poaching as a competitive learning channel. The interplay between those two channels was what interested us.

We chose the U.S. pharmaceutical industry as the context of this research, because it is where knowledge is a key factor in survival, where learning alliances are frequently formed, and where learning-by-hiring can be tracked through the patent-corporate scientist dataset (Song *et al.*, 2003). We examined whether a higher intensity of pre-alliance aggressiveness toward another firm led to more opportunistic behavior in the learning alliance in the same firm, and whether, in the context of a learning alliance, poaching corporate scientists from an alliance partner placed the sustainability of the alliance itself at risk.

Our empirical results demonstrated that a firm's competitive aggressiveness toward its competitor affected how much effort it made to misappropriate the competitor's knowledge, even after they formed an alliance for R&D purposes; and the effort to misappropriate the partner's knowledge is dependent on the pre-alliance competition. Additionally, technological similarity and geographical proximity between two firms provided alternative channels of learning, other than poaching, such as knowledge spillover and higher absorptive capacity (Jaffe *et al.*, 1993; Lane & Lubatkin, 1998), and these negatively moderated our main effect. In

[48] Oxley and Sampson (2004) find that the risk of knowledge leakage narrows the scope of alliance. In their research, the focal actor is the firm under attack of being leaked. In our research, the focal actor is the attacker who misappropriate its partner's knowledge.

addition, the specificity of the partner firm's knowledge increased the opportunistic behavior of the focal firm, because the uniqueness of the knowledge required the focal firm to poach more corporate scientists in order to acquire and decode the knowledge. We controlled the factors which may have confounded this effect, including the profitability and R&D intensity of the focal firm, the size of the corporate scientist pools of both firms, and the quality of the focal firm's scientific outputs.

Based on the previous research, we investigated factors the literature had overlooked. First, while the extant papers focused on the interplay solely in product markets, we examined how the interplay between competition and cooperation affected the outcomes outside the product market: the human capital poaching between the alliance partners. Second, we focused on how the asymmetric competitive orientation of two alliance partners led to differences in how they (mis)appropriated each other's knowledge by poaching corporate scientists (Hamel, 1991; Cui *et al.*, 2018).

Addressing those research gaps contributed to three different streams of literature. First, we contributed to the literature on the interplay between competition and cooperation (Hoffmann *et al.*, 2018). We extended this literature by demonstrating the interplay outside of the product market, while the previous literature tended to examine how firms cooperated in the product market, but competed in the same or another product market (Yu *et al.*, 2009). Our research focused on how competition in the product market affeced firms' misappropriation of partner's knowledge through poaching.

Second, we extended the alliance learning literature. The previous literature investigated how firm-level learning capacity affects the learning outcomes (Lavie, 2007; Hamel, 1991; Khanna *et al.*, 1998), but our research focused on how the relationship between alliance partners affected the outcomes of alliance learning. Regardless of their capacity to decode the transferred knowledge, firms sought to misappropriate their alliance partners' knowledge.

Third, we extended the competition literature relating to the learning race. Our findings suggested that competition in the product market, preceding an alliance, affects firms' behavior in a learning race following the alliance's formation (Cui *et al.*, 2018). It allowed us to understand the dynamics of the competition (Baum & Korn, 1996). The competition at t = 1 affected the competition at t = 2, regardless of the formation of their alliance.

Fourthly, we contributed to the learning-by-hiring literature. Whereas Mawdsley and Somaya (2015) suggested a learning alliance as an alternative to learning-by-hiring, we integrated learning alliances and learning-by-hiring in our framework. This study enriched our understanding of how those two seemingly alternative channels can be managed simultaneously in a sophisticated manner. Our findings suggested that learning-by-hiring exists within learning alliances and the level of learning-by-hiring is strongly affected by the relationship between the partners.

Lastly, we empirically contributed to the corporate scientist mobility literature by adopting new estimation strategies for the inter-firm mobility of corporate scientists. We integrated patent assignees at the level of a group of firms sharing the same ultimate owner, and we manually checked the ownership history of each assignee. We used a refined approach to track the employment history of each corporate scientist.

There are multiple limitations in our research. First, we viewed the poaching of a corporate scientist as obviously successful learning, but hiring alone does not guarantee a successful transfer of knowledge from firm A to firm B; hence, further research is needed to explicate the complex mechanisms by which poaching results in higher performance.

Second, the mobility of corporate scientists cannot be perfectly tracked through patent datasets, because the disambiguation of corporate scientist's and assignee's identities is incomplete and the timing of moves cannot be precisely measured, due to the nature of the data (Ge *et al.*, 2016; Bergek and Bruzelius, 2013). These issues are due to the fact that the USPTO does not require the unique identification and legal names of rights holders like corporate scientists and assignees, so we could not completely track the corporate scientist's affiliation if no patenting history existed, and the assignees could include corporate scientists who had never been hired by them, or were not hired by them at the time of the patent application (Ge *et al.*, 2016; Morrison *et al.*, 2018).

Third, our data has no individual-level attributes except for inventors' patenting history, while the salaries and working conditions of individual inventors are also crucial for their decision to stay or not.

3.5. CONCLUSION

This paper primarily contributes to the literature regarding the interplay between competition and collaboration. Our results suggested how pre-alliance competition in the product market affects how firms behave in the learning race during the post-alliance period—and how aggressiveness toward its future alliance partner in the product market leads a firm to be more aggressive in the learning race by poaching the partner's corporate scientists in the post-alliance period. Using datasets of alliances in the U.S. pharmaceutical industry and of U.S. patent data, we found that 1) aggressiveness positively impacts misappropriation of value and knowledge from its partner and 2) higher aggressiveness may mean that a firm's new to its partner's knowledge bases. The main effect is moderated negatively if two firms are proximate in terms of technological and geographical distances. Additionally, the firm-specificity of the partner's knowledge positively moderates the main effect. The findings extend our understanding about interplay between competition and collaboration toward the dimension of learning alliances; and we hope this research is followed by other researches which visit the dimensions of the interplay between competition and cooperation that we do not address.

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Table 1 Descriptive statistics and correlations

	Variable	Obs	Mean	Std.Dev.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Post-Alliance Mobility	1,643	7.980523	21.41558	0	221	1															
2	Competitive Aggressiveness	1,643	0.168405	0.582178	0	5.721212	-0.0288	1														
3	Technological Similarity	1,643	0.400161	0.402049	0	1	0.1318	0.1153	1													
4	Geographical Overlap	1,643	0.915399	0.40793	0	3	0.0595	0.0503	-0.0229	1												
5	Firm-Specificity (partner firm)	1,643	0.107942	0.089547	0	0.648262	-0.1101	0.0622	0.1241	-0.0125	1											
6	Pre-Alliance Mobility	1,643	3.458917	11.70293	0	111	0.3426	-0.0346	0.0185	0.0922	-0.0787	1										
7	ROA (focal firm)	1,643	-0.01343	0.4089	-1.74435	8.961605	0.0902	0.0969	0.0171	0.0099	-0.0709	0.0624	1									
8	R&D Intensity (focal firm)	1,643	1.064229	4.25789	0.003311	100.6023	-0.0674	-0.0623	0.0441	-0.07	0.0448	-0.0543	-0.1941	1								
9	Repeated Alliance dummy	1,643	0.790018	0.407419	0	1	0.1099	0.0573	0.0728	-0.019	-0.0908	0.125	0.0158	-0.0272	1							
10	Multiparty Alliance dummy	1,643	0.773585	0.418638	0	1	0.117	0.0395	0.0187	-0.0623	-0.1505	0.1051	0.0774	-0.0646	0.2245	1						
11	Alliance Scope dummy	1,643	0.47109	0.499316	0	1	0.0536	-0.0212	0.0171	0.0074	-0.0058	-0.0555	-0.0199	-0.0255	0.1213	0.2192	1					
12	Joint Venture dummy	1,643	0.046257	0.210105	0	1	-0.0294	-0.035	0.0429	-0.0112	-0.0024	0.031	-0.0361	0.1185	-0.107	-0.1509	-0.1382	1				
13	Non-Solicitation dummy	1,643	0.038345	0.192085	0	1	-0.053	-0.0578	-0.0223	-0.0052	-0.028	-0.033	-0.0247	-0.0104	-0.0371	-0.157	-0.1377	0.1975	1			
14	Post-Alliance M&A dummy	1,643	0.199026	0.399389	0	1	0.1979	-0.0272	0.0666	0.0847	0.0288	0.1719	0.0162	0.0196	0.1634	0.1058	0.0518	-0.0372	-0.0678	1		
15	Focal_USA dummy	1,643	0.637858	0.480766	0	1	-0.2592	-0.0454	-0.1871	0.266	0.1487	-0.1055	-0.1891	0.1122	-0.0558	-0.1262	0.016	0.0514	0.0845	0.0077	1	
16	Partner_USA dummy	1,643	0.559343	0.496617	0	1	0.0131	-0.0162	0.3573	0.1195	0.1837	0.0979	0.0474	0.0051	-0.0422	-0.0613	0.0321	0.0145	0.024	0.1385	-0.0209	1

Table 2 Fixed-effects analyses

	(1) **Baseline**	(2) **Main Effect**	(3) **Moderator 1**	(4) **Moderator 2**	(5) **Moderator 3**	(6) **Full Model**
Pre-alliance mobility	-0.00504*	-0.00433*	-0.00257	-0.00409*	-0.00514*	-0.00325
	(-2.45)	(-2.10)	(-1.25)	(-2.00)	(-2.46)	(-1.56)
ROA (focal firm)	0.818***	0.824***	0.977***	0.804***	0.647***	0.771***
	(6.64)	(6.55)	(7.33)	(6.39)	(5.15)	(5.67)
R&D Intensity (focal firm)	-0.0185+	-0.0177+	-0.0180	-0.0169	-0.0261*	-0.0250*
	(-1.73)	(-1.69)	(-1.63)	(-1.62)	(-2.38)	(-2.18)
Repeated Alliance dummy	0.192+	0.196+	0.199+	0.210+	0.142	0.159
	(1.68)	(1.72)	(1.76)	(1.83)	(1.24)	(1.38)
Multiparty Alliance dummy	-0.0200	-0.0254	-0.0189	-0.0337	-0.0419	-0.0431
	(-0.22)	(-0.28)	(-0.20)	(-0.36)	(-0.46)	(-0.47)
Alliance Scope dummy	-0.0340	-0.0371	-0.0289	-0.0483	-0.0286	-0.0325
	(-0.56)	(-0.62)	(-0.49)	(-0.80)	(-0.48)	(-0.55)
Joint Venture dummy	0.0339	0.0227	-0.00538	0.0543	0.00883	0.00571
	(0.21)	(0.14)	(-0.03)	(0.34)	(0.06)	(0.04)
Non-Solicitation dummy	0.144	0.282	0.141	0.267	0.161	0.0443
	(0.37)	(0.72)	(0.37)	(0.69)	(0.41)	(0.12)
Post-Alliance M&A dummy	0.378***	0.446***	0.398***	0.473***	0.467***	0.442***
	(3.93)	(4.70)	(4.27)	(4.98)	(4.86)	(4.66)
Focal_USA dummy	-0.0425	-0.0391	0.00842	-0.00993	-0.0157	0.0504
	(-0.32)	(-0.29)	(0.06)	(-0.07)	(-0.12)	(0.37)
Partner_USA dummy	0.873***	0.868***	0.730***	0.939***	0.923***	0.842***
	(6.19)	(6.12)	(4.98)	(6.60)	(6.49)	(5.70)
Focal_USA # Partner_USA	-0.178	-0.184	-0.391+	-0.304	-0.103	-0.406+
	(-0.84)	(-0.87)	(-1.82)	(-1.42)	(-0.48)	(-1.85)
Competitive Aggressiveness [H1]		0.348***	0.537***	1.208***	0.135	1.124***
		(4.89)	(6.07)	(4.03)	(1.32)	(3.63)
Technological Similarity			0.543***			0.536***
			(5.18)			(5.18)
Competitive Aggressiveness # Technological Similarity [H2]			-0.356***			-0.350***
			(-3.94)			(-3.85)
Geographical Overlap				0.250**		0.190*
				(2.96)		(2.24)
Competitive Aggressiveness # Geographical Overlap [H3]				-0.891**		-0.799**
				(-2.98)		(-2.71)
Firm-Specificity (partner firm)					-3.171***	-3.031***
					(-6.01)	(-5.63)
Competitive Aggressiveness # Firm Specificity [H4]					2.126**	1.754*
					(3.19)	(2.55)
Fixed Effects	Dyad / Year	Dyad / Year	Dyad / Year	Dyad / Year	Dyad / Year	Dyad / Year
N	1643	1643	1643	1643	1643	1643

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: standard errors are in the parentheses

Table 3 Random-effects analyses

	(1) **Baseline**	(2) **Main Effect**	(3) **Moderator 1**	(4) **Moderator 2**	(5) **Moderator 3**	(6) **Full Model**
Pre-alliance mobility	0.000821 (0.46)	0.000803 (0.45)	0.00255 (1.40)	0.00113 (0.65)	0.0000501 (0.03)	0.00220 (1.19)
ROA (focal firm)	0.340*** (4.68)	0.342*** (4.65)	0.353*** (4.43)	0.335*** (4.66)	0.304*** (4.38)	0.308*** (4.24)
R&D Intensity (focal firm)	-0.0165 (-1.55)	-0.0148 (-1.45)	-0.0169 (-1.52)	-0.0140 (-1.37)	-0.0187+ (-1.84)	-0.0200+ (-1.82)
Repeated Alliance dummy	0.482*** (5.32)	0.443*** (4.87)	0.426*** (4.69)	0.449*** (4.92)	0.409*** (4.46)	0.396*** (4.31)
Multiparty Alliance dummy	-0.0995 (-1.21)	-0.109 (-1.32)	-0.110 (-1.33)	-0.108 (-1.31)	-0.138+ (-1.69)	-0.143+ (-1.75)
Alliance Scope dummy	-0.0726 (-1.25)	-0.0656 (-1.14)	-0.0618 (-1.08)	-0.0752 (-1.31)	-0.0578 (-1.01)	-0.0617 (-1.09)
Joint Venture dummy	-0.106 (-0.71)	-0.0945 (-0.63)	-0.116 (-0.78)	-0.0756 (-0.51)	-0.121 (-0.82)	-0.134 (-0.91)
Non-Solicitation dummy	0.292 (1.23)	0.346 (1.44)	0.303 (1.26)	0.337 (1.41)	0.283 (1.17)	0.243 (1.00)
Post-Alliance M&A dummy	0.679*** (8.39)	0.679*** (8.47)	0.638*** (7.96)	0.700*** (8.74)	0.711*** (8.82)	0.689*** (8.56)
Focal_USA dummy	-0.168 (-1.40)	-0.160 (-1.32)	-0.119 (-0.97)	-0.148 (-1.23)	-0.0995 (-0.82)	-0.0458 (-0.37)
Partner_USA dummy	0.735*** (5.87)	0.730*** (5.79)	0.637*** (4.94)	0.764*** (6.04)	0.819*** (6.48)	0.747*** (5.76)
Focal_USA # Partner_USA	-0.0622 (-0.37)	-0.0479 (-0.28)	-0.155 (-0.90)	-0.115 (-0.67)	-0.0510 (-0.30)	-0.208 (-1.20)
Competitive Aggressiveness [H1]		0.353*** (6.04)	0.506*** (6.33)	0.751*** (3.92)	0.146 (1.57)	0.667** (3.18)
Technological Similarity			0.382*** (4.02)			0.400*** (4.27)
Competitive Aggressiveness # Technological Similarity [H2]			-0.276** (-3.00)			-0.280** (-2.97)
Geographical Overlap				0.237** (3.10)		0.180* (2.37)
Competitive Aggressiveness # Geographical Overlap [H3]				-0.415* (-2.18)		-0.381* (-2.01)
Firm-Specificity (partner firm)					-2.792*** (-6.08)	-2.750*** (-5.94)
Competitive Aggressiveness # Firm Specificity [H4]					2.086*** (3.35)	2.000** (3.11)
Random Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	1643	1643	1643	1643	1643	1643

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: standard errors are in the parentheses

STAKEHOLDER ORIENTATION AS A QAULITY SIGNAL IN THER LABOR MARKET: EVIDENCE FROM THE POST-M&A RETENTION OF NEWLY ACQUIRED HUMAN CAPTIAL

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ABSTRACT

A firm's stakeholder orientation is an instrument to manage its human capital including retetion. This paper particularly focuses on how a firm utilizes its attention and activities with various stakeholders to prevent leakage of its newly acquired human capital after mergers and acquisitions (M&As). The findings from my analyses of a sample of 10,728 corporate scientists from 1,463 unique acquirors indicate that an acquiror's stronger stakeholder orientation delays its target corporate scientist's departure. Stakeholder orientation works as a quality signal to the newly acquired huamn capital lacking enough information to judge the quality of their new employer. This effect is stronger if the newly acquired human capital has a pre-M&A tie with the acquiror and its inventors because the tie increases understanding of the true type of the acquriror. Such an empirical setting helps solve the potential biases from self-selection and information asymmetry, and I thus conducted several supplementary analyses to rule out multiple alternative mechanisms (e.g. using different stakeholder orientation measures, using target's stakeholder orientation).

A strand of literature identifies the roles of a firm's stakeholder orientation[49] in its employee-related performance. Specifically, in today's intensive and knowledge-driven competition, how a firm retains human capital well becomes as much crucial for achieving long-term competitive advantage as acquiring and governing human capital properly (Coff & Kryscynski, 2011; Teece, 2007; Puranam, Singh, & Zollo, 2006; Barney, 1986; Coff, 1997). Previously, the literature investigated what factors impact firm performance; founded upon instrumental stakeholder theory (Flammer, 2013; Harrison, Bosse, & Phillips, 2010). Specifically, the recent studies point at a firm's stakeholder orientation and corporate social responsibility (CSR) as causes of positive performance outcomes related to human capital, such as (1) attractiveness to job seekers (Turban & Greening, 1996; Hedblom, Hickman, & List, 2019; Burbano, 2016; de Roeck, el Akremi, & Swaen, 2016; Jones, Willness, Madey, 2014), (2) employee governance (Flammer & Luo, 2017; Burbano, Mamer, & Snyder, 2018; Gambeta, Koka, & Hoskisson, 2019), and (3) employee retention (Bode, Singh, & Rogan, 2015; Carnahan, Kryscynski, & Olson, 2017). Those research studies found a common and positive relationship between stakeholder orientation and firm performance related to human capital. As discussed below, this paper focuses on the employee retention.

However, how employees react to a firm's stakeholder orientation varies across different types of employees and firms.[50] In general, employees have heterogenous motivations to join a firm and heterogenous treatments after joining said firm, wherein an employee is counted as a type of stakeholder. So, reactions of employees on a firm's certain stakeholder related action may be reacted differetently among different types of employees. For instnace, an employee's decision to join a firm is dependent upon how he/she perceives the firm's quality, in which

[49] This paper uses the term stakeholder orientation interchangeably with corporate social responsibility.
[50] They receive heterogenous treatments after joining said firm, too.

his/her preference itself varies. Or, an employee may be well treated and well paid by the employer than the other employees. So, it is difficult to analyze how stakeholder orientation impacts employee’s behaivors.

The emergent literature on stakeholder theory proposes a sorting and matching mechanism among the firms and stakeholders that possess heterogenous preferences.[51] Two firms may have diverging stakeholder orientations and thus be appreciated by different types of stakeholders. Some stakeholders prefer stronger stakeholder orientations, whereas some others do not (Bridoux & Stoelhorst, 2014; Bundy, Vogel, & Zachery, 2018). In other words, if a firm and an employee are well matched based on their fits and similarities with regard to stakeholder activities, the duration of their relationship should last longer than the unfitting and unmatched pairs (Becker, 1973; Jovanovic, 1979; Bosse & Coughlan, 2016; Sjaastad, 1962). In most cases, employees are matched to employers based on mutual agreement such that the firms and their employees exert their best efforts to seek the most beneficial counterparts (Raffiee & Coff, 2016). If the employee or the firm disagrees with this contract, theoretically, they will get apart in a meantime.

However, not every employment contract is voluntary as firms can obtain a group of individuals through M&As (Puranam *etcof al.*, 2006; Coff, 2002). Such intake of human capital through M&A is distinguishable to the intake of human capital through the labor market because, through M&A, the acquired employees have not deliberately agreed with the ownership change from the target to the acquiror such that the newly acquired human capital would be more likely to walk out the acquiror’s door and never come back (Coff, 1997, 2003; Zollo & Meier, 2008).

[51] The literature provides examples of matching between two different actors with different matching criteria. What makes the actors matched (and sorted) is whether the criteria are high (favorable) or not. For example, the large city (in terms of population) attracts the quality firms (in terms of productivity).

Those newly acquired human captial has no concrete measure to get informed the true type of the acquiror as the employer because they have no direct contact in advance; and this paper uses stakeholder as a signal of quality that delivers information.

Extant research studies cover the impact of stakeholder orientation on employee retention (Bode *et al.*, 2015; Carnahan *et al.*, 2017), although they primarily focus on how incumbent employees who presumably joined the focal firm of their own.[52] Throughout their tenures, both the focal firm and the incumbent employees spend some necessary costs to build trust and long-term relationships. To this extent, after joining the firm, those heterogenous employees had received heterogenous treatments after joining said firm, too. The incumbent employees' responses to their employer's stakeholder orientation are uneven due to such confounders (Bridoux & Stoelhorst, 2014).

The extant researches covering both stakeholder strategy and employee retention also focuses on the sensitivity of a subgroup of professionals in consulting and law firms who have experienced some *pro bono* projects (Bode *et al.*, 2015; Carnahan *et al.*, 2017). Their implication is that a professional's involvement in a corporate social initiative (*pro bono*) increases their job's meaningfulness such that their lawyer would be less likely to leave the law firm. Indeed, what such research has investigated is the impact of employees doing good rather than the impact of their employer doing good. Further, if a *pro bono* project plays a role in employee training (Burbano *et al.*, 2018) and if training increases employee retention (Backes-Gellner & Tuor, 2010; Raffiee & Coff, 2016), then *pro bono* projects might impact employee retention—not because it is ethical or good, but because it is a special type of training. To this extent,

[52] Those studies apply samples from professional firms, such as lawyers (Carnahan *et al.*, 2017) and consultants (Bode *et al.*, 2015).

previous papers have not fully addressed the impact of firm-level stakeholder orientation on employee retention.

This paper illuminates the role of stakeholder orientation as a quality signal (Zerbini, 2017). Under imperfect conditions, signals deliver information to the receiver about the sender's true type, and the receiver uses the signal as a shortcut to infer the sender's true type in the event that doing so is cheaper than collecting more information. Signaling theory's application in the labor market has existed for several decades because a job seeker and his/her prospective employer must make their hiring/mobility decisions even though they both lack information about each other's true types as an employee and an employer, respectively (Spence, 1973; Jovanovic, 1979; Zerbini, 2017). The literautre has urged the role of stakeholder orientation and CSR as a signal appealing to various types of stakeholders like consumers. In detail, signal affects the perception of the audiences. Signaling theory therefore can be applicable to the relationship between the acquiror and the newly acquired human capital at the M&A moment because they have not experienced each other at that point, although they would now need to assess each other's first impressions as the employee suddenly becomes the firm's stakeholder. [53] Even if not every employee concerns CSR is important, I assume most employee concerns a firm's more CSR is reflected into its quality and reputation.

The extant research has not visited the role of stakeholder orientation as a signal on employee attraction and retention. A few exceptions include Turban and Greening (1996), Burbano (2016), Jones *et al.*, (2014), as well as Hedblom *et al.* (2019) find that stronger stakeholder orientation improves a firm's attractiveness such that the number of applicants, particularly those who are more productive, increases. However, they all investigates the job

[53] "Mercan (2017) also argues that more precise initial information about the quality of job matches is an important factor in accounting for the reduction in labor market flows over the last two decades." (Pries & Rogerson, 2019: 3).

seekers rather than the incumbent employees.[54] Rather than job seekers or using ertxperiments, I would focus on the incumbent employees and empirical analyses to identify the effect of stakeholder orientation on employee retention.

This paper investigates how stakeholder orientation impacts the newly acquired human capital's perception of the acquiror and how such a perception impacts the duration of their employment relationship. The sample employees are the newly acquired human capital who are presumably under-informed about the acquiror; and the sample employees has not received any direct treatment previously. Again, at the moment the M&A is announced, the newly acquired human capital does not have any informational advantage about the new employer compared to other external audiences and stakeholders. On the other hand, the acquiror may have done some due diligneces on the target's employees from the public and private information.[55] These employees have no chance to establish trust through previosous employment history at the firm because they became the firm's employees by chance, with no consent of mobility. The sorting mechanism in the labor market matches the firms and their employees with better fit; if the pair has a bad fit, either party or both parties then decide to terminate the employment. So, the pair with a bad fit will have shorter duration of employment.

To the newly acquired human capital, the acquiror's stakeholder orientation is a quality signal because it implies how attentive the acquiror is to various types of stakeholders. While the previous literature emphasizes the role "employee-related" stakeholder orientation plays with regard to employees' perceptions of their employer, I insist that employees are aware of their employer's relationships with different types of stakeholders, including non-employee

[54] This is partially because 'signal' is effective between two parties without sufficient information, but the incumbent employees usually are perceived as being informed about their employer.
[55] So, the acquiror knows well about who is the one capable of doing R&D well (star scientists) in advance.

stakeholders. For example, Google employees spoke out on issues such as (1) the company's comeback to the Chinese search engine market, (2) its contract with the Department of Defense related to the military's use of machine learning, and (3) the company's internal memo on sexism (Bermiss & McDonald, 2018; Shane & Wakabayashi, 2018). Some of these issues are employee related, while some others are not. To this extent, the employees are aware of and are sometimes seriously committed to the firm's relationships with diverse types of stakeholders—not only the employees themselves, but also communities and environmentalists. However, such an awareness does not mean all of thoes awaring employees weight CSR as the prime yardstick. They simply heuristically judge a firm's quality by observing the firm's CSR activities as they do not have better tool to do it. On the other hand, for their employer, employees have many different channels of assessing the employer's quality.

In sum, this paper examines the impact of the acquiror's stakeholder orientation on the retention of newly acquired human capital. This paper also inquires as to what happens if the newly acquired human capital or the target firm has a tie with the acquiror prior to the M&A, such as an alliance or co-patenting, because those with a previous tie with the new acquiror (or its inventors) would be more likely to have trust in or sufficient information about the acquiror that would amplify the main effect: the impact of the acquiror's stakeholder orientation on the retention of its newly acquired human capital. Lastly, this paper investigates the assortative mechanism from the labor economics in which a quality firm is matched with quality human capital (Eeckhout & Kircher, 2018).

Using patent data of 10,728 corporate scientists (1,463 unique acquirors) who experienced mobility through M&As, this paper provides empirical support for all those aforementioned predictions. The contributions of this research are categorized primarily into five parts: 1) the impact of stakeholder orientation on employee retention (Carnahan *et al.,* 2017; Bode *et al.,* 2015), 2) the impact of stakeholder orientation on post-M&A performance (Bettinazzi & Zollo, 2017), 3) skilled workers' positive assortative matching in the labor market (Moretti, 2019), 4) the impact of stakeholder orientation on the retention of employees outside the professional firms (i.e. inventor), and 5) the introduction of an empirical design that directly addresses the impact of a firm's stakeholder orientation on the newly acquired human capital—those who have no experience with and no additional information about the firm.

4.1. THEORIES AND HYPOTHESES

The recent advances in the stakeholder theory literature highlight that a firm acting ethically and maintaining an attentive attitude toward various types of stakeholders benefit the firm's performance: instrumental driver (Gond *et al.,* 2018; Harrison *et al.,* 2010). Specifically, scholars are interested in how stakeholder orientation and CSR work as tools for employee acquisition, retention (Burbano *et al.,* 2018; Carnahan *et al.,* 2017; Bode *et al.,* 2015; Turban & Greening, 1996), and governance, which consequently impact firm performance in, for instance, innovation (Flammer & Luo, 2017; Flammer & Kacperczyk, 2016, 2019; Gambeta *et al.,* 2019; Liang, Renneboog, & Vansteenkiste, 2017; Wang, He, & Mahoney, 2009). Indeed, stakeholder-related activities improve firm performance by building positive relationships with and stronger perceptions and better understanding of not only external stakeholders, but also employees as internal stakeholders (Glavas & Kelly, 2014; de Roeck *et al.,* 2016; Freeman, 1984).

A firm's stronger stakeholder orientation is an effective tool to acquire, govern, and retain strategic human capital (Ng, Yam, & Aguinis, 2018; Bhattacharya, Sen, & Korschun, 2008; Rupp, Shao, Thornton, & Skarlicki, 2013; Turban & Greening, 1996; Carnahan *et al.,* 2017; Bode *et al.,* 2015). As is widely known, human capital is key for sustainable competitive advantage (Coff & Kryscynski, 2011); particularly, the retention of preferable human capital is key for success. Russ Coff famously stated that "[t]he most obvious problem is that the firm's assets walk out the door each day, leaving some question about whether they will return" (1997: 375). Retaining preferable human capital is as important as is attracting such human capital in the age of war for talent (Sturman, Trevor, Boudreau, & Gerhart, 2003; Call, Nyberg, & Thatcher, 2015). Thus, with stronger stakeholder orientation, a firm can retain those preferable human capital effectively and therefore sustain its competitive advantage.

Retention of human capital is heavily affected by how the human capital entered to the firm. There are mainly two channels of human capital acquisition in relation to organizational learning. The first is the labor market. As the learning-by-hiring literautre indicates, a firm can absorb the extenral knowledge by hiring someone who possess the knoweldge from elsewhere (Song, Almeida, & Wu, 2003). The second is to do M&A with a firm possessing human capital with the desirable knowledge. The largest difference between those two options is whether the human capital acquisition took place in the labor market, with search and matching costs, or not (Mercan, 2017). In the prior setting, firms and human capital reached an employment agreement, while in the latter, the human capital had no chance to agree or disagree. The employment contract is transferred from the acquired target firm to the acquiror firm.

According to the strategic factor market theory, a firm acquires another firm to obtain the target's resources, including its human capital and patents/trademarks (Barney, 1986; Coff, 2002). The other types of assets and resources can easily be transferred as ownership changes, but human capital is difficult to transfer thoroughly. In particular, the acquiror would not lose corporate scientists because acquiring the target's human capital itself is often the purpose of the acquisition and the departure of those actors automatically results in a undesirable loss and leakage of knowledge in their brains to the competitors (Coff, 1997).[56] Such a post-M&A leakage of human capital occurs within 2 years from the M&A announcement (Arnold, 2020). The effect of employee turnover itself dampens the productivity of the personnels and organizations regardless of which industry it is (Kuhn & Yu, 2019). As the target's corporate scientists are a source of sustainable competitive advantage, the acquiror intends to avoid losing them for at least a certain duration after the M&A. It takes a certain length of time for the acquiror to absorb the newly acquired human capital's knowledge, and an early departure of said newly acquired human capital results in an imperfect transmission of knowledge.

Here, this paper predicts that the acquiror's stakeholder orientation prior to the M&A positively affects its perception of the newly acquired human capital (i.e., corporate scientists) at the moment the M&A is announced such that the departure of those corporate scientists is prolonged. However, higher employee retention may be a result of self-selecting or sorting employees in the labor market rather than a result of higher stakeholder orientation (Burbano, 2016). Firstly, employees and firms do self-select. In the labor market, a firm solicitates the human capital that is likely to fit the firm; conversely, employees at a firm with a higher stakeholder orientation may join the firm because they are aware of stakeholder orientation, whereas other employees do not consider stakeholder orientation a crucial matter in their job selection (Burbano *et al.*, 2018; Bode *et al.*, 2015; Bridoux & Stoelhorst, 2014; Bermiss & McDonald, 2018). Secondly, a firm may disguise its true type to its external audiences, including job seekers and external evaluators (Crilly, Hansen, & Zollo, 2016). How a firm treats its internal stakeholders (i.e., its employees) might deviate from how it is viewed by its external evaluators.

[56] Some extant papers discuss the positive side effects of a firm losing its corporate scientists founded upon the perspective of learning and social networking (Corredoira & Rosenkopf, 2010; Wagner & Goossen, 2018). However, the departure of corporate scientists induces the loss of their acquired knowledge as well as the transfer of their knowledge to the firm's rivals; thus, we may assume that the retention of target corporate scientists is an M&A performance measure, as Zollo and Meier (2008) urge.

Thus, a firm that disguises its true type to its external raters may be able to attract external talent but may consequently fail to retain its incumbent employees by acting unfavorably (Campbell, Kryscynski, & Olson, 2017). Those two issues are the potential sources of biases, and to omit those potential biases, I adopt an empirical setting with the types of employees who are accidently hired by new employers: those who are acquired through M&As. I refer them as 'newly acquired human capital' throughout this paper.

The literature finds that stakeholder orientation serves as a firm's quality signal to its external audiences, such as its financial investors and prospective employees (Gao, Lisic, & Zhang, 2014; Zerbini, 2017; Turban & Greening, 1996; Crilly *et al.,* 2012). Prior to the M&A announcement, the target's employees receive virtually no information about the acquiror, nor do they have any particular intention to favor or dislike said acquiror. Those employees merely become the acquiror's employees as a consequence of ownership transactions. To this extent, the acquiror's stakeholder orientation at the moment of the M&A announcement determines the target employees' first impression of the acquiror. Additionally, it takes a certain duration for the target employees to become informed about the acquiror's true type, which is known as the "honeymoon period" (Pries & Rogerson, 2019). Also, Arnold (2020) finds that the departure of newly acquired employees is 13% higher than the matched control groups those who have not experienced acquisition; and such an effect only exists in the year of M&A and the year next. So, most of the departure happens before the newly acquired human capital experience the new employer well. Put simply, the retention of the target employees following the M&A is highly dependent upon the acquiror's stakeholder orientation at the M&A announcement.[57] An M&A is

[57] This paper's motivation is founded upon two assumptions. Firstly, those target employees would not join the acquiror of their own will such that they do not experience the self-selection issue. Secondly, those target employees are not well informed about the true quality of the acquiror because they have not previously worked under the acquiror's supervision. The acquiror's true type is revealed proportionally as time proceeds.

a strategic choice that derives impact on both ends—that is, upon the acquiror and the target. Thus, the literature is interested in the consequences and performances of particular M&As. Employee retention is often counted as a performance measure in M&As because employees are often motivated by obtaining the target's human capital (Zollo & Meier, 2008; Puranam *et al.*, 2006). For instance, the acquisition of Zenith, an American electronics firm, by LG Electronics, a Korean electornics firm, in 1990s, causes extremely severe leakage of the corproate scientists from Zenith immediately after the acquisition, which was not intended by LG Electronics (Lee, Lim & Song, 2005). In addition, Park, Howard, and Gomulya (2017) indicate that the inventor's higher retention enhances post-M&A innovative performance (e.g., patent quality). To explain heterogenous M&A performances, some extant papers illuminate how post-merger integration is coordinated and conducted; conversely, this paper focuses on the employee's perception of the acquiror at the moment the M&A is announced. The acquiror's stakeholder orientation contributes a higher retention of the newly acquired human capital, which represents an M&A performance.

Impact of the Acquiror's Stakeholder Orientation on the Newly Acquired Human Capital

Retaining the newly acquired human capital is crucial for a successful M&A. I herein focus on corporate scientists because they hold human capital and carry knowledge. Corporate scientists are also freer to leave the acquiror because their human capital is relatively general and their quality is relatively easy to be understood by a prospective employer as their past performances well disclosed via their patent packages. Further, those who possess transferable technological knowledge and general human capital face lower barriers in their inter-firm mobility (Zucker, Darby, & Brewer, 1998).

Before the M&A is announced, corporate scientists of the target firm are uninformed about the acquiror as severely as are the other external audiences; they have no willingness or interest to know of the acquiror, yet they suddenly, and by chance, became entitled as employees of said acquiror. On the other hand, the acuqiror might have done due diligences on the target's corporate scientists. Thus, the acquired corporate scientists start assessing the acquiror's quality as an employer with limited information. To them, the acquiror's stakeholder orientation works as a quality signal (Zerbini, 2017). In the absence of perfect information, such a signal helps the audiences who are external to the acquiror—including the newly acquired human capital—make a judgment as to the acquiror's true type. Such a quality signal as a first impression affects the duration of the acquired corporate scientist's career with the acquiror. In reality, the acquiror's stakeholder orientation helps the corporate scientists guess their new employer's true type during the transitional period following the M&A announcement stage. The information is not perfect although nevertheless helps the newly acquired human capital. Therefore, I predict:

H1: the higher acquiror's pre-M&A stakeholder orientation, the lower the newly acquired corporate scientists' departure after the M&A.

Assortative Matching Between the Acquiror and the Corporate Scientist

Positive assortative matching implies that the high-quality actors in a group are matched with the high-quality actors in another group. Simutaneously, it also means that low-quality actors are matched to each other as a conseuqnece of labor market activities. This matching pattern is widely observed; for example, positive assortative matching is found in the marriage market (Becker, 1973; Siow, 2015; Cornelson & Siow, 2016), start-ups and venture capitals (Akcigit, Dinlersoz, Greenwood, & Penciakova, 2019), the acquiror and target firms in M&As (Bettinazzi, Miller, Amore, & Corbetta, 2018), among academic researchers (Azoulay, Zivin, & Wang, 2010), firms and spatial locations (Gaubert, 2018), and some papers that identify that the sorting mechanism leads high-quality firms to match with high-quality employees and vice versa (Eeckhout & Kircher, 2018; Mackey, Molloy, & Morris, 2014; Ejermo & Schubert, 2017). This mechanism is consistent within the relationship between the acquiror and its newly acquired human capital. Under the assortative matching, if the acquiror is of high quality, then the higher-quality target corporate scientists prefer to stay rather than leave. Particularly, those higher-quality corporate scientists are freer to move because the other firms compete to hire such individuals. As a result, for the low-quality acquiror, lower-quality corporate scientists are more likely to stay than are high-quality corporate scientists, while for the high-quality acquiror, higher-quality corporate scientists are more likely to stay than are low-quality corporate scientists. For instance, Hedblom *et al.* (2019) reported that "a firm advertises work as socially oriented … attracts employees who are more productive" (p. i).

This moderation effect means not only the high-quality corporate scientists are sensitive on the acquiror's quality. This means that everybody cares about her employer's quality, but only high-quality corporate scientists whose skills are appreciated virtually everywhere can choose where to stay or to leave. So, the high-quality corporate scientists have thier own deliberate freedom to choose stay or not based on their impression on the acuqiror quality. On the other hands, the low-quality corporate scientists have no choice because their skills are less appreciated outside than those high-quality ones.

Also, those high-quality corporate scientists are the pool of knowledge so that the acquiror, of which had conducted due diligence thoroughly, would not hand over them to its competitors. So, knowing if the high-quality individuals stay at the acquiror, then it is a result of both the acquiror's effort to retain them and the reaction of the high-quality corporate scientists to the quality signal of the acquiror.

So, depsite both high-quality and low-quality coprorate scientists dislike the low-quality acquiror over the high-quality acquiror, only the high-quality corproate scientist can leave the low-quality acquiror to the high quality one. In other words, only the acquiror can choose whether to retain the low-quality ones or not. Eventually, the high-quality corproate scientists can make their decision freely based on their notion of the acquiror's qualtiy whereas the low-quality corproate sicentists cannot. Also, the high-quality acquiror which could retain the high-quality corporate scientist may be able to lay-off the low-quality corproate scientists, which sounds less likely to happen in the low-quality acquiror which would be less likely to be chosen by the high-quality corporate scientists. Also, given that the acquiror have known the quality of each newly acquired human capital in advance through due diligence, the low-quality corporate scientists become more likely to be discharged from the high-quality acquiror as the acquiror can retain the high-quality newly acquired human capital and the other high-quality individuals attracted the firm in the labor market.

Whereas the acquiror's quality is proxied by its stakeholder orientation, the acquired corporate scientist's quality is proxied by her patents' number of citations received (Flammer & Kacperczyk, 2016; Hall, Jaffe, & Trajtenberg, 2001). The previous papers apply this proxy as quality, and thus hypothesize that:

H2: The negative impact of stakeholder orientation on the target corporate scientist's departure after an M&A is stronger if the target corporate scientist's quality as an inventor is higher.

Stakeholder orientation works as a quality signal providing 'information' of the true type of the new employer to the newly acquired humna capital. So, the alternative channels of informtion would complement the retention effect of stakeholder orientation. Those alterantives moderate the effect of signal. In the previous hypotheses, I predicted that the acquiror's stakeholder orientation is a quality signal that helps the acquired corporate scientists judge whether they should stay or start searching for another employer. However, the signal itself is imperfect and is only helpful when the perfect information is absent. If both the acquiror and the target corporate scientists have had an alternative channel of knowing each other's true type ahead of the M&A, the effect of the stakeholder orientation as the quality signal would be amplifieid.[58]

The acquiror did due diligence ahead of M&A so that the acquiror had known of the qualities of newly acquired human capital before the M&A announcement, but the newly acquired human capital themselves have a limited source of infomration of the acquiror except for the quality signal from its stakeholder orientation. So, having a pre-M&A tie only increases the newly acquired human capital's undertanding about the acquiror and the opposite is not true as the acquiror knew the target's corporate scientists in advance of the M&A announcement. Assuming that target corporate scientist has altenrative channel of knowing the acquiror before the M&A announcement, the target corporate scientists would be able to be more confident on the information from the signal so that the post-M&A mobility of the target corportae scientsits would be suppressed, too.[59]

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[58] This logic does not apply to a situation where the acquiror's high stakeholder orientation is a disguise rather than a reflection of its true type (Crilly *et al.*, 2012). I assume that in most cases stakeholder orientation as a quality signal is positively associated with the firm's true quality (Zerbini, 2017).

[59] The alliance literature suggests that the formation of alliance ties increases the trust between the two parties (Das & Teng, 1998; Zaheer, McEvily, & Perrone, 1998; Kang & Zaheer, 2018; Dyer & Singh, 1998), and such trust can be shared among the employees of both the acquiror and the target such that the target corporate scientist's departure is lowered. Also, the advantage of the acquiror from being informed about the employee well before the M&A exists. However, those effects are NOT related to the stakeholder orientation. Also, the latter effect may selectively impact only the favorable employees (e.g. star scientists).

I would suggest pre-existing alliance tie between the acuqiror and the target as a moderator amplifying the main effect. With an inter-firm alliance tie, the employees in the target would be more informed about the acquiror than the other audiences/evaluators. Without such a tie, only that is externally visible is what the target corporate scientists and the external evaluators know about the acquiror, and the acquiror's true type may be invisible from the outside (Crilly *et al.*, 2012). Again, such an information asymmetry can be mitigated if a previous tie exists between the acquiror and the target. The experience or repetitive experiences of a formal tie improves information efficiency between the two parties, and the literature on inter-firm alliances takes the higher information flow between two alliance partners as a given (Kang & Zaheer, 2018; Zollo, Reuer, & Singh, 2002). Indeed, information asymmetry is present between the acquiror and the external audiences with regard to the former's true type, which may be greater or lesser than it appears (Crilly *et al.*, 2012). However, some channels exist whereby corporate scientists know of the acquiror more so than do other external audiences. I therefore predict:

> *H3: The negative impact of stakeholder orientation on the target corporate scientist's departure after an M&A is stronger if the acquiror and the target experienced alliance formation prior to the M&A.*

This paper's fourth hypothesis also focuses on the pre-M&A tie between the target's corporate scientists and the acquiror. During the pre-M&A periods, an acquired corporate scientist might have collaborated with the acquiror's inventors, which can occur if the target corporate scientist had previously worked for the acquiror as an employee (and then moved to the target) or if the target corporate scientist engaged in a collaborative patenting project with the acquiror and its scientists regardless of whether it was a strategic alliance or a contractual Research and

Development. Such an experience also decreases information asymmetry and increases trust, as previously discussed. Thus, I predict:

H4: The negative impact of stakeholder orientation on the target corporate scientist's departure after an M&A is stronger if the acquiror and an acquired corporate scientist have a co-patenting history prior to the M&A.

4.2. DATA AND METHODOLOGY

Analysis

This paper's hypotheses test how pre-M&A stakeholder orientation impacts the post-M&A mobility of the target firm's corporate scientists. In other words, this paper inquires as to how inventors' responses to acquisitions vary across different types of acquirors. At the time an M&A is announced, stakeholder orientation as a quality signal affects the mobility decisions of the newly acquired corporate scientists. Thus, how the stakeholder orientation of the acquiror changes across time is not accounted for in the model.

Following the literature (Breschi, Lissoni, & Miguelez, 2018; Bode *et al.,* 2015; di Lorenzo & Almeida, 2017; Palomeras & Melero, 2010; Azoulay, Ganguli, & Zivin, 2017), I employ a survival analysis with clustered standard errors. One rationale for this model choice is that a corporate scientist might stay at the firm without changing her employer until the end of her career, and such a censorship issue may be solved by the survival analysis models.

The survival analysis estimates the hazard ratio an individual will face an event in each period. If this ratio is lower, then the individual will survive for a longer period. In the context of this paper, a target corporate scientist stays at the acquiror longer following the M&A. Each individual faces the event or is censored, and due to such rationales, survival analysis is widely implemented among the research on individual decisions of moving across firms and regions (Palomeras & Melero, 2010; Bode *et al.*, 2015; Breschi *et al.*, 2018; Azoulay *et al.*, 2017).

Among various survival analysis models, I chose the Cox proportional-hazards model—a semi-parametric survival analysis model—to test the hypotheses. I applied the *stcox* command in STATA15, and in the event that time-dependent changes were encountered among the control variables, I used the *tvc* and *nohr* options.[60][61] I also implemented year fixed effects because the liquidity in the labor market varies across years (Pries & Rogerson, 2019) as the major reason of leaving is inter-firm mobility rather than retirement. I set the M&A announcement year for each deal, and to control the biases from the deal-level characteristics of each M&A deal, I clustered the standard errors using the deal-level ID numbers.

Empirical Setting and Sample

This paper investigates the mobility of corporate scientists after their affiliations were acquired. This setting allowed me to cope with the issues arising from self-selection and information asymmetry in the mobility literature. Firstly, self-selection issues arise due to the heterogeneity among the firms and individuals, both of which have preferences. The sorting mechanism in the labor market allowed both parties to be matched through mobility. Recent research on stakeholder theory suggests that some stakeholders prefer stronger stakeholder orientation, whereas others prefer profitability over stakeholder orientation (Bridoux & Stoelhorst, 2014). Thus, in general, both the incumbent and novice employees were at the firm because they had already self-selected whether to stay or leave when they joined the firm of their own will.[62]

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[60] For a robustness check, I removed the *tvc* option for the *stcox* commands in STATA15 without removing the control variables themselves. The results were consistent regardless of whether the *tvc* option was on or off.

[61] The *nohr* option provides coefficients for each variable rather than the hazard ratio.

[62] As is discussed in the introductory section of this paper, the previous papers on the impact of stakeholder orientation on employee retention used the incumbent employees' reactions on the firm's stakeholder orientation (Bode *et al.,* 2015; Carnahan

However, the acquired corporate scientists are not those who willingly joined the firm. Thus, immediately following the M&A, they were not at the acquiror due to their certain fit. Secondly, since they unintentionally transferred to the acquiror, they were not well informed about the acquiror. The sample corporate scientists were equally uninformed about the acquiror simply because they were external to it. Such information asymmetry leads individual corporate scientists to solely rely on the stakeholder's quality signal to judge their new employer's quality as an employer.

The basic premise of this paper is that the newly acquired human capital are the ones who needs and desires to know the true qualtiy of the acuqiror from the signal. I assume that the acquiror had sensed all the necessary information about the target corporate sceintists at least those who are worthy to retain before acquisition from the patent database, technological due diligence, and reputations. So, information asymmetry bounds the target corporate scientists.

The mobility of newly acquired human capital is not immediate; it takes some time for an employee to both seek a more favorable alternative from the outside and become familiar with the employer's true type if it were disguised. The acquiror and the acquired corporate scientists endure a sort of "honeymoon period," during which the acquiror's true type is revealed to the newly acquired human capital (Pries & Rogerson, 2019). Also, as time passes, factors such as the post-M&A financial performance attenuate the impact of stakeholder orientation on the acquired corporate scientists' departure. Thus, the impact of stakeholder orientation is most salient to the acquired corporate scientist at the moment the M&A is announced. Thus, I chose the survival analysis, which measures how an impact affects the duration of the survival or hazard rate during each period.

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et al., 2017). Even those papers examined if an incumbent employee doing CSR activities (pro bono) lowers their mobility decisions, which is not exactly equal to the firm-level stakeholder orientation.

This paper's sample covers the target firm's corporate scientists who were acquired from 1991 to 2016. To measure their mobility, I downloaded the patent data from the U.S. Patent and Trademark Office's (USPTO) Patentsview, which provides disambiguated inventor-level and assignee-level ID numbers. Although the USPTO does not collect any data, we tracked its applicants' identities via the machine learning algorithm introduced in Patentsview, which disambiguates them using various types of information in the application packages, such as names and technological classifications (Monath & McCallum, 2015). Patentsview also provides information such as the patent application and grant years, the inventors' geolocations, and the "citing-cited" relationships between patents. The corporate scientist sample comprises the inventors who were estimated as residing in the U.S. during the year the sample M&As were held. Firms can still operate their R&D activities in the U.S. even in the event that their nationalities (e.g., headquarters location, country of incorporation) are not American.

Regarding M&As, this paper utilized SDC Platinum to collect the year the M&As were announced, the acquiror, and target-specific attributes, such as locations and deal-specific attributes (e.g., the dummy if a deal is a merger). SDC Platinum is a standard source of M&A data (Rossi & Volpin, 2004; Hawn, 2016; Ahern, Daminelli, & Fracassi, 2015; Valentini, 2012); I filtered out those M&A deals of which the acquired share was less than 20% of the deal and the after-acquisition share was less than 50%. I also dropped the asset acquisition deals because it was unclear whether or not the corporate scientists moved through those deals. Put simply, the sample of my interest is limited in ownership transfers in which a firm's entire ownership was traded.

Stakeholder orientation was measured using Kinder, Lydenber, & Domini (henceforth, KLD) data.[63] KLD reports a firm's attention and commitment to various types of stakeholders, including employees, general society, the environment, and corporate governance (MSCI, 2015). KLD offers its users aggregated firm-level stakeholder orientation as well as the stakeholder orientation of specific areas, such as employees, diversity, social, environmental, and community, among others. This data allowed me to take a look at the effect of stakeholder orientation on employee retention from various aspects. For the additional stakeholder orientation source, I applied ASSET4 from Thomson Reuters, which also provides information about a firm's stakeholder orientation at the aggregate firm level alongside other subcategories, including environmental, social, economic, and corporate governance.

To construct the sample, I merged the firm-level stakeholder orientation data from KLD, corporate scientist data from Patentsview, and M&A data from SDC Platinum. The sample included 10,728 corporate scientists who had been working at the target firm during the year the M&As were announced, and the acquiror's stakeholder orientation scores one year prior to the M&A announcements were located through KLD or ASSET4. The M&As ranged from 1991 to 2014, and the inventor's affiliations were estimated from 1975 to 2018 in the event that any records were present. Furthermore, KLD provides stakeholder orientation data from 1991 to 2013, while ASSET4 provides stakeholder orientation data from 2001 to 2013.

Data and Variable Definitions

Dependent Variable.

[63] KLD has been renamed MSCI ESG DATABASE.

My goal in this research is to measure the hazard rate of each newly acquired human capital at an acquiror, which is the opposite of the survival rate in that a lower hazard rate indicates the acquired corporate scientist stays at the acquiror for a long duration. Thus, I coded the year of the corporate scientist's joining to the acquiror as the M&A announcement year; and the duration of the M&A announcement to the corproate scientist's departure is estimated for individual corproate scientist.

I use patent data to track down the corporate scientists' year of mobility. As Ge and colleagues (2016) pointed, there are some measurement issues in this methodology, but I utilized a sophisticated algorithm to estimate the mobility history with manual corrections and better disambiguation techniques than what is criticized in Ge and others (2016).

Since the target firm may operate without changing its name after an M&A, an inventor's affiliation that does not change after an M&A (i.e., patenting remains under the target's name) is considered immobile. Also, the corporate scientist is immobile if she started patenting in the acquiror's affiliation following an M&A. Any other changes of affiliation among the sample corporate scientists other than the target and the acquiror following the focal M&A were considered a mobility. If a corporate scientist did not change her affiliation until her last or latest patents, then I coded her as censored.

Independent Variable.

This paper's explanatory variable is the acquiror's stakeholder orientation in the year prior to the M&A announcement (y = -1). This variable reflects the acquiror's quality signal, which affects the external audiences, such as the CSR evaluators and employees of the firms other than the acquiror. KLD reports a firm's number of strengths and concerns with regard to various types of stakeholders, although I solely involved the number of strengths in accordance with Flammer and Kacperczyk's (2016) suggestion. I included the number of strengths in various subcategories of KLD, including corporate governance, community, diversity, employee relations, environment, and product. Above them, I created an overall index by summing up all the acquiror's strengths.

Moderators.

Inventor Quality. Hypothesis 2 tests the positive assortative matching mechanism between the acquiror and the corporate scientist. If the higher-quality firms—measured by stakeholder orientation—attracted higher-quality corporate scientists, then the low-quality corporate scientist was sorted to the low-quality acquiror. To measure the corporate scientists' quality using patents, I referred to the number of citations received by a corporate scientist's patents (Hall *et al.*, 2001; Flammer & Kacperczyk, 2016). I exclusively included the citations received during the ten-year period after the application year of the corporate scientists' patents. I aggregated the patents' number of ten-year citations [y = +1 ~ y = +10], which were granted between the five-year period prior to the M&A [y = -4 ~ y = 0]. Thus, this variable was 0 if the corporate scientist did not patent anywhere during the five-year window.

Pre-M&A Alliance. Hypothesis 3 tests the moderation effects of the alliance tie between the target and the acquiror. To do so, I collected the alliance data from SDC Platinum and counted the number of alliances that had formed between the two parties prior to the M&A.

Pre-M&A Co-Working Experience. Apart from alliance experiences, a corporate scientist might have worked at or co-worked with the acquiror prior to the M&A. Thus, I coded a dummy variable as 1 if the corporate scientist had ever patented with one or more inventors whose affiliation was the acquiror prior to the M&A.

Control Variables.

This paper adopts control varaibles from M&A litearture as well as stakeholder literature. First, related to M&A type, this paper controlled whether or not the M&A was followed by a merger between the acquiror and the target. An acquiror often faces a dilemma between coordination and autonomy (Puranam *et al.*, 2006), and once the acquiror desires to absorb the target's knowledge and capabilities, it chooses to integrate the target's employees in a quicker manner. However, such an integrative post-merger strategy risks a loss in the exploration capacity of the target employees due to a loss of autonomy (Gambardella, Khashabi, & Panico, 2019; Puranam *et al.*, 2006). Also, the changes in organizational architecture subsequent to the M&A—if any—negatively impact the target employees' psychological stability due to the anticipated or actual conflicts between the acquiror and the target (Cartwright & Cooper, 1997; Ullrich & van Dick, 2007). Hubbard and Purcell (2001) find that the risk of breach in pscyhological contracts by the acquiror leads the target employees' concerns about organizational injustice during the post-merger integration phase. Such a negative impact renders the target corporate scientists more likely to leave (Zollo & Meier, 2008). Thus, I coded 1 if the specific M&A deal was a merger deal in which we might expect higher integration and greater conflict and 0 if the deal was simply an acquisition. Moreover, I used SDC Platinum to classify the types of M&A deals.

Second, to control M&A type, too, this paper also controlled whether or not the target and/or the acquiror are U.S. firms. The sample of the corporate scientists was located in the U.S., and I presume that the firms' nationalities would matter in terms of their hiring pattern in the U.S. and the acquiror's perception among the target corporate scientists. A firm is considered a U.S. firm if the acquiror's nationalities in the SDC Platinum are indicated as American. The target's nationality also affects the emotional attachment of the U.S. corporate scientists upon them. I controlled the state overlapping between the target and the acquiror, too, if they were headquartered in the same U.S. state, then the target corporate scientists would have been more informed about the acquiror prior to the M&A due to knowledge spillovers (Jaffe, Trajtenberg, & Henderson, 1993; Arora, Belenzon, & Lee, 2018).

Third, I controlled whether or not the acquiror had already been a major shareholder of the target firm prior to the M&A. The sample comprised the M&As at which the acquiror purchased more than 20% at once and achieved higher than 50% of the shareholding. Such restrictions allow an acquiror to be a minor shareholder (i.e., less than 50% shareholding), but if the acquiror had been a shareholder of the target ahead of the focal M&A, then the target's employees had been more attentive to the acquiror, prior to the M&A, such that they were more informed. In such cases, the corporate scientists would often already have some emotional ties with the acquiror.

Fourthly, for the corporate scientist-level control, I also controlled the number of years the corporate scientists had spent at the target prior to the M&A, where the short stayer was assimilated to the job hoppers (Fallick, Fleischman, & Rebitzer, 2006) who moved from one firm to another without a barrier.

Fifthly, The tenure at the M&A announcement year was also controlled because it is a proxy of the corporate scientist's lifecycle as both a person and an inventor.

Lastly, I controlled for whether or not the primary three-digit SIC codes of the target and the acquiror overlapped to absorb the effects from two firms having product market-level relatedness. If they are proximate in terms of industry or product market, then the newly acquired corproate scientists were more attentive on the prospective acquiror ahead of the M&A. In addition, the need for post-M&A layoffs get emerged between two firms in the same industry, due to the overlaps in their knowledge bases.

4.3. RESULTS

Table 4.1. displays the summary statistics and correlations among the variables from the dataset.

Insert Table 4.1. about here

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Table 4.2. presents the results for my test of Hypothesis 1 using the Cox proportional hazards model. The results fully support Hypothesis 1. The *nohr* option of *stcox* returned the exponential coefficient for the independent variables and moderators (Cleves, Gould, & Marchenko, 2010). The overall stakeholder orientation coefficient was -0.0627; a unit of stakeholder orientation, which is an additional strength in the KLD dataset, decreased the hazard (the corporate scientist's departure) by 6.1% because exp(-0.0627) = 0.939 and 1 – 0.939 is 0.061. The corporate governance stakeholder orientation coefficient was -0.324, (27.7% decrease in hazard), while the community stakeholder orientation coefficient was -0.136 (12.7% decrease in hazard). The diversity coefficient was -0.0503 (4.9% decrease in hazard), the employee relation coefficient was -0.0197 (2.0% decrease in hazard), the environment stakeholder orientation coefficient was -0.0262 (2.6% decrease in hazard), and lastly, the product stakeholder orientation coefficient was -0.109 (10.3% decrease in hazard). The coefficients were significant except for that of product stakeholder orientation, which was between 0.05 and 0.10. The interaction effects of the stakeholder orientation variables and the inventor quality measures achieved negative coefficients, thereby implying that the inventors with higher patent quality prior to the M&A were less likely to leave the acquiror or more likely to stay at the acquiror longer if it had a

higher stakeholder orientation. These results imply that the acquiror's stakeholder orientation negatively impacted the hazard rate of the acquired corporate scientists' departure following the M&A, and such impacts were relatively even across the various stakeholder orientation types.

Insert Table 4.2. about here

Table 3 contains the results of the Cox Proportional Hazard model for Hypothesis 2. This hypothesis inquires as to the moderation effect of each corporate scientist's quality as an inventor to the main effect between the acquiror's pre-M&A stakeholder orientation and the departure of the target corporate scientists following the M&A. In other words, the hypothesis predicted the negative impact upon the relationship between the acquiror's stakeholder orientation and the departure of the target corporate scientists. The interaction effect between inventor quality and overall stakeholder orientation was -0.0000518, and a one-unit increase in this stakeholder orientation led a 6.0% decrease in the hazard rate (the corporate scientist's departure) because exp(-0.0000518 + -0.0617) = 0.9401. In this case, -0.0617 was the coefficient of the overall stakeholder orientation in the interaction effect's presence. The interaction effect between inventor quality and corporate governance stakeholder orientation was -0.0.000743 (26.8% decrease in hazard), while the interaction effect between inventor quality and community stakeholder orientation was -0.000339 (12.3% decrease in hazard). The interaction effect between inventor quality and diversity stakeholder orientation was -0.000272 (4.5% decrease in the hazard), -0.000227 between inventor quality and employee relationship stakeholder orientation (17.7% decrease in hazard), -0.000182 between inventor quality and environment stakeholder orientation (22.8% decrease in hazard), and lastly, -0.000702 between inventor quality and product stakeholder orientation (9.6% decrease in hazard). The coefficients were all significant ($p < 0.05$), and these results imply that the high-quality corporate scientist is more likely to stay longer at the acquiror if it has a stronger stakeholder orientation, which is also perceived as a quality signal (Zerbini, 2017; Glavas & Kelly, 2014).

Insert Table 4.3. about here

Table 4 includes the results of the Cox Proportional Hazard model for the Hypothesis 3. Here, this paper examines the moderation effect of the number of alliances formed between the target and the acquiror. The rationale behind this hypothesis is that the inter-firm tie from the alliances prior to the M&A drives the target's corporate scientists to become more informed about the acquiror's true type prior to the M&A announcement. The interaction effect between the pre-M&A alliance and overall stakeholder orientation was -0.0724 (12.6% decrease in hazard), -0.644 between the pre-M&A alliance and corporate governance stakeholder orientation (61.9% decrease in hazard), -0.438 between the pre-M&A alliance and community stakeholder orientation (43.4% decrease in hazard), -0.186 between the pre-M&A alliance and diversity stakeholder orientation (21.0% decrease in hazard), -0.188 between the pre-M&A alliance and employee relationship stakeholder orientation (31.9% decrease in hazard), -0.323 between the pre-M&A alliance and environment stakeholder orientation (44.2% decrease in hazard), and lastly, -0.587 between the pre-M&A alliance and product stakeholder orientation (49.7% decrease in hazard). All coefficients except for that of employee relationships were significant ($p < 0.05$). In other words, the effect of employee relationships on the mobility decision of the newly acquired human capital is insignificant if the corporate scientist has already had the opportunity to both become familiar with the acquiror's employee relationships and build trust with said acquiror (Das & Teng, 1998).

Insert Table 4.4. about here

Table 5 includes the results of the Cox Proportional Hazard model for Hypothesis 4. Similarly to Hypothesis 3, it predicts that the individual corporate scientist's previous co-patenting experience with the acquiror at the co-patenting moment has a negative moderation effect on this paper's main effect regardless of the affiliation at which the focal corporate scientist was situated. The interaction effect between the pre-M&A co-patenting with the acquiror and overall stakeholder orientation was -0.0847 (13.7% decrease in hazard), -0.435 between the pre-M&A co-patenting with the acquiror and corporate governance stakeholder orientation (53.0% decrease in hazard), -0.567 between the pre-M&A co-patenting with the acquiror and community stakeholder orientation (50.5% decrease in hazard), -0.318 between the pre-M&A co-patenting with the acquiror and diversity stakeholder orientation (30.7% decrease in hazard), -0.240 between the pre-M&A co-patenting with the acquiror and employee relationship stakeholder orientation (35.3% decrease in hazard), -0.000155 between the pre-M&A co-patenting with the acquiror and environment stakeholder orientation (23.2% decrease in the hazard), and lastly, -0.766 between the pre-M&A co-patenting with the acquiror and overall stakeholder orientation (58.1% decrease in the hazard). In this hypothesis, all moderation effects except for that of environment stakeholder orientation were significant.

Insert Table 4.5. about here

4.4. DISCUSSION

Consistent with the previous literature, first, this study finds that stakeholder orientation positively affects employee retention (Bode *et al.,* 2015; Burbano *et al.,* 2018; Carnahan *et al.,* 2017; Turban & Greening, 1996). Second, different from previous studies in the inventor mobility literature and stakeholder literature, this study included corporate scientists from the acquired firms as a sample. Alongside some assumptions, this sampling allowed this paper to avoid biases that typically arise from self-selection and asymmetric information. Third, this study adds empirical findings to the relationship between M&A performance and stakeholder orientation (Bettinazzi & Zollo, 2017), which is a new topic at the intersection of the literature on M&A performance (Zollo & Meier, 2008) and the role of stakeholder orientation on firm performance (Eccles *et al.,* 2014). Fourth, this study contributes to the microfoundations of competitive advantage by furthering the collective understanding of the micro-dynamics of acquisition and retention in the strategic factor market (Ganco, Ziedonis, & Agarwal, 2015; Felin, Foss, & Ployhart, 2015; Barney & Felin, 2013). Fiv, this paper attends on a unique type of employees: newly acquried human cpaital. Last, this paper provides evidence for positive assortative matching between a firm and its (knowledge) workers because high-quality firms is matched with high-quality individuals and vice versa (Hoisl, 2007; Kaiser, Christian, & Rønde, 2015; Lopes de Melo, 2017; Eeckhout & Kircher, 2011).

The purpose of this paper is to contribute to the strategic human capital litearture to the extent that presenting a quality singal, in this case of high stakeholder orientation, in advance of the acquistiion provides the newly acquired human capital a good impression so that they would not leave soon after the acquisition. As Arnold (2020) finds, most of the employee departure posterior to M&A happens within two years after the M&A. So, making the newly acuqired human capital hesistate to leave at the very initial stage of post-M&A period will result in successful M&A performance (Zollo and Meier, 2008).

Moreover, from the viewpoint of sample, this paper differs from past literautre which linked indivdual employee's commitment to CSR. That an employee has a 'CSR' experience in a firm is not equal to that the firm is committed to CSR. This paper highlights how an employee foreign to the firm reacts to the company's stakeholder orientation regardless of the employee's experience at the firm. Also, this setting allows me to avoid a selection bias from the fact that a firm and an employee usually selects each other to sign an employment contract. So, our results show that a firm's stakeholder orientation can be interpreted as a quality signal to the extenral audiences like the prospective workers or future acquistion target's employees (Zerbini, 2017).

Additionally, this paper suggests the positive assortative matching mechanism, according to which a high quality actor [i.e. firm] is matched with another high quality actor [i.e. employees]. The analysis reveals that a newly hired human capital with high producitivity, measured by the number of citations received per year, will be more likely to remain in the acquired firm only if the firm has relatively higher pre-M&A stakeholder orientation. This effect does not assume that every corproate scientist aware of her employer's CSR. What this paper assumes is that every corporate scientist aware of the quality of her employer, and such a quality can be and is proxied by the firm's stakeholder orientation in the absence of sufficient information.

Such a finding provides the evidence for the positive assortative matching as the more productive individuals can easily find alternative working place if they find their new employer, which they has not chosen by oneself, is low in terms of quality. In this situation, the individuals whose productivity is relatively low would only remain in the low quality acquiror as they are not welcomed by extenral employers. This assortative matching happens as the more productive ones can relatively free to choose whereas the less productive ones can't freely choose their employer. Also, the results from Hypothesis 3 and Hypothesis 4 testify that more information about the acquiror in addition to the information from its stakeholer orientation as a quality signal positively modrates the main retention effect.

4.5. LIMITATIONS

The empirical analyses in this paper pose several limitations. First, it is possible that corporate scientists would leave the acquiror against their will; for instance, layoffs can be implemented immediately following the acquisition for restructuring purposes. However, it is difficult to say that an acquiror would remove those newly acquired corporate scientists who possess scarce and valuable knowledge, which is often immediately irreplaceable. From the perspective of organizational learning, the newly acquired human capital would not leave until it deliberately desired to move.

Second, this paper's sample (i.e., corporate scientists) may involve an excessively specific employee type, and thus future research should test the current idea or an improved idea in a more generalizable setting.

Third, the sample corproate scientists in this paper are those who have patented more than two patents in the sample period. This is about the half of the USPTO's inventors. So, investigating the inventors with more than two patents during the research period limits my sample and may be a source of potential bias. Also, many of corporate scientsits do researches which do not result in patenting based on their institutions' or firms' R&D strategies (Ge *et al.*, 2016). So, the behaviors of my sample corporate scientists may not be generalizable.

Fourth, due to the lack of data, this paper does not control the wage-differentials across or within firms. Consequently, I implicitly assumed that firms, not only the acquiror, but also its labor market competitiors, do know and can afford the amount of wage and other compensations that each individual newly acquired human capital deserve. This assumption may be unrealistic and damages this paper's generalizability.

Fifth, this paper implicitly assumes that firms do not disguise their true stakeholder orientation to the outside audiences including the newly acquired human capital and the CSR raters. This may be a big assumption as a strand of researches report that firms and their managers in fact they may disguise (*faking*) their stakeholder orientation (Crilly *et al.*, 2012).

Last, despite this paper's attempt to remove the potential biases from self-selection and information asymmetry, the survival analysis model itself did not allow me to claim a strong causal relationship between stakeholder orientation and the retention of the acquired corporate scientists.

4.6. ROBUSTNESS CHECKS

To eliminate the alternative mechanisms, I conducted several robustness checks. For instance, I have 1) added the target's stakeholder orientation, 2) added alterantive stakeholder orienation measures from ASSET4, 3) added the acquiror's profitability as an alterantive quality measure, 4) added previous M&A experiences, 5) ran Schoenfeld residual test. None of them changes the above results.[64]

I conducted several robustness checks to eliminate alternative explanations. In the empirical context, stakeholder and CSR research relies on an evaluation of the focal firms' diverse activities. The professionals at various service providers (e.g., MSCI, Thomson Reuters) continuously monitor and evaluate firms from several aspects, although such scores are the subject

[64] The analyses and their results tables are provided upon request.

of potential biases. Firstly, external evaluators may not accurately measure the firm's true type when the firm does not intend to disguise itself. Secondly, the focal firm may disguise its stakeholder orientation (Crilly *et al.*, 2012), and thirdly, each evaluator has different scoring standards and categorizations of stakeholder activities such that an area that evaluator A weighs may not be of concern to evaluator B. Related to such sources of bias, the recent literature suggests the use of more than two scores to measure a firm's stakeholder orientation and CSR (Chatterji, Durand, Levine, & Touboul, 2016; Flammer & Kacperczyk, 2019). I added analyses using ASSET4, which is also a widely applied database that measures firm-level stakeholder orientation and CSR. From ASSET4, I employed the ESG score for the proxy of overall stakeholder orientation as well as scores for corporate governance, economy, environment, and society for individual categories. These ASSET4 scores ranged from the period of 2001 to 2015. Due to the narrower time window, the corporate scientist sample decreased in size [n = 448] more so than that of the main analysis. The results were consistent for most variables although far less significant. Particularly, the survival analysis using ASSET4 presents the interaction effect of inventor quality and the economic stakeholder-related score was positive, whereas the hypothesis predicted a negative score. In addition, the interaction effects of the pre-M&A alliance dummy and the social stakeholder-related score were positive, which was also hypothesized as negative. It must however be noted that none of those interaction effects that achieved opposite signs were significant.

Without matching between the acquiror and the target, the assortative matching mechanism between firms and employees may have dealt a bias to the main effect. For instance, a corporate scientist who was matched to the target firm based on the quality criterion would be acquired, yet the acquiror may have achieved a far different level of stakeholder orientation from the target and its corporate scientists. In such a case, the corporate scientist would be more likely to leave the new employer once the stakeholder orientation was determined to not fit. To control the chasm between the acquiror and the target in stakeholder orientation, I added the target's pre-M&A stakeholder orientation to control the fit between the acquiror and the target. Each model possessed varying dimensions of target stakeholder orientation, as each model expressed different dimensions in the acquiror's stakeholder orientation. For instance, the target's community score aligned with the acquiror's community score.

The findings from Bettinazzi *et al.*, (2018), Bundy *et al.*, (2018), and Bridoux and Stoelhorst (2014) imply that matching occurred based on their similarity between the acquiror and the target. The acquisition might have been motivated by how the acquiror and the target were similar in terms of stakeholder orientation. If the target corporate scientists had already joined and retained the target firm prior to the M&A because the target firm's stakeholder orientation aligned with them more closely (Bundy *et al.*, 2018; Bauer & Matzler, 2014) and if the acquiror chose a firm with a stakeholder orientation similar to that of an M&A target, then we can presume that the acquired corporate scientists may have already been sorted prior to the M&A.

To deal with those two biases related to the sorting mechanism in both the M&A market and the labor market, I added the target firm's stakeholder orientation from KLD as a control variable due to the propensity that the target's stakeholder orientation may determine the post-M&A performance or the acquisition's motivation. For example, the acquisition was motivated by two firms' similarity in their stakeholder orientation, which emerged as an expectation of harmonious post-merger integration (Bridoux & Stoelhforst, 2014). The target corporate scientist sample size decreased to 3,337 because a fewer number of targets were scored by KLD, although the results hold true for all hypotheses. The sample size did not impact the coefficients' signs or seriously deteriorate their levels of significance, and the results were consistent among all independent variables for all hypotheses.

Profitability can also be a quality signal of the firm with regard to Hypotheiss 1. Although the audiences often do not remember the exact financial numbers of individual firms, they can sense whether or not a firm is doing well via media and word of mouth. A sentiment clearly exists among the mass public about whether are not a firm is doing financially well; if a firm is indeed doing well, then the media outlets not only mention but also endorse or embrace that firm. Since instrumental stakeholder theory claims that financial performances (e.g., profitability) accompany stronger stakeholder orientation (Eccles, Ioannou, & Serafeim, 2014), I would apply the acquiror's return on assets (ROA) in the year prior to the M&A as a proxy for its profitability. ROA data originates from COMPUSTAT. Related to Hypothesis 2, as more profitabile firms have more financial slack to pay more salary to the high quality inventors upon necessity, this robustness check eliminates the alternative mechanism arguing that high quality indivdiuals are not attracted by stakeholder orientation but by salary increase. Using the U.S. microdata, Arnold (2020) finds that the salary level decreases immediately after M&A. Since some sample acquirors report neither net income nor total assets, the sample size for this analysis is slightly decreased to 10,708. All coefficients remained negative alongside the main analyses, and all coefficients were significant except that of product stakeholder orientation (p-value = 0.079).

In M&A, the acquiror selects its target with due diligence according to various aspects. Due diligence processes are performed not only by hired consultants, but also by the acquiror itself. The literature reports that past M&A experiences has positive impact on the acquiror's post-M&A performance (Zollo & Sigh, 2004; Barkema & Schijven, 2008), while those experienced firms are believed to be more capable of determining such an acquisition target with a better fit (Kim &

Finkelstein, 2009). If an M&A is motivated by knowledge acquisition, then the acquiror would seek to buy a target in which it can expect higher human capital retention. Thus, I added the number of M&As that the acquiror conducted during the past ten years [y = -10 ~ y = -1] as a control,[65] for which all the results were consistent and significant.

Lastly, as suggested by Cleves *et al.,* (2010), I conducted the Schoenfeld residual test to determine whether or not the model violates the proportional-hazard assumption. I implemented the *estat phtest* command after running stcox in STATA15 for the main effect, and the results were determined consistent.

4.7. CONCLUSION

This paper's goal was to examine and determine, in alignment with instrumental stakeholder theory, that stronger stakeholder orientation is a great tool for retaining newly acquired human capital. I specifically focused on the retention of newly acquired human capital by empirically testing the role the acquiror's stakeholder orientation plays in the retention of newly acquired corporate scientists.

I integrated the U.S. M&A data, from SDC Platinum, between 1991 and 2014 with the inventor-level data from Patentsview, the latter of which allowed me to construct mobility data of corporate scientists. I referred to the acquiror's (and the target's) stakeholder orientation scores from KLD and ASSET4 as well as applied a survival analysis to measure the impact of the acquiror's stakeholder orientation on the retention duration of the newly acquired human capital. The final sample size was 10,728 corporate scientists with 1,463 unique acquirors.

This paper's results suggest that an acquiror's stronger stakeholder orientation one year prior to an M&A would decrease the departure of the newly acquired human capital—in other

[65] This variable does not include the number of asset transactions whereby the acquirors cannot accumulate their experiences to inspect and assess human capital-related issues.

words, extend the human capital's duration of staying with the acquiror. Such a finding is moderated more strongly by the lower information asymmetry and trust formation resulting from the historical collaboration experience between the acquiror and the target or between the acquiror and the acquired corporate scientists. I additionally identified a positive assortative matching mechanism between the acquiror and the corporate scientists. Specifically, the inventor's quality measured by the number of citations received is positively associated with the acquiror's stakeholder orientation such that a higher-quality acquiror measured by stakeholder orientation results in its newly acquired human capital remaining for a longer duration. This paper mainly examines two ideas: 1) stakeholder orientation as a quality signal in the labor makret and 2) assortative matching in the labor market. Broadly speaking, both are not the first of their kinds. However, they were supported by a particular sample, which is new to the litearture: the newly acquired human capital.

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Table 1. Descriptive Statistics

		Observations	Mean	StdDev	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	SO - Overall	11,201	5.7157	4.8593	0	22	1																	
2	SO - Corporate Governance	11,201	0.2936	0.5561	0	3	0.5877	1																
3	SO - Community	11,201	0.8073	0.9919	0	4	0.6604	0.2984	1															
4	SO - Diversity	11,201	1.9539	1.7893	0	7	0.7613	0.3958	0.5642	1														
5	SO - Employee Relations	11,201	1.2205	1.4421	0	9	0.7065	0.2389	0.3048	0.2876	1													
6	SO - Environment	11,201	1.0345	1.3552	0	5	0.731	0.4843	0.2737	0.3336	0.4925	1												
7	SO - Product	11,201	0.3531	0.5799	0	3	0.4706	0.2378	0.207	0.3009	0.2474	0.2819	1											
8	Inventor Quality	30,436	15.707	77.579	0	8892	0.0305	0.0223	0.0501	0.012	-0.007	0.0408	0.0388	1										
9	Pre-M&A Coworking	30,436	0.0245	0.1546	0	1	-0.096	-0.038	-0.096	-0.066	-0.063	-0.064	-0.062	-0.011	1									
10	Pre-M&A Alliance	30,436	0.0084	0.1653	0	10	-0.01	0.0226	0.0007	0.0088	-0.018	-0.024	-0.017	0	-0.012	1								
11	Merger	30,436	0.6557	0.4751	0	1	0.0755	0.0096	0.0809	0.083	0.0383	0.029	0.0626	0.0072	0.051	0.0204	1							
12	US_Acquiror	30,436	0.714	0.4519	0	1	0.1319	0.0053	0.1007	0.1301	0.0975	0.0662	0.0917	-0.016	0.0235	0.0118	-0.046	1						
13	US_Target	30,436	0.834	0.3721	0	1	-0.096	-0.122	-0.06	-0.023	-0.058	-0.13	-0.056	-0.177	0.0329	0.0118	0.0345	0.0506	1					
14	Pre-M&A Shareholding	30,436	0.0196	0.1388	0	1	0.0073	0.0151	0.0001	0.0033	0.0107	0.0084	-0.032	-0.007	0.0099	-0.005	-0.062	0.0132	0.0132	1				
15	Years at the Target	30,389	4.6935	4.6323	0	38	0.0734	0.0721	0.0701	0.042	0.0643	0.0415	-0.008	-0.004	0.0114	-0.02	0.0914	-0.026	0.0688	-0.025	1			
16	State_overlap	30,436	0.2813	0.4496	0	1	-0.079	-0.011	-0.108	-0.125	-0.009	-0.026	-0.044	-0.022	-0.082	0.0015	-0.029	0.0545	0.0545	-0.036	-0.04	1		
17	Tenure	30,436	9.745	7.2851	1	42	0.0158	0.0283	0.0321	0.009	0.0029	0.0154	-0.023	0.1094	0.0412	-0.011	0.0657	-0.018	-0.09	-0.036	0.6483	-0.042	1	
18	Industry_overlap	30,436	0.5026	0.5	0	1	0.0905	0.001	0.1619	0.1144	0.0306	0.0089	0.0292	0.0195	0.0916	0.0193	0.1826	0.209	0.0682	-0.098	0.0762	-0.065	0.0617	1

Table 2. The Impact of the Acquiror's Stakeholder Orientation on the Post-M&A Inventor Mobility

Stakeholder Orientation	(1) Cox Hazard	(2) Cox Hazard	(3) Cox Hazard	(4) Cox Hazard	(5) Cox Hazard	(6) Cox Hazard	(7) Cox Hazard	(8) Cox Hazard
Overall		-0.0627***						
		(0.00995)						
Corporate Governance			-0.324***					
			(0.0652)					
Community				-0.136*				
				(0.0555)				
Diversity					-0.0503**			
					(0.0171)			
Employee Relations						-0.197***		
						(0.0272)		
Environment							-0.262***	
							(0.0311)	
Product								-0.109+
								(0.0634)
Control Variables								
Merger dummy	-0.0301**	-0.00756	-0.0273*	-0.0240*	-0.0252*	-0.0107	-0.00983	-0.0267*
	(0.0110)	(0.0120)	(0.0119)	(0.0116)	(0.0118)	(0.0122)	(0.0122)	(0.0119)
US Acquiror dummy	0.0894**	0.0832	0.0784	0.0820	0.0720	0.109+	0.108+	0.0808
	(0.0343)	(0.0635)	(0.0597)	(0.0603)	(0.0618)	(0.0616)	(0.0634)	(0.0612)
US Target dummy	0.0511*	-0.0374	-0.0122	-0.0203	-0.0149	-0.00184	-0.0124	-0.00878
	(0.0243)	(0.0472)	(0.0402)	(0.0432)	(0.0423)	(0.0441)	(0.0471)	(0.0409)
US Acquiror-Target Interaction	-0.135***	-0.0649	-0.0836	-0.0750	-0.0698	-0.0946	-0.0997	-0.0766
	(0.0390)	(0.0690)	(0.0652)	(0.0658)	(0.0672)	(0.0671)	(0.0692)	(0.0662)
Pre-M&A shareholding dummy	-0.0665**	-0.106*	-0.111*	-0.117*	-0.110*	-0.101*	-0.110*	-0.119*
	(0.0229)	(0.0443)	(0.0450)	(0.0479)	(0.0472)	(0.0409)	(0.0463)	(0.0473)
Inventor's tenure at the Target	0.00234+	0.00168	0.00121	0.000518	0.000333	0.00145	0.00210	0.000260
	(0.00138)	(0.00140)	(0.00124)	(0.00137)	(0.00134)	(0.00134)	(0.00139)	(0.00135)
Target Overlap dummy	0.0109	-0.0237	-0.0139	-0.0159	-0.0152	-0.0136	-0.0241	-0.0153
	(0.0142)	(0.0157)	(0.0159)	(0.0157)	(0.0164)	(0.0170)	(0.0162)	(0.0159)
Inventor's tenure	-0.00466***	-0.00328***	-0.00266***	-0.00237**	-0.00227**	-0.00310***	-0.00369***	-0.00224**
	(0.000745)	(0.000802)	(0.000769)	(0.000739)	(0.000759)	(0.000809)	(0.000786)	(0.000767)
Industry Overlap dummy	-0.00516	-0.00910	-0.0115	-0.00969	-0.0139	-0.0160	-0.0138	-0.0168
	(0.0122)	(0.0149)	(0.0136)	(0.0143)	(0.0143)	(0.0142)	(0.0140)	(0.0139)
M&A Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	28947	10728	10728	10728	10728	10728	10728	10728

Standard errors in parentheses

\+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3. The Interaction between the Acquiror's Stakeholder Orientation and Inventor Quality on the Post-M&A Inventor Mobility

Stakeholder Orientation	(1) Cox Hazard	(2) Cox Hazard	(3) Cox Hazard	(4) Cox Hazard	(5) Cox Hazard	(6) Cox Hazard	(7) Cox Hazard	(8) Cox Hazard
Co-Working Experience		0.000832*** (0.000235)	0.000786*** (0.000205)	0.00105*** (0.000243)	0.000912*** (0.000239)	0.000550** (0.000208)	0.000854*** (0.000230)	0.000807** (0.000273)
S.O. – Overall		-0.0617*** (0.00993)						
Co-Working Experience # S.O. – Overall		-0.000052** (0.0000169)						
S.O. – Corporate Governance			-0.312*** (0.0659)					
Co-Working Experience # S.O. - Corp. Gov.			-0.000743*** (0.000200)					
S.O. – Community				-0.131* (0.0556)				
Co-Working Experience # S.O. – Community				-0.00034*** (0.0000809)				
S.O. – Diversity					-0.0458** (0.0171)			
Co-Working Experience # S.O. – Diversity					-0.000272** (0.0000850)			
S.O. – Employee Relations						-0.194*** (0.0270)		
Co-Working Experience # S.O. – Employee Relations						-0.000227* (0.000112)		
S.O. – Environment							-0.259*** (0.0311)	
Co-Working Experience # S.O. – Environment							-0.000182** (0.0000561)	
S.O. – Product								-0.101 (0.0637)
Co-Working Experience # S.O. – Product								-0.000702* (0.000273)
Control Variables								
Merger dummy	-0.0301** (0.0110)	-0.00715 (0.0120)	-0.0264* (0.0119)	-0.0233* (0.0116)	-0.0250* (0.0119)	-0.0103 (0.0123)	-0.00898 (0.0122)	-0.0260* (0.0119)
US Acquiror dummy	0.0894** (0.0343)	0.0817 (0.0644)	0.0776 (0.0609)	0.0817 (0.0612)	0.0708 (0.0630)	0.107+ (0.0625)	0.106+ (0.0643)	0.0785 (0.0626)
US Target dummy	0.0511* (0.0243)	-0.0425 (0.0472)	-0.0184 (0.0402)	-0.0278 (0.0432)	-0.0185 (0.0422)	-0.00579 (0.0441)	-0.0166 (0.0470)	-0.0163 (0.0407)
US Acquiror-Target Interaction	-0.135*** (0.0390)	-0.0590 (0.0701)	-0.0767 (0.0666)	-0.0674 (0.0668)	-0.0657 (0.0685)	-0.0897 (0.0681)	-0.0947 (0.0701)	-0.0675 (0.0678)
Pre-M&A shareholding dummy	-0.0665** (0.0229)	-0.105* (0.0443)	-0.110* (0.0450)	-0.116* (0.0476)	-0.110* (0.0470)	-0.101* (0.0410)	-0.109* (0.0464)	-0.118* (0.0472)
Inventor's tenure at the Target	0.00234+ (0.00138)	0.00175 (0.00141)	0.00128 (0.00126)	0.000574 (0.00139)	0.000412 (0.00136)	0.00152 (0.00136)	0.00219 (0.00140)	0.000326 (0.00136)
Target Overlap dummy	0.0109 (0.0142)	-0.0236 (0.0158)	-0.0138 (0.0159)	-0.0159 (0.0158)	-0.0149 (0.0165)	-0.0136 (0.0170)	-0.0239 (0.0163)	-0.0155 (0.0158)
Inventor's tenure	-0.00466*** (0.000745)	-0.00335*** (0.000815)	-0.00269*** (0.000791)	-0.00243** (0.000760)	-0.00235** (0.000779)	-0.00317*** (0.000824)	-0.00377*** (0.000792)	-0.00231** (0.000788)
Industry Overlap dummy	-0.00516 (0.0122)	-0.00984 (0.0149)	-0.0121 (0.0136)	-0.0105 (0.0143)	-0.0147 (0.0143)	-0.0165 (0.0142)	-0.0145 (0.0140)	-0.0172 (0.0139)
M&A Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	28947	10728	10728	10728	10728	10728	10728	10728

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4. The Interaction between the Acquiror's Stakeholder Orientation and Pre-M&A Alliance on the Post-M&A Inventor Mobility

Stakeholder Orientation	(1) Cox Hazard	(2) Cox Hazard	(3) Cox Hazard	(4) Cox Hazard	(5) Cox Hazard	(6) Cox Hazard	(7) Cox Hazard	(8) Cox Hazard
Co-Working Experience		1.201*** (0.212)	1.058*** (0.222)	1.106*** (0.201)	1.231*** (0.229)	0.930*** (0.215)	0.986*** (0.211)	0.939*** (0.215)
S.O. – Overall		-0.0622*** (0.00995)						
Co-Working Experience # S.O. – Overall		-0.0724*** (0.0214)						
S.O. – Corporate Governance			-0.322*** (0.0655)					
Co-Working Experience # S.O. - Corp. Gov.			-0.644** (0.200)					
S.O. – Community				-0.132* (0.0554)				
Co-Working Experience # S.O. – Community				-0.438* (0.177)				
S.O. – Diversity					-0.0501** (0.0172)			
Co-Working Experience # S.O. – Diversity					-0.186** (0.0622)			
S.O. – Employee Relations						-0.196*** (0.0271)		
Co-Working Experience # S.O. – Employee Relations						-0.188 (0.139)		
S.O. – Environment							-0.261*** (0.0313)	
Co-Working Experience # S.O. – Environment							-0.323* (0.126)	
S.O. – Product								-0.101 (0.0635)
Co-Working Experience # S.O. – Product								-0.587*** (0.144)
Control Variables								
Merger dummy	-0.0301** (0.0110)	-0.00868 (0.0120)	-0.0280* (0.0118)	-0.0248* (0.0116)	-0.0259* (0.0118)	-0.0116 (0.0123)	-0.0105 (0.0121)	-0.0274* (0.0119)
US Acquiror dummy	0.0894** (0.0343)	0.0831 (0.0633)	0.0783 (0.0595)	0.0829 (0.0601)	0.0724 (0.0615)	0.109+ (0.0615)	0.108+ (0.0633)	0.0813 (0.0609)
US Target dummy	0.0511* (0.0243)	-0.0366 (0.0470)	-0.0118 (0.0401)	-0.0189 (0.0432)	-0.0149 (0.0422)	-0.00162 (0.0440)	-0.0117 (0.0470)	-0.00818 (0.0408)
US Acquiror-Target Interaction	-0.135*** (0.0390)	-0.0659 (0.0688)	-0.0843 (0.0651)	-0.0767 (0.0656)	-0.0709 (0.0669)	-0.0956 (0.0669)	-0.101 (0.0691)	-0.0781 (0.0660)
Pre-M&A shareholding dummy	-0.0665** (0.0229)	-0.0998* (0.0476)	-0.106* (0.0480)	-0.112* (0.0510)	-0.105* (0.0497)	-0.0964* (0.0434)	-0.106* (0.0487)	-0.113* (0.0499)
Inventor's tenure at the Target	0.00234+ (0.00138)	0.00172 (0.00141)	0.00126 (0.00124)	0.000536 (0.00137)	0.000377 (0.00135)	0.00150 (0.00135)	0.00215 (0.00139)	0.000340 (0.00135)
Target Overlap dummy	0.0109 (0.0142)	-0.0241 (0.0157)	-0.0146 (0.0158)	-0.0157 (0.0157)	-0.0160 (0.0164)	-0.0143 (0.0170)	-0.0242 (0.0162)	-0.0158 (0.0159)
Inventor's tenure	-0.00466*** (0.000745)	-0.00334*** (0.000797)	-0.00272*** (0.000762)	-0.00240** (0.000733)	-0.00233** (0.000751)	-0.00315*** (0.000805)	-0.00374*** (0.000781)	-0.00231** (0.000759)
Industry Overlap dummy	-0.00516 (0.0122)	-0.00887 (0.0148)	-0.0113 (0.0135)	-0.00995 (0.0142)	-0.0136 (0.0142)	-0.0159 (0.0142)	-0.0139 (0.0139)	-0.0165 (0.0139)
M&A Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	28947	10728	10728	10728	10728	10728	10728	10728

Standard errors in parentheses
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5. The Interaction between the Acquiror's Stakeholder Orientation and Pre-M&A Co-work on the Post-M&A Inventor Mobility

Stakeholder Orientation	(1) Cox Hazard	(2) Cox Hazard	(3) Cox Hazard	(4) Cox Hazard	(5) Cox Hazard	(6) Cox Hazard	(7) Cox Hazard	(8) Cox Hazard
Co-Working Experience		-0.150 (0.185)	-0.271+ (0.162)	-0.333+ (0.181)	0.198 (0.268)	-0.174 (0.154)	-0.408* (0.160)	-0.180 (0.158)
S.O. – Overall		-0.0627*** (0.00997)						
Co-Working Experience # S.O. – Overall		-0.0847** (0.0290)						
S.O. – Corporate Governance			-0.321*** (0.0659)					
Co-Working Experience # S.O. - Corp. Gov.			-0.435** (0.143)					
S.O. – Community				-0.138* (0.0560)				
Co-Working Experience # S.O. – Community				-0.567*** (0.111)				
S.O. – Diversity					-0.0488** (0.0168)			
Co-Working Experience # S.O. – Diversity					-0.318* (0.131)			
S.O. – Employee Relations						-0.196*** (0.0273)		
Co-Working Experience # S.O. – Employee Relations						-0.240* (0.109)		
S.O. – Environment							-0.264*** (0.0316)	
Co-Working Experience # S.O. – Environment							-0.000155 (0.0553)	
S.O. – Product								-0.104 (0.0635)
Co-Working Experience # S.O. – Product								-0.766*** (0.167)
Control Variables								
Merger dummy	-0.0301** (0.0110)	-0.00597 (0.0120)	-0.0262* (0.0118)	-0.0224+ (0.0116)	-0.0243* (0.0118)	-0.00966 (0.0122)	-0.00835 (0.0122)	-0.0255* (0.0119)
US Acquiror dummy	0.0894** (0.0343)	0.0812 (0.0630)	0.0773 (0.0593)	0.0804 (0.0599)	0.0708 (0.0615)	0.108+ (0.0611)	0.106+ (0.0631)	0.0797 (0.0606)
US Target dummy	0.0511* (0.0243)	-0.0397 (0.0471)	-0.0133 (0.0400)	-0.0224 (0.0433)	-0.0161 (0.0421)	-0.00278 (0.0439)	-0.0142 (0.0470)	-0.00977 (0.0409)
US Acquiror-Target Interaction	-0.135*** (0.0390)	-0.0619 (0.0685)	-0.0818 (0.0649)	-0.0722 (0.0655)	-0.0679 (0.0669)	-0.0932 (0.0667)	-0.0973 (0.0689)	-0.0752 (0.0657)
Pre-M&A shareholding dummy	-0.0665** (0.0229)	-0.104* (0.0449)	-0.110* (0.0454)	-0.116* (0.0484)	-0.109* (0.0477)	-0.0994* (0.0414)	-0.108* (0.0469)	-0.117* (0.0477)
Inventor's tenure at the Target	0.00234+ (0.00138)	0.00173 (0.00142)	0.00121 (0.00125)	0.000547 (0.00138)	0.000291 (0.00135)	0.00148 (0.00136)	0.00211 (0.00140)	0.000330 (0.00137)
Target Overlap dummy	0.0109 (0.0142)	-0.0244 (0.0157)	-0.0142 (0.0158)	-0.0165 (0.0157)	-0.0156 (0.0164)	-0.0138 (0.0169)	-0.0244 (0.0162)	-0.0156 (0.0159)
Inventor's tenure	- 0.00466*** (0.000745)	- 0.00328*** (0.000806)	- 0.00265*** (0.000771)	-0.00235** (0.000739)	-0.00230** (0.000770)	- 0.00309*** (0.000809)	- 0.00367*** (0.000783)	-0.00225** (0.000773)
Industry Overlap dummy	-0.00516 (0.0122)	-0.00556 (0.0151)	-0.00900 (0.0137)	-0.00676 (0.0143)	-0.0114 (0.0144)	-0.0130 (0.0144)	-0.0111 (0.0142)	-0.0139 (0.0141)
M&A Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	28947	10728	10728	10728	10728	10728	10728	10728