Knowledge Spillovers and the Geography of Entrepreneurship and Innovation

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Summary

The revolution of communications technology now allows firms and individuals to acquire knowledge and information that stems from distant geographies. Yet, the geographic proximity to knowledge sources continues to play a central role in fostering knowledge transfers. This dissertation examines the role of knowledge spillovers within geographies in influencing entrepreneurship and innovation outcomes. In particular, I investigate underexplored dynamics of geographic agglomeration of industry activity and how they affect knowledge spillovers that are central to entrepreneurship and innovation. I base my investigation on two studies. In the first study, I use data on nanotechnology firms to examine the effects of de-agglomeration, in the form of a proximate industry peer's relocation, on firm innovation. Contrary to expectation, I find that a proximate industry peer's relocation to another region increases a firm's innovation performance. Knowledge exchange channels that exist between proximate industry peers before relocation transform into inter-region knowledge conduits post-relocation. Hence, firms gain greater access to distant knowledge once a proximate industry peer relocates to that region. In the second study, I examine the effects of industry agglomeration on the gender gap in employee entrepreneurship. This study proposes that female employees are disadvantaged in gaining knowledge on entrepreneurial resources relative to male employees when the level of industry agglomeration increases in the employee's region. I combine several datasets to construct an employee panel on the universe of U.S.-based biotechnology employees from 2005 to 2019. I find that industry agglomeration facilitates female employees' transitions into entrepreneurship but at a significantly lower rate than male employees. This study demonstrates that agglomeration may be exacerbating the gender gap in regional employee entrepreneurship and provides insights into conditions that could reduce the gap.

Chapter 1: Introduction and Background

> **"***When an industry has thus chosen a locality for itself, it is likely to stay there long: so great are the advantages which people following the same skilled trade get from near neighborhood to one another. The mysteries of the trade become no mysteries; but are as it were in the air, and children learn many of them unconsciously."* (Marshall, 1920; 156)

When an industry agglomerates in a locality, the mysteries of trade spill over in the area. This dissertation investigates how industry agglomeration impacts entrepreneurship and innovation in the local area through the spillover of mysteries of trade (i.e., industry-relevant knowledge and information). In the two chapters of this dissertation, I provide evidence that knowledge spillovers from local firms are fundamental in shaping the innovation performance of firms and the founding rates of prospective entrepreneurs. More importantly, I theorize and document the dynamics of industry agglomeration that have been underexplored in the research on geography of entrepreneurship and innovation.

Geography provides a platform for organizing innovation and entrepreneurial activities (e.g., Feldman & Kogler, 2010). Various elements of the geographic environment including the geographic concentration of industry activities (e.g., Marshall, 1890; Delgado, Porter, & Stern, 2010; McCann & Folta, 2011), regulations (Castellaneta, Conti & Kacperczyk, 2020), infrastructures (Agrawal, Galasso, & Oettl, 2017; Furman, Nagler, & Watzinger, 2021; Dutta, Armanios, & Desai, 2022), and culture (Saxenian, 1994), can impact firms' and entrepreneurs' innovation and entrepreneurial activities. Because of variations in the presence of these elements

across geographies, firms and entrepreneurs prefer to spatially cluster in certain regions where geographic advantages are greater (e.g., Alcácer & Chung, 2007; Guzman, 2019).

A key element of geography that has gained extensive attention in research on entrepreneurship and innovation is the geographic concentration of industry activities, a phenomenon known as "agglomeration" or "clustering". The central theme of this research is that the agglomeration of industry activity within a locality creates a fertile environment for knowledge exchange. Industry agglomeration facilitates formal and informal face-to-face interactions between the same industry firms and employees because of geographic proximity (Saxenian, 1994; Andrews, 2019; Roche, 2020). Since face-to-face interactions assist the transmission of knowledge (Daft & Lengel, 1986; Von Hippel, 1994), firms and employees gain greater access to distant knowledge from other firms and employees when the industry is agglomerated in a locality.

How do such knowledge spillovers from the geography influence entrepreneurship and innovation outcomes? When firms and employees gain distant knowledge from local industry peers, they recombine them with their existing knowledge stock to increase innovation (Fleming, 2001). Much scholarship, therefore, documents that as the agglomeration level increases in the region, innovation performance of firms (e.g., Folta, Cooper & Baik, 2006; Gilbert, McDougall, & Audretsch, 2008; McCann & Folta, 2011; Funk, 2014; Mathias, McCann, & Whitman, 2021), and inventors (Moretti, 2021) increase. Similarly, prospective entrepreneurs also leverage knowledge spillovers from local industry peers to develop their business ideas (Stuart & Sorenson, 2003). Ample studies, therefore, find that knowledge spillovers play a significant role in facilitating entrepreneurial mobility and engendering higher rates of new venture founding in

the region as the region becomes more agglomerated (e.g., Glaeser & Kerr, 2009; Delgado, Porter, & Stern, 2010; Hervas-Oliver, Lleo, & Cervello, 2017). In addition, industry agglomeration also facilitates diffusion of information on available entrepreneurial resources in the region (Stuart & Sorenson, 2003). Hence, prospective entrepreneurs gain greater access to entrepreneurial resources in the locality and have better chances of mobilizing resources for venture creation.

Although scholars have made a significant progress in understanding the importance of agglomeration of industry activity and the role of knowledge spillovers in fostering local entrepreneurship and innovation, the existing research have investigated agglomeration with a limited view. The works from this stream of research primarily focus on theorizing how firms and prospective entrepreneurs benefit from increasing returns to scale of agglomeration-driven knowledge spillovers. Therefore, studies generally investigate how the *increase* in the industry agglomeration level of the region *positively* affects regional entrepreneurship and innovation. Yet, due to this focus on increasing returns, comparatively little attention has been devoted to systematically theorizing the dynamics of industry agglomeration that may have *negative* consequences on entrepreneurial and innovation activities in the geographical area (e.g., Sorenson & Audia, 2000; Rosenthal & Strange, 2012). In particular, I identify two implicit but incomplete assumptions of this literature: first, all employees equally benefit from knowledge spillovers; second, industry *de*-agglomeration reduces knowledge spillovers. In my dissertation, I revisit these assumptions and expand our understanding of the effect of knowledge spillovers on regional entrepreneurship and innovation as the local agglomeration level changes.

Extant research provides some insights with respect to why employees may benefit at different levels from agglomeration externalities. One such stream of research looks at the heterogeneity in a firm's ability to utilize externalities. Studies provide a rich account of the ways in which firms have asymmetric benefits from agglomeration because some firms are better equipped with knowledge and resources than other firms in accessing and utilizing knowledge and resources from the region (e.g., Shaver & Flyer, 2000; McCann & Folta, 2011; Pe'er & Keil, 2013; Rigby & Brown, 2015). Similar heterogeneity in access to agglomeration externalities can also exist for employees. Like firms, employees have different levels of knowledge, skills, and abilities. Employees in different job positions or in different firms also vary in terms of the level of firm resources they can utilize to gain knowledge from industry peers. Although the impact of agglomeration on regional entrepreneurship and innovation has been examined less at the individual level (e.g., Moretti, 2021), insights from firm-level studies suggest that heterogeneity in employees' capabilities and resources would also create variance in employees' abilities to access and exploit agglomeration externalities.

Moreover, some groups of employees may systematically have higher capabilities or more opportunities than others to exploit agglomeration externalities. Economic opportunities are often not distributed equitably to employees within a region or within a firm (e.g., Fischer & Massey, 2000; Acker, 2006; Fairlie, Robb, & Robinson, 2022). If individuals' access to agglomeration externalities differs along the lines of demographic or economic characteristics of individuals, such that racial majorities or economically affluent individuals systematically have greater access, then agglomeration may be reinforcing inequalities in entrepreneurship and innovation activities. When focusing on increasing returns to scale, the dynamics between agglomeration and inequalities in regional entrepreneurship and innovation are difficult to

observe since disadvantaged individuals may also benefit from agglomeration. It is, therefore, important to consider the demographic or economic characteristics of employees to fully capture how agglomeration may benefit employees at different levels.

Reflecting on this importance, in chapter two, I explore whether industry agglomeration facilitates employees' transitions into entrepreneurship differently by gender. As aforementioned, industry agglomeration increases employees' access to entrepreneurial resources (e.g., potential co-founders, early-stage employees, venture funding), thereby facilitating new venture founding in the region. However, does industry agglomeration increase female employees' access to resources at a similar rate as male employees? Based on existing literature, I develop a theory about how agglomeration increases the availability of knowledge spillover opportunities for all employees, but at a lower rate for female employees than male employees. Therefore, I suggest that there is a *'gendered effect'* of agglomeration on employees' access to resources. I further explore the condition that would reduce the gendered effect of agglomeration. I find that agglomeration facilitates female employees' transitions into entrepreneurship but at a disproportionately lower rate than male employees, particularly in regions with a low proportional representation of women in senior executive positions.

The second assumption that I revisit is that industry de-agglomeration reduces localized externalities. Extant research simplifies theorizing the impact of agglomeration by just explaining how agglomeration externalities become more available within a local area when the industry becomes more agglomerated. However, the process of de-agglomeration of an industry in a region may affect agglomeration externalities in ways that are not understood by simply assuming that externalities decrease when the industry becomes less agglomerated in the region.

For example, the dissolution of a rival firm in the same region can open up new opportunities and resources and, therefore, motivate firm employees to become founders (Kacperczyk & Marx, 2016; Carnahan, 2017). Similarly, when Pfizer closed down its Ann Arbor operations in 2007, employees who did not transfer to other Pfizer locations started their own ventures, increasing new venture founding rates in the region (Shaffer, 2007). These accounts are contrary to what research on agglomeration and entrepreneurship predicts. This suggests that the de-agglomeration of an industry may affect regional entrepreneurship and innovation in ways that are different from how extant research theorizes.

Exploring the complex dynamics of how a region becomes less agglomerated can also be important not just in terms of understanding different dimensions of agglomeration but also in developing research designs to identify causal effects of agglomeration. Theories of agglomeration do not predict when a firm will leave and relocate to another region or when a firm downsizes its local operations. Such firm-driven changes can be used to infer exogenous variations in agglomeration externalities with respect to the innovation performance of proximate firms, which are most likely to be affected.

In the third chapter, I develop a new empirical strategy based on de-agglomeration to explore the relationship between agglomeration, firm innovation, and the theorized mechanism of knowledge spillovers. Although extant research hypothesizes that knowledge spillovers are the driving force in the relationship between agglomeration and firm innovation, there are limitations of existing empirical approaches for isolating this mechanism because of the endogenous nature of agglomeration. I propose a novel research design that is less susceptible to endogeneity concerns: a geographically proximate firm's relocation to another region. I expect the relocation

of a proximate firm (i.e., located within 10 miles distance) to another region to decrease the focal firm's innovation performance because relocation results in de-agglomeration and reduction of knowledge spillovers. Contrary to expectations, I find that relocations of proximate firms increase the focal firm's innovation performance. I employ an abductive approach and undertake several ex-post analyses to uncover what might lead to the positive impact of de-agglomeration on firm innovation. I show that exit from a cluster can enhance cluster innovation under certain circumstances and provide novel and nuanced insights into cluster dynamics.

In the fourth chapter, I discuss the implications of this dissertation and provide potential avenues for future research.

Overall, this dissertation contributes to the existing literature in several ways. First, I examine the impact of industry agglomeration beyond the traditional focus on increasing returns to scale and uncover complex dynamics. This will enrich the understanding of the relationships between industry agglomeration and regional entrepreneurship and innovation outcomes. Second, the implications of the first essay on the gender gap can help the wider society address inequalities in regional entrepreneurship. This essay also provides insights into conditions that can exacerbate or mitigate the inequalities. Third, the implications of the second essay can also open up new research avenues on cluster dynamics since the essay documents that *de*-agglomeration affects firms in ways that are contrary to what extant research theorizes.

Chapter 2: Industry Agglomeration and the Gender Gap in Employee Entrepreneurship

ABSTRACT

Does industry agglomeration exacerbate the gender gap in employee entrepreneurship? Prior research suggests that industry agglomeration plays an important role in facilitating employee entrepreneurship by increasing employees' access to entrepreneurial resources. Yet, less is known about whether agglomeration enhances both male and female employees' access to resources to a similar degree. This study proposes that female employees are disadvantaged in searching for entrepreneurial resources compared to male employees when the industry agglomeration increases in the employee's region. I further argue that the gendered effect of agglomeration is mitigated in regions where women's proportional representation in industry leadership positions is high. I combine several datasets to construct an employee panel on the universe of U.S.-based biotechnology employees from 2005 to 2019. To address identification challenges related to sorting and simultaneity, I include employee fixed effects and use the employment level of local firms' establishments in other regions as an instrument for the agglomeration level of the focal employee's location. I find that agglomeration facilitates female employees' transitions into entrepreneurship but at a significantly lower rate than male employees. However, in regions with a high proportional representation of women in industry leadership positions, the gendered effect disappears. This study demonstrates that agglomeration may be exacerbating the gender gap in regional employee entrepreneurship and provides insights into conditions that could reduce the gap.

2.1 INTRODUCTION

Employee entrepreneurship is a career choice of employees in paid employment (Rider et al., 2019). While various elements of employee-employer dynamics "push" employees to become venture founders (e.g., Ganco, 2013; Sørensen & Sharkey, 2014; Kaul, Ganco, & Raffiee, 2021; Yang, Kacperczyk, & Naldi, 2023), several features of employees' regional environments also "pull" employees from paid employment (e.g., Carnahan, 2017; Shah, Agarwal, & Echambadi, 2019; Castellaneta, Conti, & Kacperczyk, 2020). In particular, a common environmental force that facilitates employees' entrepreneurial entry is the geographic agglomeration of industry

activity in the employee's region (Hervas-Oliver, Lleo, & Cervello, 2017; Furlan & Cainelli, 2020). The central idea is that industry agglomeration enhances employees' access to entrepreneurial resources (e.g., co-founders, early-stage employees, venture funding, knowledge, etc.). Industry agglomeration enhances the availability of entrepreneurial resources in the region (Glaeser & Kerr, 2009; Delgado, Porter, & Stern, 2010; Kolympiris, Kalaitzandonakes, & Miller, 2011) and, at the same time, fosters networking opportunities between employees in the region, through which employees can search for resources (e.g., Stuart & Sorenson, 2003).

Does industry agglomeration enhance *both* male and female employees' access to resources to a similar extent? For the most part, past studies primarily examine the impact of industry agglomeration on prospective entrepreneurs as a group, implicitly assuming that all prospective entrepreneurs gain greater access to resources when the industry agglomeration increases in the region. Yet, not all prospective entrepreneurs are exposed to information on resources to the same degree in their region (e.g., Dahl & Sorenson, 2012; Samila & Sorenson, 2017). In particular, the availability of networking opportunities differs along the lines of gender (Ibarra, 1992; Singh, Hansen, & Podolny, 2010; Rosenthal & Strange, 2012; Abraham, 2020; Kalnins & Williams, 2021), suggesting that information on available resources may reach employees at different rates by gender when the industry agglomeration increases in the region.

Despite the potential gender-based differences in employees' ability to attain information on resources, our understanding of whether there is a *gendered* effect of agglomeration on employee entrepreneurship is limited. Given the significant disparity in entrepreneurship participation rate by gender (e.g., Guzman & Kacperczyk, 2019; Miric, Yin, & Fehder, 2023), this oversight is problematic since agglomeration can exacerbate or mitigate the gender gap in the region, depending on how it affects female employees relative to male employees. This

emphasizes the need to consider the impact of agglomeration on employees' access to entrepreneurial resources with respect to employees' gender. Hence, the research question of this study is: does industry agglomeration facilitate employee entrepreneurship differently by employee gender? If so, why is there a differential impact, and under what conditions does the differential impact of agglomeration narrow or widen?

In this study, I propose a theoretical framework that links the geographic agglomeration of industry activity to gender-based differences in employees' access to and search of entrepreneurial resources. The primary point of departure for theory is that industry agglomeration reduces challenges that employees face in accessing resources through two features: (1) increasing the availability of human and financial capital in employee's region (Glaeser & Kerr, 2009; Delgado, Porter, & Stern, 2010; Kolympiris, Kalaitzandonakes, & Miller, 2011) and (2) fostering networking opportunities between the same industry employees, through which employees gain information on resource providers in the environment (e.g., Stuart & Sorenson, 2003; Rosenthal & Strange, 2012). My main proposition is that female employees are disadvantaged in gaining networking opportunities when the industry agglomeration increases in the region. As networks play an important role in the search for information on resources (Dahl & Sorenson, 2012; Clough et al., 2019), I argue that female employees' access to entrepreneurial resources increases at a lower rate than male employees when the industry agglomeration increases in employees' region. In other words, I contend that industry agglomeration exacerbates the gender gap in entrepreneurship. Furthermore, I propose that in regions with high representation of women in industry leadership positions, the *gendered* effect of agglomeration would be mitigated since the presence and visibility of women as leaders mitigate gender-based disadvantages in workplaces in the region (Beaman et al., 2009; Kalnins & Williams, 2021).

To test my theoretical argument, I empirically capture how changes in the likelihood of male and female employees' pursuit of employee entrepreneurship correlate with changes in the agglomeration of industry activity over time and then compare the estimates between male and female employees. To observe employees' locations and career paths over time, I construct an employee panel by collecting LinkedIn profiles of all employees who were employed by U.S.-based biotechnology firms from 2005 to 2019. The data contains rich information on the employee's location, experience, education, and job titles, as well as information on employers. The final sample includes about 300,000 employees with 1 million employee-year observations. The focus on employee entrepreneurship provides an empirical advantage over just examining the number of new venture founders in the region. Investigating employee entrepreneurship with the employee panel data allows me to observe the entire set of male and female employees at risk of pursuing employee entrepreneurship. Additionally, I can examine how male and female employees' likelihood of pursuing alternative career outcomes (e.g., mobility to another firm or founding a venture not in the former employer's industry) changes when the industry agglomeration increases in the employee's location.

To address alternative mechanisms that might affect male and female employees' pursuit of employee entrepreneurship differently, I account for various time-varying observable factors at the state, region, firm, firm-region, and employee level. Additionally, the models include region, firm, and employee fixed effects to control for time-invariant unobservable characteristics. Even with numerous controls and fixed effects, there remain two main empirical challenges. One is sorting, which is the possibility that employees' ability to select into agglomerated regions to become founders in a later period can be different by employee gender. The other is simultaneity, which is the concern that employees' new ventures influence the

agglomeration level by hiring employees from other regions or from other industries within the region. The new founder's ability to hire early-stage employees can also be different by gender because of the challenges that female entrepreneurs face in accessing financial resources (Kanze et al., 2017, 2018; Guzman & Kacperczyk, 2019). I address sorting by including employee-fixed effects. I take on simultaneity by using the expansion of an employee's local firms' establishments in other regions as an instrument for the agglomeration level of a focal employee's location. Lastly, I check how other factors that influence employee entrepreneurship, such as the opportunity cost of leaving paid employment and the risk of starting a new venture, change as the industry agglomeration increases in the employees' location.

Several noteworthy results emerge from the analyses. First, results show that both male and female employees are more likely to leave paid employment and become biotech venture founders in the same region when the industry agglomeration increases in the employee's region. However, the likelihood of female employees' transition into entrepreneurship increases at a significantly lower rate than male employees. A one standard deviation increase in the agglomeration level of an employee's location increases a male employee's likelihood of transitioning into entrepreneurship by 2.14 times greater than the increase in a female employee's transition likelihood. This demonstrates that agglomeration has a gendered effect on employees' transitions into entrepreneurship.

To add further support to the theoretical arguments, I examine several other career outcomes that could explain the gendered effect of agglomeration on employees' transition into entrepreneurship. One such mechanism is that female employees may prefer to move to work at other biotech firms in the region at a higher rate than male employees when the industry agglomerates, which would explain their lower transition rate. Interestingly, I also find a

gendered effect of agglomeration on an employee's mobility likelihood. Since information on new job positions also travels through informal encounters between employees (Granovetter, 1973; Schmutte, 2015), this finding further supports the mechanism that female employees gain networking opportunities at a lower rate than male employees when the industry agglomerates in the employee's region. Another explanation for the gendered effect of agglomeration is that female employees may access resources to start a non-biotech venture in the region to avoid heightened risk from greater competition with other biotech firms in the region. I do not find any significant effect of agglomeration on both male and female employee's likelihood of starting a non-biotech venture in the region.

I also find support for the mechanisms I proposed in my theory. First, if female employees are constrained in gaining networking opportunities, the gendered effect of agglomeration would be smaller in regions with lower levels of gender biases in the industry. Consistent with expectations, I observe that the gendered effect of agglomeration disappears in regions with a high proportional representation of female senior executives. However, in regions with a low proportional representation of women as senior executives, the gendered effect of agglomeration is larger than the effect on the whole sample. Second, I further explore whether gender biases drive the gendered effect of agglomeration by splitting the sample into high career experience years and low career experience years. The rationale behind this analysis is that female employees who are mothers encounter more significant gender biases (Correll, Benard, & Paik, 2007; Heilman & Okimoto, 2008) and have less time to invest in new networking opportunities than male employees with more career experience (e.g., Eagly & Steffan, 1984; Carr, 1996). I do find a *gendered* effect of agglomeration between employees with high career experiences (years > 12), who are likely to be parents, but not between employees with low

career experiences (years ≤ 12). These results support the mechanism that the gendered effect is driven by the differential increase in networking opportunities.

This paper makes several meaningful contributions. First, this study represents one of the first attempts to directly explore the link between agglomeration and gender-based inequalities, an underexplored area of research in strategy and entrepreneurship (e.g., Rosenthal & Strange, 2012). Prior research tends to focus mainly on the positive impact of industry agglomeration on firms and employees (e.g., knowledge spillovers, productivity, innovation, etc.) (e.g., Audretsch & Feldman, 1996; Glaeser & Kerr, 2009; Moretti, 2021). In contrast, I directly explore how agglomeration can reinforce existing inequalities by showing that female employees exploit agglomeration externalities at a lower rate than male employees. Insights from this study can be applied to understand how agglomeration may be reinforcing the disparity in outcomes between male and female employees in areas such as patent invention and productivity. This is critical for informing firms that seek to improve the performances of their female employees.

Second, I contribute to the research on the gender gap in entrepreneurship. Prior studies primarily focus on specific resource appropriation processes (e.g., venture capital funding) to illuminate the sources of the gender gap (Kanze et al., 2017, 2018; Guzman & Kacperczyk, 2019). This study suggests that the gender gap may partially be driven by discrepancies in resource search, which is the stage prior to the resource appropriation process (Clough et al., 2019). If female prospective entrepreneurs gain information on the availability of resources at a lower rate than male prospective entrepreneurs, they are likely to miss resource appropriation opportunities and, therefore, be underrepresented in entrepreneurship.

Lastly, I contribute to the literature on women in firm leadership positions (e.g., Gibson & Lawrence, 2010; McGinn & Milkman, 2013). Studies show that female leaders reduce gender-

based discrimination and disparity within workplaces (Hultin & Szulkin, 1999; Cohen & Huffman, 2007). This study explores the influence that female leaders can have on regional female employees beyond the boundaries of their firms. The results of this study suggest that the greater representation of women in leadership positions has positive externalities on regional female employees in terms of enhancing their ability to exploit agglomeration benefits.

2.2 THEORY

2.2.1 Employee Entrepreneurship and Search for and Access to Resources

Access to entrepreneurial resources refers to the process in which the resource provider agrees to deploy resources to a prospective entrepreneur. While employees consider opportunities, opportunity costs and risks associated with founding a venture before leaving paid employment (Shane & Venkataraman, 2000; Amit, Muller, & Cockburn, 1995; Douglas & Shepherd, 2000; Campbell et al., 2012; Carnahan, Agarwal, & Campbell, 2012; Sørensen & Sharkey, 2014; Carnahan, 2017; Marx, 2022), once opportunities are identified, and costs are assessed, entrepreneurial entry depends on the ability of the prospective entrepreneur to access and mobilize human and financial capital needed to start a venture (Aldrich & Zimmer, 1986; Simoes, Crespo, & Moreira, 2016; Clough et al., 2019; Castellaneta, Conti, & Kacperczyk, 2020). For example, starting a new venture requires working with potential co-founders with complementary skills or contracting industry-relevant suppliers in the region. Prospective entrepreneurs also need financial capital. Without sufficient funding from angel investors or venture capital firms, leasing office spaces or hiring skilled employees can be difficult for new founders. Because founding new ventures without sufficient resources entails a high risk of failure (e.g., Cooper, Gimeno-Gascon, & Woo, 1994), access to resources is a critical element in

employees' decision to leave paid employment and founding a venture (e.g., Castellaneta, Conti, & Kacperczyk, 2020).

Access to entrepreneurial resources is, however, contingent on prospective entrepreneurs being aware of and having information on resources (e.g., Stuart & Sorenson, 2003; Clough et al., 2019). Even when resources are available in the environment, prospective entrepreneurs are not always certain about where in the local environment they can find the resources they seek (Grossman, Yli-Renko, & Janakiraman, 2012). Search for resources, therefore, precedes access to resources for most prospective entrepreneurs (Clough et al., 2019). Before prospective entrepreneurs can secure attention and agreement from resource providers, they first seek information on resources to approach and negotiate with resource providers. For this reason, entrepreneurs often locate their businesses in regions in which they have lived because they possess local information and connections for mobilizing capital and personnel (Dahl & Sorenson, 2012).

The process of searching for resources often involves the use of networks (Aldrich & Zimmer, 1986; Cooper, Folta, & Woo, 1995; Clough et al., 2019). Prospective entrepreneurs contact colleagues, friends, or family members in search of information on resource providers. Indeed, in my interviews with venture founders, founders indicated that the search for resources began with contacting their networks. One founder, who left paid employment to start a venture, noted,

> *I knew from day one I needed to have a technical expert, and I was looking for a chief technical officer, like a co-founder to join me, and I couldn't find that person. What did I do? I started going down my entire LinkedIn connections, just from person to person to person and connecting.*

Another founder shared,

> *It was really helpful to have past industry experiences because I did have a network. I had attorneys that I could talk to. I had intellectual property resources and people that I could talk to. And even some investors as well. Some of the investors I had gotten close to, I could reach out and let them know what I was doing.*

These accounts of venture founders point out the influential role of networks in the search for resources. Research echoes these accounts by finding that most of the entrepreneurs' resources are mobilized through their networks (Ruef, Aldrich, & Carter, 2003; Shane & Cable, 2002). In addition to existing contacts, some prospective entrepreneurs actively seek new contacts, such as through networking events, to identify available resources beyond the scope of their existing networks (Vissa, 2012). While significant research gaps remain on who engages in proactive networking and who prefers to utilize existing networks, existing literature generally emphasizes the importance of networks in resource search and in accessing resources.

While the process of searching for and accessing resources is likely to be challenging for all employees in paid employment, they are particularly more difficult for female employees. First, women are unlikely to be able to search for resources as extensively as men. Traditional household responsibilities like childcare are disproportionately allocated to women (Eagly & Steffan, 1984; Carr, 1996), thereby making it more challenging to find time to search for resources than men. Since women also have smaller networks than men and are less likely to be networked (e.g., Rosenthal & Strange, 2012; Abraham, 2020), their search effort for resources is expected to be confined and restricted. Second, even when female employees successfully identify resource providers in the local area, systematic gender stereotypes against women create challenges for female entrepreneurs in mobilizing resources. Resource providers evaluate female entrepreneurs with negative gender stereotypes and perceive women to be less competent entrepreneurs (Thébaud, 2015; Kanze et al., 2018; Guzman & Kacperczyk, 2019). Therefore, compared to male entrepreneurs, female entrepreneurs are often disadvantaged in accessing

venture capital funding (Kanze et al., 2017, 2018; Guzman & Kacperczyk, 2019), labor (Kacperczyk, Younkin, & Rocha, 2022), and mentors (Rocha & van Praag, 2020).[1]

Given these challenges that women face in searching for and accessing resources, women are less likely than men to be venture founders (e.g., Jennings & Brush, 2013). Recent studies find that female employees transition into entrepreneurship at lower rates than male employees (e.g., Miric, Yin, & Fehder, 2022; Manchester, Benson, & Shaver, 2022; Marx, 2022). For example, Miric, Yin, and Fehder (2022) find that the likelihood of a female employee becoming a venture founder is 50.3% lower than for male employees in technology industries and 23.3% lower in nontechnology industries. Similarly, Marx (2022) finds that the negative impact of noncompete covenants on the likelihood of transition into entrepreneurship is about 15% stronger for female employees. Findings from these works help to underscore that the gender-based disadvantages encountered in the process of searching and accessing resources are highly associated with the nature of lower participation of female employees in becoming venture founders.

2.2.2 Industry Agglomeration and Employees' Search for and Access to Resources

An important factor that reduces challenges for employees in accessing entrepreneurial resources is the geographic agglomeration of industry activity in the employee's location. Industry agglomeration achieves this through two features. First, agglomeration increases the pool of industry-relevant resources, such as labor and suppliers in the region (e.g., Marshall, 1920),

[1]On the other hand, recent research on crowdfunding shows that gender-based disadvantages in gaining financial capital can partly be ameliorated through crowdfunding as female founders are more likely to succeed at crowdfunding by receiving more investments from female investors (Greenberg & Mollick, 2016; Bapna & Ganco, 2021)

which employees could leverage to create their venture. Given the greater availability of industry-relevant labor and suppliers that operate in agglomerated regions, prospective entrepreneurs, like employees in paid employment, can find human and financial capital with fewer difficulties. For example, an employee in the manufacturing industry is more likely to find other employees in the manufacturing industry who could potentially be their co-founders or early-stage employees in a region where the industry is agglomerated compared to employees in regions where the manufacturing industry is less agglomerated, because more personnel work for the manufacturing industry in agglomerated regions (Pe'er and Keil, 2013). Similarly, employees can more easily find and contract industry-relevant suppliers in regions where the industry is concentrated (e.g., Glaeser & Kerr, 2009). Industry-specific venture capital firms also choose to locate in agglomerated regions because they tend to invest locally to monitor their investments (Kolympiris, Kalaitzandonakes, & Miller, 2011).

A second feature of agglomeration that contributes to employees' greater access to resources is that it fosters networking opportunities between employees in the region. A large literature finds that geographic co-location facilitates the formation of new alliances between firms and increases job-hopping of employees (e.g., Almeida & Kogut, 1999; Freedman, 2008; Reuer & Lahiri, 2014), thereby fostering formal encounters between firms' employees. Employees are also more likely to meet employees of other firms serendipitously in agglomerated regions through professional associations or industry networking events (e.g., Saxenian, 1994). Through these formal and informal encounters, employees in agglomerated regions are presented with more opportunities to network with employees of other firms in the region. Since networking opportunities serve as information channels for identifying human and financial capital (Sorenson & Stuart, 2003; Rosenthal & Strange, 2012; Samila & Sorenson,

2017; Kalnins & Williams, 2021), industry agglomeration reduces challenges in searching for resources by exposing employees to more networking opportunities.

Overall, agglomeration increases employees' access to entrepreneurial resources by increasing the availability of human and financial capital in the region and, at the same time, fostering networking opportunities between employees in the region. Since employees gain information on resource providers through networking opportunities, they can identify and contact available resource providers, such as potential co-founders or angel investors, to construct an agreement to mobilize their resources. This intertwined nature of resource availability and networking opportunities in shaping an employee's access to resources, therefore, suggests that lower levels in one component would reduce the level of access that employees gain from agglomeration.

2.2.3 Increase in Networking Opportunities by Employee Gender

If low access to resources restrains female employees from pursuing their ideas for new ventures, then increasing the access to resources in the local environment may provide female employees with more comparable access to resources as male employees. The motivation to act on increased access to resources might be higher for female employees, particularly if they initially planned on becoming founders but could not mobilize resources. For example, a recent study finds that when institutional changes reduce barriers to entrepreneurship, women launch new ventures at higher rates than men because they previously faced greater obstacles to entrepreneurship (Castellaneta, Conti, & Kacperczyk, 2020). Similarly, Kalnins and Williams (2021) finds that female-owned businesses exhibit higher survival duration relative to male-owned businesses as the representation of female-owned businesses increases in the geographical

area because female-owned businesses disproportionately gain more material and knowledge resources from local stakeholders as the representation increases. Taking these studies into account, agglomeration can have a similar effect. Female employees may gain greater access to resources than male employees because barriers to resources were higher for them relative to male employees.

However, certain groups of individuals may systematically gain networking opportunities at higher rates than others when the industry agglomeration increases in the region. Social exchange theory offers some insights into why this might be the case. This theory suggests that relationship-building processes are guided by instrumental concerns. The heart of the exchange theory lies with reward and value. Individuals pursue relationships in a self-interested manner, seeking to maximize the benefits and minimize the costs of their social relationships (Blau, 1964; Molm & Cook, 1995). Blau specifically defined exchange behavior as "voluntary actions of individuals that are motivated by the returns they are expected to bring." (Blau 1964:91). In accordance with Blau, Homans (1974) suggests that the probability of establishing a social relationship with another individual increases if the potential value of the relationship increases. In other words, when selecting among alternatives, a person is more likely to choose to network with the one that is most likely to bring value (Borgatti & Cross, 2003). It is generally understood that an intelligent and well-informed actor formulates probabilities and estimates expected utilities for alternative actions prior to deciding and acting.

Insights from social exchange theory suggest that employees would generally assess the potential value of another employee before deciding to network with the employee to maximize benefits from exchange opportunities. Based on these insights, agglomeration can provide networking opportunities at different rates for employees in the region, depending on how the

value of networking with a certain employee is evaluated. Since individuals manage networking opportunities such that they can extract value from their contacts, employees would be motivated to select to exchange information with others that they perceive to be more valuable than other opportunities (Kleinbaum, 2018). Hence, when formal and informal encounters between employees increase as the industry agglomerates, employees with low perceived value are likely to be exposed to fewer networking opportunities than employees with high perceived value.

It is conceivable that compared to male employees, female employees are likely to be considered as contacts with lower value for information exchange. Gender is often factored into evaluation both in the presence and absence of information on quality (e.g., Heilman, 2001; Castilla & Benard, 2010). Especially in male-dominated domains, the prevalence of gender stereotypes and biases lead evaluators to devalue women's competence in workplaces (Eagly and Steffen, 1986; Cejka and Eagly, 1999; Moss-Racusin et al., 2012; Kleinbaum et al., 2013). Systematic gender stereotypes, therefore, restrain female employees from acquiring opportunities within workplaces that would increase their value as information exchange contacts to employees of other firms. First, female employees are less likely to be promoted to managerial positions than male employees (e.g., Maume, 1999; Ryan & Haslam, 2007; Ibarra, Carter, & Silva, 2010). Since managerial positions are central to producing and processing industry-related information in firms (e.g., Tushman & Romanelli, 1983), female employees are likely to lack valuable information that would attract the interest of employees in other firms. In a similar vein, the low prospect of female employees being promoted to managerial positions would encourage employees of other firms to invest time in forming networks with male employees compared to female employees.

Second, as gender stereotypes bias others' judgments of women's competence, women also have more significant difficulties in building connections within workplaces (McDowell, Singell, & Stater, 2006; Moss-Racusin et al., 2012; Bapna & Funk, 2020). Connections with colleagues, especially with stars, can help employees directly gain new information and knowledge (Azoulay, Graff Zivin, & Wang, 2010; Oettl, 2012). Indirectly, employees can also form relationships with their colleagues' peers in other firms through referrals (Kossinets & Watts, 2009). Additionally, having connections within workplaces would signal to employees of other firms that the employee might possess industry-relevant information that might be valuable. On the other hand, if an employee lacks connections within the workplace, the employee is likely to be perceived as not possessing less information and knowledge that might be valuable. Employees of other firms would, therefore, be discouraged from investing time in networking with employees with fewer connections. Consequently, because female employees are likely to have fewer connections and collaborators within workplaces, they will have fewer opportunities to network or connect with employees of other firms through their workplace colleagues.

While colleagues of female employees at the firm can reassess their evaluation of female employees' value as information exchange contacts, employees of other firms are not likely to have such opportunities for reassessment. To assess the potential value of the employee as a network contact, employees of other firms, therefore, rely on more observable information such as the employee's position title, connections, collaborators, and gender. Hence, given that gender stereotypes restrain opportunities within workplaces, female employees, on average, are likely to be less valuable contacts for networking.

Moreover, in addition to systematic gender stereotypes limiting the value of networking with female employees, homophily in building networks is likely to further disadvantage female employees from gaining networking opportunities when the industry agglomeration increases. The similarity in characteristics, such as gender, facilitates interactions between employees. A long tradition of studies suggests that female employees are more likely to interact with female employees while male employees network with male employees within workplaces (e.g., Ibarra, 1992; Bapna & Funk, 2020; Mehra, Kang, & Dolgova, 2023). In technology industries, which is the focus of this study, since men constitute the majority of employees, gender-based homophilous connections provide female employees with fewer opportunities to network both within and outside their workplaces with industry-specific employees.

Lastly, gender roles in society with respect to childcare and family responsibilities inhibit female employees from engaging in networking opportunities. While interactions between employees of different firms may take place in formal workplace settings, oftentimes, such interactions take place in nonworkplace settings such as bars (Andrews, 2019) and professional associations (Saxenian, 1994). Because networking in nonworkplace settings requires employees to invest additional time outside of their house, female employees, who disproportionately manage childcare responsibilities (e.g., Eagly & Steffan, 1984; Carr, 1996), are disadvantaged in building networks relative to male employees.

Taken together, the extent to which agglomeration increases networking opportunities for employees in paid employment will be different by the gender of employees. Because of systematic biases in workplaces, non-work related gender roles, and homophily, agglomeration will increase employees' networking opportunities with employees of other firms at a lower rate for female employees than for male employees. Since networks are essential for prospective

entrepreneurs in identifying resource providers, female employees would be disadvantaged in gaining access to resources when the industry agglomeration increases the availability of resources in the region. Hence, I offer the following hypothesis:

> *Hypothesis 1: When the industry agglomeration increases in the region, female employees' likelihood of transitioning into entrepreneurship increases at a lower rate than male employees.*

2.2.4 Regional Differences: Proportional Representation of Female Senior Executives

I expect the gendered effect of agglomeration to vary across regions. Gender stereotypes are outcomes of social structure and local ecology (Eagly and Steffen, 1984; Bussey and Bandura, 1999). Not all female entrepreneurs face gender biases to the same extent (Kalnins & Williams, 2021). Female entrepreneurial rates are higher in some regions than in others (Ghani, Kerr, & O'Connell, 2013), and female entrepreneurs outperform male entrepreneurs in some industries (Kalnins & Williams, 2014). Differences in outcomes of female entrepreneurs suggest that structural differences in the industry across regions can reinforce or weaken negative gender stereotypes about female employees and, subsequently, their access to networking opportunities.

One structural characteristic that engenders differences in gender stereotypes is the level of women's representation in industry leadership roles in the region. Exposure to regional female leaders weakens gender-based stereotypes in the region both in the public and domestic spheres (Beaman et al., 2009; Beaman et al., 2012) and also increases networking opportunities for women (Kalnins & Williams, 2021). This suggests that if employees are located in a region where a high proportion of industry leadership positions are occupied by women, systematic gender stereotypes about female employees in the industry would be lower in the region. Female

employees in such a region would have more networking opportunities than female employees in other regions and gain more information on resources.

Taken together, in regions where women's representation in leadership roles is high, the level of gender-based biases and disadvantages that female employees encounter will be lower than in regions where women's representation in leadership roles is low. Consequently, female employees will be valued more highly as network contacts in such regions and have greater access to networking opportunities when the industry agglomeration inreases. I, therefore, predict that the differential impact of agglomeration on male and female employees' access to entrepreneurial resources will be mitigated in regions with a high representation of women in leadership positions.

Hypothesis 2: The gendered effect of agglomeration on employees' transition into entrepreneurship is weakened in regions with high proportional representation of women in industry leadership positions.

2.3 DATA AND EMPIRICAL DESIGN

2.3.1 Empirical Context

The empirical context of this study is the U.S. biotechnology industry. This empirical setting is particularly well suited for exploring the arguments for several reasons. First, biotechnology firm employees often transition into entrepreneurship by becoming venture founders in this industry (Agarwal & Shah, 2014). This feature of the context provides variation in this study's outcome of interest. Second, biotechnology firms are locally agglomerated across diverse geographic regions to varying degrees (e.g., McCann & Folta, 2011), which provides variation I can use to study the effect of industry agglomeration. Third, the biotechnology industry is well recognized

as a context where the geographic agglomeration of industry facilitates the founding of new ventures in the region (e.g., Stuart & Sorenson, 2003).

2.3.2 Data

The data used for the analysis in this study is assembled by merging several data sources. First, data on U.S.-based biotechnology firms comes from the Crunchbase database. Crunchbase collects data from multiple channels, including an active venture program with more than 3,000 venture partners who provide portfolio data, machine-learning tools that process news articles which their internal analysts add-in on a daily basis, and an active community of contributors who provide data on their own companies as well. Their internal team also inspects their data to ensure that no incorrect information is added. An advantage of Crunchbase data is that they identify firms in the biotechnology industry that range from small firms that have less than ten employees to large biotechnology giants such as Amgen, Genentech, and Gilead Sciences. This feature of the Crunchbase data on the biotechnology industry allows me to observe the universe of biotechnology firms in the U.S. Another advantage is that Crunchbase data includes LinkedIn URLs of firms, which I use to obtain data on employees.

Using the LinkedIn URLs, I collect publicly available LinkedIn profiles (i.e., resumes) of all employees who have worked or are currently working in the sample biotechnology firms.[2] For those firms for which Crunchbase does not have LinkedIn URL information, I manually collect their LinkedIn URLs using the name and location of the firm. LinkedIn profiles of employees include extensive information, such as the years of employment, locations, job titles,

[2]Public LinkedIn profiles can be seen by anyone while private LinkedIn profiles have varying degrees of restrictions on who can see the profile or contact the user. Most users generally keep their profile public to maximize exposure and enhance business communication.

education, and descriptions of employment. With such information, I can also infer the gender and age of each employee. More importantly, LinkedIn profile data allows me to more accurately identify whether the employee stays in the firm, moves to another firm, or becomes a founder of another firm over the years in their career. This is an advantage compared to more conventional ways of identifying employee mobility using Patent data (e.g., Ge et al., 2016).

Third, I collect patent data from the U.S. Patent and Trademark Office (USPTO) PatentsView database. To identify the patents of each sample firm, I first clean the names of patent firm assignees and sample firm names (e.g., remove "inc," "limited," "co." etc.) and standardize firms with various forms of names. Then, I use fuzzy matching algorithms to match firm names to identify patents assigned to sample firms. To identify patents granted to individual employees, I take a further step and fuzzy match names of inventors from patent data and names of employees from LinkedIn data, conditioned on matches between firm names. This process allows me to identify the number of patents that each firm and employee successfully filed each year. There are 2,941 firms (45.7% of all firms) with at least one patent and 12,951 employees (4.3% of all employees) with at least one patent between 2005 and 2019.

Fourth, I collect data on state-level incentives and subsidies for the biotechnology industry (e.g., Maryland's Biotechnology Investment Incentive Tax Credit (BIITC)). I build on Moretti and Wilson (2014)'s list of tax credits and subsidies to the biotechnology industry. Because Moretti and Wilson (2014)'s analysis period ended in 2010, I gathered additional data on state-level incentives and subsidies since 2010 from the Biotechnology Innovation Organization (www.bio.org).

Lastly, from the Center for American Women and Politics, a unit of the Eagleton Institute of Politics at Rutgers University, I collect data on the proportion of elected politicians who are

women in each state's legislature body. This information is gathered to address changes in the local perception of women as leaders, which is a confounding factor in the relationship between the regional proportion of senior executives who are women and female employees' transition rates. I also supplement data from the Census Bureau to collect more region-level characteristics (e.g., regional economic conditions). The final sample comprises 299,645 employees that have been employed by 6,440 U.S.-based biotechnology firms between 2005 and 2019. I chose 2005 as the starting year since LinkedIn started service in 2003, and some of the variables require lagged measures. The year 2019 is the end year for the purpose of ending the analyses before the outbreak of the pandemic. The final dataset is at the employee-year level with 1,144,514 observations.

2.3.3 Variables

Dependent Variable. The challenge in measuring an employee's transition into entrepreneurship is observing an employee's career and location movements over the years. LinkedIn profile data helps overcome this difficulty as it provides information on an employee's employer, position, and location over time. Using this information, I measure an employee's transition into entrepreneurship as a binary variable. The variable *Employee's transition into biotech entrepreneurship* takes a value of 1 if an employee *i* leaves the employer *j* in region *k* to become a founder of a biotechnology venture in region *k* at *t*, and 0 if otherwise (e.g., Elfenbein, Hamilton, & Zenger, 2010; Kacperczyk & Marx, 2016). I identify founders with job titles. If an

employee's job title includes strings "founder," "owner," "entrepreneur," or "enterpriser," I code the employee as being a founder.[3]

Explanatory Variables. The purpose of this paper is to examine whether industry agglomeration in the region may affect employees' transition into entrepreneurship differently by gender. To compute each region's agglomeration level, I take the following steps. First, I define regions as Metropolitan Statistical Areas (MSA), which is a common approach in prior research that examines regional differences in the U.S. context (e.g., Rosenthal & Strange, 2012; Agrawal et al., 2014). I disambiguate different formats of employees' locations (e.g., cities, zip codes, counties, etc.) and code them into MSA formats. Second, I identify employees of sample biotechnology firms that are located in each MSA *k* at year *t.* For each employee's region at year *t*, I measure the *Agglomeration level* with the total number of employees employed by sample biotechnology firms located in the MSA *k*, excluding the focal employee's firm, at year *t* (Moretti, 2021).[4] For the purpose of displaying coefficients and interpretation, the explanatory variable, *Agglomeration level*, is in ten thousand. Using LinkedIn data provides an advantage in computing this measure since employees who are not inventors nor are located in regions of their firms' corporate or regional headquarters are often not accounted for when measuring agglomeration level.

[3] This measure excludes the possibility of the dependent variable capturing hybrid entrepreneurs who are employees start new ventures but stay employed in firm *j*. This study does not include hybrid entrepreneurship as part of transition into entrepreneurship because the determinants of hybrid entrepreneurship is different from transitions into entrepreneurship (Folta, Delmar, & Wennberg, 2010). For example, hybrid entrepreneurs do not require office spaces and often do not hire employees. It also does not involve the employee leaving the employer in pursuit of a different career. Hence, hybrid entrepreneurship will not necessarily be driven by access to resources.

[4] I utilize several alternate measures of region's agglomeration level as robustness checks such as the natural log of the number of employees and the proportion of biotechnology employees located in the region. Results are consistent and I show these results in robustness check section.

To identify each employee's gender, I remove titles, degrees, punctuations, numbers, and nonalphabetic characters from each employee's name. I then utilize gender disambiguation algorithms to identify the gender that is most likely associated with each employee's first name. The algorithms give probabilities that a name is associated with a particular gender. If the probability is 0.75 or higher, I record the recommended gender. When the probability is lower than 0.75 (i.e., the name has a high probability of being gender neutral), I use middle names (when available) to complete the gender coding. Taken together, I assign gender to 92.58% of the employees in the study.[5] Among those that are assigned gender, there are 118,071 (42.56%) unique female employees and 159,354 (57.44%) unique male employees in the dataset. *Female employee* is a binary variable that identifies employees that are women.[6]

Lastly, I further predict that the effect of agglomeration on female employees' likelihood of transitioning into entrepreneurship is contingent upon the proportional representation of women in industry leadership positions in the region in the industry. To evaluate this prediction, I measure the *Regional proportion of female senior executives* for each MSA *k* in each year *t* defined as the proportion of senior executives that are women and are employed by large biotechnology firms (i.e., firms that employ at least 1,000 employees at year *t*) in the region.[7]

[5] Gender is not identified for 22,219 employees (7.42% of all employees). These employees are not excluded from the sample and are included when measuring agglomeration level. The results are consistent when they are excluded from the sample.

[6] A survey report from Biotechnology Innovation Organization shows that 45% of biotechnology employees are women in 2019 (Biotechnology Innovation Organization, 2022). This percentage is not too different from the percentage from the data, which includes 42.56% of employees who are women. This mitigates any potential concerns that women may be less likely to have public LinkedIn profiles than men, and therefore may be underrepresented in the data.

[7] I measure the *Regional proportion of female senior executives* with senior executives of large biotechnology firms to be consistent with the theoretical argument that higher proportion of female senior executives would reduce gender-based stereotypes in the region. Senior executives of large firms are more difficult positions to achieve than the same positions in smaller firms. They are also more visible to firms and employees in the region. Hence, greater presence of women in large biotechnology firms' senior positions, would have influence on the perception of female employees' role and ability in the biotechnology industry. This definition also excludes senior executives of new ventures, who are also less likely to influence perception of employees in the region.

Employees are identified as senior executives with job titles. If each employee's job title assigns their position as a member of the top management team (e.g., CEO, CFO, CTO, etc.) or other senior management positions (e.g., vice president, director, etc.), I identify the employee as a senior executive of the firm.

Control Variables. To control for alternative mechanisms that might affect (1) an employee's likelihood of transitioning into entrepreneurship or (2) the difference in the transitioning likelihood by gender, I include the following control variables in the models. First, at the employee level, I control for human capital characteristics that might affect male and female employees' transition into entrepreneurship differently (e.g., Campbell et al., 2012; Carnahan, Agarwal, & Campbell, 2012). I control for *Senior executive position,* which takes the value of 1 if the employee is occupying top management team positions (e.g., CEO, CFO, CTO, etc.) or other senior management positions (e.g., vice president, director, etc.) at *t* and 0 if otherwise. *Doctoral degree* takes the value of 1 if the employee has a doctoral degree at *t* and 0 if otherwise. Both *Senior executive position* and *Doctoral degree* control for heterogeneity in employees' human capital and earnings since employees with high human capital are less likely to leave the firm (Campbell et al., 2012). Concurrently, *Senior executive position* also accounts for the difference in promotion opportunities that are available to employees by gender. Similarly, *Doctoral degree* addresses the limited opportunities for women to increase their human capital since only 16-20% of engineers with Ph.D. degrees were women in the 2000s (West et al., 2013). With the variable *Ln(Employee's patent stock)*, I control for the natural log of the cumulative number of patents for employee *i* at time *t* to mitigate the influence of outliers. Patents signal an employee's capability in producing new knowledge, and women are also less likely to be patent inventors, with only 12% of patented inventors being women as recently as 2016 (Toole et al.,

2019). I also control for *Founder experience*, defined as taking the value of 1 if an employee has experience of being a founder of another firm prior to *t*, and 0 if otherwise. Employees with founder experience are more likely to become founders again, while male employees are more likely to have founding experiences than female employees (Miric, Yin, & Fehder, 2022).

Because many firms have facilities in multiple regions, I include firm-region level controls to address facility-specific factors that affect an employee's transition likelihood. Employees may decide to transition into entrepreneurship when their colleagues leave and become founders (Nanda & Sørensen, 2010; Kacperczyk, 2013; Markussen & Røed, 2017). To account for peer effects, I control for the *Transition of colleagues*, measured as the number of transitions into entrepreneurship by employees from firm *i* in region *k* at years *t-1* and *t-2*. Similarly, to address the possibility that employees may refrain from transitioning into entrepreneurship because of the myriad of opportunities to work in other firms in the region, I control for the *Mobility of colleagues*, which is the number of employees moving to other firms from firm *i* in region *k* at year *t-1* and *t-2*. Both variables also account for the possibility that an employee may prefer to become a founder at *t* because the employer's facility at the region is downsizing or not performing well at years *t-1* and *t-2*.

At the firm level, I include *Ln(Number of employees in the firm)*, measured as the natural log of the total number of employees at firm *i* in year *t* to mitigate the influence of outliers, to account for firm size. Larger firms are more likely to have internal entrepreneurial opportunities that discourage employees from transitioning into entrepreneurship (e.g., Kacperczyk & Marx, 2016), but at the same time, employees with entrepreneurial intentions may select to work at smaller firms (e.g., Elfenbein, Hamilton, & Zenger, 2010). To address heterogeneity in the knowledge-producing capabilities of the firm, I follow prior research and include *Ln(Firm's*

patent stock), which is measured as the natural log of the cumulative number of granted patents applied by firm *j*, depreciating by 15 percent annually (Funk, 2014). I also control for *Proportion of female senior executives in the firm* to account for the proportion of senior executives that are women in the firm. Female employees are less likely to leave the firm if there is a higher proportion of female superiors in the firm (McGinn & Milkman, 2013).

An employee's transition into entrepreneurship can also be influenced by region-level characteristics. To account for the level of competition for resources in the region, I control for *Cluster motion,* which indicates the pace of expansion or contraction of the industry size in region *k* over a period of time (Kim, Shaver, & Funk, 2022). I measure *Proportion of female employees (region)* as the proportion of employees that are women in the region to account for the impact of homophily in building networking opportunities for female employees in the region. I control for local economic conditions with *Unemployment rate,* defined as the unemployment rate of region *k* at year *t*, with data from the Local Area Unemployment Statistics program of the U.S. Bureau of Labor Statistics. This variable addresses the possibility that regional economic conditions influence the agglomeration level in the region and the likelihood of an employee's transition into entrepreneurship. I control for the size of the labor force in the region by *Regional population,* measured as the population of region *k* at year *t* in ten thousands with data from the Census Bureau.

Lastly, at the state level, I control for *State biotech incentives,* which takes the value of 1 from *t,* and afterward, if the state government adopted policies that provide incentives or subsidies for biotechnology firms and ventures (e.g., Maryland's BIITC) at *t*. Incentives for biotech companies by states increase the level of biotech employment within the state (Moretti & Wilson, 2014) and may also encourage employees to start new ventures. I also control for

Women in the state legislature, defined as the proportion of elected female politicians in the state legislature (i.e., senate and the house of representatives of the state) of the region *k*'s state at year *t.*[8] This control is included to address the changes in the perception of women as leaders within the state, which is a confounder in the relationship between *Regional proportion of female senior executives* and female employee's *Transition into entrepreneurship*.

Table 1 provides descriptive statistics. The likelihood of an employee transitioning into entrepreneurship in the biotechnology industry is 0.05% for all employees, 0.07% for male employees, and 0.03% for female employees.[9] The mean values of all variables across Column 2 (male employees) and Column 3 (female employees) are similar. However, the mean values of employee-level characteristics are different across genders. Columns 5 and 6 include standard deviations of variables across and within employees to show that there is sufficient within-employee variation over the years for both the dependent and independent variables. Table 2 shows a correlation matrix for variables.

Insert Tables 1 and 2 here

2.3.4 Estimation Models

I have panel data on employees employed by biotechnology firms, and the dependent variable is a binary variable. As a result, I employ a linear probability model (LPM). Prior studies that

[8] For MSAs that span multiple states such as the Washington-Arlington-Alexandria MSA, I assign them to states that constitutes the largest portion of the population of the MSA.

[9] There are employees that transition by starting a non-biotechnology business. The non-biotechnology transitions include employees starting non-technology related businesses such as restaurants, or technology related businesses in medical device, pharmaceutical, nanotechnology, etc. Including both biotech and non-biotech transitions, in total, there are 2,076 events of transitions and the likelihood is 0.23% for male employees and 0.14% for male employees. In supplementary analyses, I show the association between agglomeration level and transition into non-biotechnology entrepreneurship.

examine employees' transitions into entrepreneurship also use this form of the model (e.g., Marx, 2022; Miric, Yin, & Fehder, 2022), as LPM simplifies the interpretation of the coefficient estimates. Additionally, I include region-, firm-, employee-, and year-fixed effects. Together with the set of controls, the models compare employees to themselves over time within the region and the firm to estimate the impact of agglomeration on an employee's likelihood of transitioning into entrepreneurship. It is, therefore, practical to use LPM and not logit nor probit models because there is no fixed-effect transformation for logit and probit models. The model takes the following form:

$$(1)\ \Pr(\text{Male employee's transition} = 1)_{ijkt} = \alpha + \beta_1 Agglomeration_{ijkt} + X + \theta_i + \sigma_j + \eta_k + \mu_t$$

$$(2)\ \Pr(\text{Female employee's transition} = 1)_{ijkt} = \alpha + \beta_2 Agglomeration_{ijkt} + X + \theta_i + \sigma_j + \eta_k + \mu_t$$

where *i* indexes employees, *j* indexes firms, *k* indexes regions, and *t* indexes years. X is the vector of all controls that influence the probability of employees transitioning into entrepreneurship, as well as the difference in probabilities by gender. θ captures employee fixed effect, σ captures firm fixed effects, η captures region fixed effects, and μ is year fixed effects. I report robust standard errors clustered at the region level.[10] I split the sample by employee gender and utilize segment regression models to address the concern that interaction models use both within and across variations (Shaver, 2019). In sum, I test the null hypothesis that β_1 from equation (1) and β_2 from equation (2) are equal to empirically test my arguments.

[10] I use the sandwich estimator to cluster samples by regions.

2.3.5 Identification Challenges

The inclusion of control variables mitigates the possibility that my findings are driven by omitted variables. The inclusion of region, firm, and employee fixed effects also addresses potential time-invariant unobservable regional (e.g., culture that attracts business and/or discourages women's participation in entrepreneurship), firm (e.g., firms' tendency to assign employees with high human capital into agglomerated regions), and employee-level (e.g., individual's inherent tendency to become an entrepreneur) characteristics that could affect both the agglomeration level of an employee's location and the gender difference in transitioning into entrepreneurship.

In particular, employee-level fixed effects are crucial to address the concern of employees sorting into agglomerated regions. Some individuals have an inherently higher tendency to pursue entrepreneurship than others (Nicolaou et al., 2008). If individuals with high entrepreneurial tendency ex-ante select to work in more agglomerated regions to become founders in a later period, comparing agglomerated regions to isolated regions may yield biased estimates of agglomeration effects. More importantly, this tendency and the ability to select into regions may also differ by gender (e.g., men have more location choices). If this is the case, observing a higher likelihood of transition into entrepreneurship for male employees in agglomerated regions may be driven by male employees' ability to sort into the region and not by higher access to resources in agglomerated regions. The inclusion of employee fixed effects accounts for the differences in both the entrepreneurial tendency and the ability to work in regions along the lines of gender.[11]

[11] A similar concern would be that the ability to change locations after starting to work in the industry would be different by employee gender. To address this concern, I run models with employee-region fixed effects and without employee and region fixed effects. The results are consistent.

While the controls and fixed effects help address potential confounders, they do not rule out the concern of simultaneity. This concern is the possibility that new ventures found by employees increase the agglomeration level of the region by hiring employees from other regions or other industries within the region. Because of gender biases in the resource appropriation process (Kanze et al., 2017, 2018; Guzman & Kacperczyk, 2019), male founders may have greater levels of financial resources to hire more employees than female founders. In such cases, the coefficient estimate of agglomeration on employees' likelihood of transitioning into entrepreneurship may be inconsistent both for male and female employees.

To address this identification concern, I employ an instrument to leverage the exogenous part of the variation in the agglomeration level of each employee's location. The instrument follows the instrumental variable strategy from Moretti (2021), which examines the impact of agglomeration level on an inventor's productivity. The study leverages firms with locations in multiple regions to build an instrument that isolates variation in the local region's agglomeration level. The idea behind Moretti (2021)'s instrument is that changes in the number of inventors employed in other regions by firms in the focal inventor's region, excluding the focal inventor's firm, from *t-1* to *t* predict changes in the employment of inventors by local firms in the focal inventor's region from *t-1* to *t* and are unlikely to be correlated with variation in the focal inventor's productivity.

Building on the instrumental variable strategy of Moretti (2021), the instrument of this study is the number of employees of local firms' establishments located in other regions, excluding the focal employee's firm, at *t-1*. For each firm *i* in region *k*, I identify peer firm group *l* that has employees in the same region. I then aggregate the number of employees that group *l* has in other regions at year *t-1*. The first stage, therefore, captures whether the changes in the

level of local firms' employment in establishments located in other regions from *t-1* to *t* predict the number of employees by local firms in the focal employee's region at *t.*

To see the intuition behind this instrument, consider cases of firms hiring or laying off employees in establishments in other regions. For example, the biotechnology firm Bristol-Myers Squibb (BMS) closed its San Diego-based operations in 2014. BMS is headquartered in the New York City area. To a biotechnology employee in New York City who is employed by a firm other than BMS, the first stage captures whether the number of biotechnology employees in New York City increases or decreases as BMS lays off San Diego-based employees. If BMS is downsizing following its closing of San Diego-based operations, BMS can also lay off New York-based employees. Similarly, if a biotechnology firm A, with operations in Minneapolis and Chicago, decides to expand and hire more employees in Minneapolis, then it is also likely that they will hire more employees in Chicago the following year. For the biotechnology employee located in Chicago hired by biotechnology firm B, the first stage removes the endogenous effects from the number of biotechnology employees in Chicago by utilizing firm A's expansion in Minneapolis. This instrument also satisfies the exogeneity condition. Expansion or downsizing of local firms' establishments in other regions is unlikely to affect access to resources, opportunity costs, or other factors that influence an employee's decision to leave paid employment and become a venture founder, and the difference between male and female employee's transition likelihood.

To study the effect of agglomeration level—instrumented by the employment of local firms' establishments located in other regions at *t-1*—on employees' transition into entrepreneurship by gender, I use two-stage least squares (2SLS). In the first stage, I regress the employment of local firms in other regions at *t-1* on the agglomeration level of the employee

(i.e., the number of biotechnology employees excluding the focal employee's firm). The predicted values from the first stage provide the instrumented agglomeration level, which, in other words, is the exogenous component of the agglomeration level. In the second stage, I then re-estimate equations (1) and (2) using the instrumented agglomeration level in place of the *agglomeration level*.

2.4 RESULTS

In Figure 1, I first show descriptive bar graphs. Figure 1 shows the proportion of employee entrepreneurship by female employees in regions with low, middle, and high levels of agglomeration. The agglomeration level is partitioned into three terciles. The figure shows the proportion of employee entrepreneurship by female employees is highest in regions with low agglomeration (e.g., 31.4% of employee entrepreneurs are women) and lowest in regions with high agglomeration (e.g., 20% of employee entrepreneurs are women). The figure provides descriptive evidence suggesting that female employees' participation rate in employee entrepreneurship relative to male employees is negatively associated with the agglomeration level.

2.4.1 Main Results

In Table 3, I first show models that examine the relationship between agglomeration level and employees' transition into entrepreneurship for all employees. In columns (1)-(4), I show various fixed effect combinations with control variables. Column (4) is the fully specified regression model with all fixed effects. Columns (1) leverage within-region variation, comparing employees within the same region. Columns (2) utilize within-firm variation, such that employees in different regions are compared for firms with multiple locations. Column (3) uses within-

employee variation, comparing employees to themselves over time. Lastly, column (4) includes all fixed effects, utilizing within-employee variations within a region and a firm over time. Across all models, I find that there is a positive association between agglomeration level and an employee's transition into entrepreneurship. Based on column (4), the marginal effect of an increase in one standard deviation of agglomeration level in the region is 0.0012, which translates to an increase in the likelihood of transitioning into entrepreneurship by 0.12 percentage points ($\beta = 0.0025$, $p = 0.0000$). While the coefficient is small, considering that the mean likelihood of transitioning is 0.05%, this effect size is economically significant. In columns (5)-(8), I run simple regressions of *Employee's transition into biotech entrepreneurship* on *Agglomeration level* with no covariates to check whether the results are due to collinearity between the *Agglomeration level* and control variables. The coefficients of *Agglomeration level* show positive coefficients with similar magnitude and p-value as those in columns (1)-(4). Consistent with prior research, these results suggest the employees are more likely to leave paid employment and become biotech venture founders in the region when the regional biotech industry becomes more agglomerated.

Table 4 presents the main models, which examine the effect of agglomeration level on employees' transition into entrepreneurship by gender. I expect that the impact of agglomeration level on male employees would be greater than the impact on female employees. In columns (1)-(6), I split the sample by gender. Consistent with my expectation, I find that the coefficient of agglomeration level is positive and significant for both male and female employees, suggesting that agglomeration increases both male and female employees' likelihood of transitioning into entrepreneurship. Again, consistent with the theoretical argument that male employees gain greater access to resources, the coefficient for agglomeration is greater for male employees

(column (3): β = 0.0031, p = 0.0000) than for female employees (column (4): β = 0.0015, p = 0.0008). The coefficients in the two models are statistically different from one another (p=0.0061), which suggests that there is a gendered effect of agglomeration. When the region's agglomeration level increases by one standard deviation, male employees' likelihood of transitioning into entrepreneurship increases by 0.15 percentage points, but for female employees, the likelihood increases by 0.07 percentage points. Figure 2 displays the association of agglomeration and employees' transition into entrepreneurship from column (3) and column (4). The figure shows that the likelihood of female employees' transition into entrepreneurship increases at a lower rate than male employees when the industry becomes more agglomerated, suggesting that male employees gain greater access to resources than female employees.

Insert Figures 1 and 2 here

To test whether the results hold for the full sample analyses, in columns (7) and (8), instead of splitting the sample by gender, I include the binary variable, *Female employee*, that indicates whether the employee is a female employee or not. In these models, I include the interaction term between *Agglomeration level* and *Female employee* to examine whether agglomeration has a different impact on female employees. Because gender affects the values of employee-level control variables, in column (8), I include interaction terms between *Female employee* and all control variables. The interaction terms between *Agglomeration level* and *Female employee* across columns (7) and (8) are all negative and statistically significant. Based on column (8), the marginal effect of an increase in one standard deviation in agglomeration level is 0.0005 for male employees (0.05 percentage points increase) and 0.0003 for female employees (0.03 percentage points increase). In sum, I find positive associations between

agglomeration and employee transition likelihood for both male and female employees, with the magnitude of the association being statistically greater for male employees.

Insert Tables 3 and 4 here

In Table 5, I address the concern of simultaneity by using 2SLS with the employment of local firms in other regions as an instrument for the agglomeration level of the focal employee's location. Columns (1) and (3) are only male employees, and columns (2) and (4) include just female employees. Columns (1) and (2) are without control variables. Because of the large sample size, the F-statistic is large for all columns, well above the threshold for strong instruments (Staiger & Stock, 1997). The first stage displays a positive coefficient, which is consistent with Moretti (2021). The coefficients of the instrumented agglomeration level for male employees are statistically significant and positive across columns (1) and (3) (column (3): $\beta = 0.0030$, $p = 0.0000$). The coefficients of the instrumented agglomeration level for female employees are also positive across columns (2) and (4) (column (4): $\beta = 0.0013$, $p = 0.0158$). Consistent with results from Table 4, The coefficients of instrumented agglomeration for gender split samples are statistically different from one another between columns (1) and (2), and (3) and (4) (difference between columns (3) and (4): $p = 0.0295$). Taken together, analyses consistently document that the agglomeration level has a gendered effect on an employee's likelihood of transitioning into entrepreneurship, even after addressing the simultaneity issue. Therefore, hypothesis 1 is supported.

Insert Table 5 here

2.4.2 Gendered Effect of Agglomeration by the Proportion of Female Senior Executives in the Region

Next, I examine the role of the regional proportion of female senior executives of large biotechnology firms. I theorize that in regions where the proportional representation of women in industry leadership positions is high, the differential impact of agglomeration on employees will be smaller because gender stereotypes are lower for the industry in these regions. There is one issue with the evaluation of this argument. There are time-varying changes in regional culture or norms regarding how the region values women's roles as business leaders. This confounder can affect both the proportion of female senior executives in the region and the regional female employees' likelihood of becoming venture founders. The control variable, *Women in the state legislature,* measured as the proportion of elected women in the state legislature, reflects the region's view or perception of women's role as leaders. This control variable addresses the confounder.

The results testing these arguments are presented in Table 6. Panel A shows results with LPM, and Panel B shows results with 2SLS. Columns (1) and (2) only include regions with a low regional proportion of senior executives who are women, while columns (3) and (4) are regions with a high regional proportion of senior executives who are women.[12] Panel A shows that for LPM results, the coefficients of agglomeration are significantly different from one another between male and female employees in regions with a low proportion of female senior executives (p=0.0034). In contrast, the coefficients are not different for regions with a high proportion of female senior executives (p=0.8329). In Figure 3, I plot all four models. Figure

[12]Regions are split to high and low regions by the median of regional proportion of senior executives that are women.

3(a) shows regions with a low proportion of female senior executives. The slopes of the plots are different between male and female employees, and the confidence intervals do not overlap. Figure 3(b) shows regions with a high proportion of female senior executives. There are only minimal differences in slopes between plots for male and female employees in these regions, and the confidence intervals overlap in most ranges of agglomeration level.

The results are replicated in Panel B using 2SLS. I find that the coefficients of the instrumented agglomeration are significantly different between Table 6 columns (1) and (2) (p=0.0202), which are columns for regions with a low regional proportion of senior executives who are women. However, in regions with a high proportion, columns (3) and (4), coefficients are not statistically different (p=0.8638). The difference in the magnitude of coefficients of instrumented agglomeration between columns (1) and (2) is 0.0033, which is larger than the difference between columns (3) and (4) in Table 5. The coefficient is also not statistically significant for female employees (column (2): p=0.1243). These results suggest that female employees face more significant challenges in gaining access to agglomeration externalities in regions where gender stereotypes are strong.

Taken together, the results from both LPM and 2SLS show that agglomeration does not have a gendered effect for regions with a high proportion of female senior executives. In contrast, the gendered effect of agglomeration persists in regions with a low proportion of female senior executives. The results support hypothesis 2 and are consistent with the theoretical argument that in regions with a high proportion of female senior executives, there will be less severe gender stereotypes that limit female employees' opportunities within workplaces. Hence, female employees will gain comparable information and access to entrepreneurial resources as male employees when the industry agglomerates.

Insert Table 6 and Figure 3 here

2.4.3 Influence on Alternative Career Options by Employee Gender

The main results demonstrate that industry agglomeration affects employee entrepreneurship differently by employee gender. Prior research suggests that in addition to employees' transition into entrepreneurship, agglomeration also facilitates employees' move to other firms in the region (i.e., job hopping within the region) (e.g., Almeida & Kogut, 1999; Freedman, 2008). One alternative explanation for the gendered effect on employee entrepreneurship is the possibility that female employees may prefer to move to other biotech firms in the region than become entrepreneurs, while male employees prefer to become entrepreneurs more. This difference in career preferences by gender may explain the lower increase in the likelihood of transitioning for female employees compared to male employees when the industry agglomeration increases.

I test this alternative explanation and show the results in Table 7 columns (1)-(3). The dependent variable is a binary variable that indicates whether an employee leaves the current employer and moves to another biotechnology firm in the region at *t*. I use the same instrument since the employment of local firms in other regions in the previous period is not correlated with an employee's likelihood of moving to another biotech firm within the region. Column (1) shows results for all employees. Based on this column, agglomeration increases the likelihood of mobility for employees, which is consistent with prior research. I split the sample by gender into columns (2) and (3). The results display a positive and significant coefficient of instrumented agglomeration for male employees, but the coefficient is insignificant for female employees. The coefficients are weakly but statistically different from each other ($p = 0.0513$). The results do not

support the alternative explanation that suggests female employees may prefer to move to another firm in the region when the industry agglomerates. Interestingly, agglomeration also has a gendered effect on mobility. Agglomeration increases male employees' mobility likelihood but has no effect on female employees' mobility likelihood. As job referrals and information on available job positions also channel through interactions between individuals (Granovetter, 1973; Schmutte, 2015), these results further provide evidence that female employees are exposed to fewer networking opportunities with employees of other firms than male employees when the industry agglomerates.

Moreover, the results on employee mobility also suggest that the positive effect of agglomeration on employee entrepreneurship is not driven by lower opportunity costs in leaving paid employment. When the industry agglomerates in the region, more alternative employment options become available, which would reduce the opportunity cost of employees leaving their current employer. However, Table 7 shows that the instrumented agglomeration level does not have any significant effect on female employee's likelihood of moving to another biotech firm in the region. Unless agglomeration does not affect female employees' opportunity costs but only male employees', the null effect on female employees' mobility suggests that agglomeration does not significantly lower employees' opportunity costs in leaving their current employer. Rather, agglomeration seems to facilitate employee mobility by increasing networking opportunities through which employees gain job referrals and information on available job positions.

To add further support to the theoretical arguments, I examine several other mechanisms that may partially explain the gendered effect. One explanation is that female employees may prefer to become venture founders of non-biotech businesses at a higher rate than male

employees when the industry agglomerates. Because industry agglomeration increases new biotechnology ventures in the region, agglomeration can also escalate competition for customers amongst new ventures. Female employees may prefer to start non-biotechnology ventures to avoid competition because female employees are more risk-averse (Marx, 2022). If this is the case, then I would observe a greater impact of agglomeration on female employees' transition into non-biotech entrepreneurship than for male employees. In Table 7 columns (4)-(6), I test this explanation. The dependent variable is a binary variable that indicates whether an employee creates a non-biotechnology venture in the same region at *t.* Across all three columns, I find that coefficients of instrumented agglomeration are not statistically significant. These results, along with the main results, indicate that agglomeration only facilitates employees' transition into entrepreneurship in the core industry. The results also suggest that the gendered effect of agglomeration is not driven by heightened risk.

Insert Table 7 here

2.4.4 Mechanism Test

I also conduct analyses to isolate the mechanism of my theory further. The main mechanism of this study is that gender stereotypes are likely to hinder female employees from gaining networking opportunities to the same extent as male employees. To test this mechanism, in the previous section, I compare regions with high and low proportions of female senior executives to give variations in gender stereotypes in the industry across regions. I further examine this mechanism by splitting the sample by the career experience years of employees. Career experience years calculate the years of first employment since the college graduation year of each employee. If the employee does not have education information, I calculate the years since

the first year of employment. I split by the median career experience years for all employees, which is 12. The logic behind the split is that female employees with high career experience years (e.g., more than 12 years of experience) are more likely to be mothers who are susceptible to motherhood biases. Motherhood is particularly associated with lower competence expectations (Heilman & Okimoto, 2008). Additionally, because childcare responsibility is disproportionately given to mothers, employees who are mothers are likely to invest less time in networking opportunities. Hence, I expect the gendered effect of agglomeration to be stronger amongst employees with high career experience years than employees with low career experience years.

Table 8 shows 2SLS models with the sample split by career experience years. The coefficients for instrumented agglomeration level are statistically different between male and female employees amongst employees that have more than 12 years of career experience (p = 0.0339). On the contrary, while the coefficient on instrumented agglomeration level for female employees is not significant, the coefficients are not different between male and female employees in the sample with low career experience years (p = 0.7237). The split-sample analyses display a gendered effect for the sample where the gender stereotypes against female employees are stronger. Therefore, I provide further evidence that differences in networking opportunities affect the rate at which employees gain access to resources when the industry agglomeration increases in the region.

Additionally, to show that agglomeration increases knowledge and information spillovers in the region within this context, I aggregate the data to the region-year level and examine the impact of agglomeration on the number of citations for biotech patents across firms within the region each year. USPTO's Technology Center 1600 specializes in biotechnology and organic chemistry and identifies patent subclasses where biotechnology inventions are likely to be

classified. I extract all patents that are classified in the biotechnology subclasses and identify the number of citations that are made to other patents in the same region each year, excluding citations to the same firm and citations made by the patent examiner. I then aggregate the number of citations between firms within the same region to the region level for each year. In Table 9 columns (1) and (2), the dependent variable is the number of within-region cites of biotech patents, and for columns (3) and (4), the dependent variable is the normalized within-region cites of biotech patents. I use pseudo-maximum likelihood Poisson models in columns (1) and (2) because the dependent variable is a count variable. I employ Ordinary Least Squares regression, which is used for models in columns (3) and (4). Across the models, I find that the agglomeration level has a positive relationship with the number of across-firm citations within the region, providing support that knowledge spillovers increase with agglomeration.

2.4.5 Alternative Measurements

Lastly, I run tests to explore whether the results are robust to alternative measurements. First, in Table 10 columns (1) and (2), I rerun the main analyses with 2SLS after redefining the *Agglomeration level* as the natural log of the number of employees in the region. The results are consistent with the main analyses. The coefficients are positive and significant for both male and female employees but also are statistically different from one another ($p = 0.0355$). In columns (3) and (4), I redefine the *Agglomeration level* as the proportion of biotechnology employees in the U.S. located in the focal region. The coefficients of the instrumented variable are again positive and significant for both male and female employees and are statistically different from one another ($p = 0.0374$). Together, the analyses using alternative measurements of agglomeration present results that are consistent with the main analyses.

Insert Tables 8, 9, and 10 here

2.5 DISCUSSION AND CONCLUSION

Ample scholarship has examined the relationship between geographic agglomeration of industry activity and new venture founding rates in the region and documented a positive impact of agglomeration (Sorenson & Audia, 2000; Stuart & Sorenson, 2003; Glaeser & Kerr, 2009; Delgado, Porter, & Stern, 2010). However, little research has paid attention to whether the impact is different by gender of employees or prospective entrepreneurs. The objective of the present study was to theorize the differential impact of agglomeration on employees' transitions into entrepreneurship by gender of employees. I aimed to explore whether and to what extent agglomeration affects female employees differently from male employees. I propose that female employees gain networking opportunities at a lower rate than male employees when the industry agglomerates because of gender stereotypes in workplaces.

Using fine-grained employee panel data and an instrumental variable strategy, the present study produces several noteworthy findings. First, this study finds that both male and female employees' likelihood of transitioning into entrepreneurship increases when the industry agglomerates in the region. However, female employees' transition into entrepreneurship increases at a lower rate than male employees. Second, I find that the gendered effect of agglomeration is also contingent on the characteristics of the industry in the region. Specifically, in regions where women have a significant presence in senior executive positions, agglomeration does not affect employees' transitions differently by gender. Because gender stereotypes are lower in these regions, female employees are likely to have more networking opportunities through which they gain information on entrepreneurial resources. Furthermore, I also find that

agglomeration has a gendered effect on an employee's likelihood of moving to another firm in the region. Because people gain information on jobs through interactions (Granovetter, 1973), the result on mobility further suggests that female employees gain less information than male employees when the industry agglomerates.

With these findings, the study makes several contributions. The results suggest that attending to the gendered effect on agglomeration is essential for advancing research on the gender gap in various dimensions. The differential impact of agglomeration by gender is an overlooked dynamic in prior research. By showing that agglomeration affects employees differently by gender, the study suggests that the gendered effect of agglomeration may also play a role in influencing the gender gap in other outcomes, such as invention and promotion. These insights could expand our understanding of the gender gap in the performances of employees across multiple outcomes. Beyond that, this study also stimulates inquiry into identifying conditions where agglomeration can contribute to reducing the gender gap in the region.

Second, this study adds to the vast literature on agglomeration (e.g., Audretsch & Feldman, 1996; Glaeser & Kerr, 2009; Moretti, 2021). The limelight of this literature is documenting the positive effect of agglomeration on firm performance. In contrast, the question of whether there are negative effects of agglomeration has received little attention. In particular, whether agglomeration reinforces inequalities within the region has been unexplored. This is surprising given the importance of agglomeration on the regional economy. To the best of my knowledge, this paper is one of the first to examine how agglomeration interacts with gender inequalities to affect employees' entrepreneurial mobility. By doing so, it represents the first step in making a direct link between agglomeration and inequalities in entrepreneurship.

Third, this study sheds new light on the role of female senior executives in the agglomeration-economic outcome relationship. In particular, vibrant literature examines how the presence of female leaders influences the economic outcomes of women by reducing gender stereotypes (e.g., Hultin & Szulkin, 1999; Cohen & Huffman, 2007; Kalnins & Williams, 2021). This study contributes to this body of work by exploring an additional avenue through which female senior executives can reduce inequities in the region. I document that the high presence of female senior executives in the regional industry can increase female employees' abilities to exploit agglomeration externalities. In this regard, I provide insights into how the gender gap in entrepreneurship can be reduced and how female senior executives in the region can increase the economic outcomes of women beyond the boundaries of the firm.

Lastly, this paper also contributes to the field of entrepreneurship. Prior studies have suggested that changes in the external environment influence employees' likelihood of transitioning into entrepreneurship (e.g., Carnahan, 2017; Starr, Balasubramanian, & Sakakibara, 2018). However, previous studies mostly focused on how the changes in the institutional environment affect employee transitions. No studies have yet explored the effect of agglomeration on an employee's likelihood of founding a firm. By focusing on agglomeration, this study is one of the first to isolate how the regional industry structure affects employee's career choices.

Table 1 – Descriptive statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Mean (full sample)	Mean (male employees)	Mean (female employees)	S.D. (full sample)	S.D. (across employees)	S.D. (within employees)	Min (full sample)	Max (full sample)
Outcome								
Transition into entrepreneurship	0.0006	0.0007	0.0003	0.0236	0.0158	0.0201	0	1
Explanatory								
Agglomeration level	0.4275	0.4291	0.4255	0.4815	0.5163	0.1708	0	1.8608
Regional proportion of female senior executives	0.2875	0.3291	0.3354	0.1275	0.1150	0.0642	0	1
Controls								
State								
State biotech incentives	0.6109	0.6134	0.6073	0.4876	0.4754	0.1323	0	1
Women in the state legislature	0.2611	0.2610	0.2613	0.0549	0.0531	0.0220	0.082	0.524
MSA								
Cluster motion	-89.8035	-86.6171	-94.4688	282.794	248.8355	196.5896	-1,343.32	568.2901
Unemployment rate	0.0542	0.0543	0.0541	0.0216	0.0174	0.0148	0.0159	0.1910
Regional population	552.6846	544.347	564.6403	558.4195	550.5398	115.9385	0	1
Proportion of female employees (region)	0.4122	0.4081	0.4181	0.0514	0.0480	0.0208	0	1
Firm								
Ln(Firm employees)	7.0409	6.9383	7.1831	2.6835	2.5937	0.7174	0	10.6582
Ln(Firm's patent stock)	3.8823	3.8864	3.8727	2.8451	2.7595	0.7807	0	8.8135
Proportion of female senior executives	0.3034	0.2857	0.3286	0.1502	0.1466	0.0653	0	1
Firm-MSA								
Transition of colleagues at t-1 and t-2	0.6160	0.6283	0.6750	1.4576	1.2852	0.8591	0	13
Mobility of colleagues at t-1 and t-2	26.1101	26.1295	29.3217	49.2838	48.3776	19.9343	0	365
Employee								
Senior executive position	0.1586	0.1966	0.1224	0.3653	0.3237	0.0853	0	1
Doctoral degree	0.0178	0.0193	0.0154	0.1322	0.1256	0.0160	0	1
Founder experience	0.0151	0.0219	0.0064	0.1219	0.0994	0.0238	0	1
Ln(Employee's patent stock)	0.0789	0.1112	0.0334	0.3759	0.2726	0.1310	0	6.5497

Table 2 – Correlations

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)	Transition into entrepreneurship	1.000																	
(2)	Agglomeration level	0.015	1.000																
(3)	Regional proportion of female senior executives	0.001	0.074	1.000															
(4)	State biotech incentives	0.009	0.465	0.016	1.000														
(5)	Women in the state legislature	0.003	0.171	-0.003	0.318	1.000													
(6)	Cluster motion	-0.005	-0.410	-0.054	-0.185	-0.217	1.000												
(7)	Unemployment rate	-0.005	-0.304	-0.052	-0.037	-0.069	0.196	1.000											
(8)	Regional population	0.001	0.421	0.026	0.255	0.244	-0.210	0.089	1.000										
(9)	Proportion of female employees (region)	-0.003	0.017	-0.003	-0.093	-0.045	-0.117	-0.038	0.169	1.000									
(10)	Ln(Firm's employees)	-0.012	-0.124	0.040	-0.113	-0.041	0.050	0.082	0.074	0.046	1.000								
(11)	Ln(Firm's patent stock)	-0.007	-0.089	0.037	-0.039	-0.023	0.088	0.144	0.073	-0.043	0.787	1.000							
(12)	Proportion of female senior executives (firm)	-0.002	0.059	-0.011	0.012	0.045	-0.082	-0.079	0.032	0.128	0.256	0.088	1.000						
(13)	Transition of colleagues	0.019	0.176	0.078	0.097	0.068	-0.066	-0.071	0.126	0.033	0.297	0.295	0.154	1.000					
(14)	Mobility of colleagues	-0.002	0.169	-0.009	0.042	0.111	-0.091	-0.064	0.218	0.079	0.411	0.385	0.201	0.714	1.000				
(15)	Senior executive position	0.021	0.085	-0.009	0.063	0.019	-0.024	-0.014	0.041	-0.008	-0.245	-0.154	-0.058	-0.051	-0.072	1.000			
(16)	Doctoral degree	0.006	0.053	-0.016	0.071	0.038	-0.032	-0.017	0.008	-0.003	-0.029	-0.018	0.056	0.038	0.043	-0.007	1.000		
(17)	Founder experience	0.041	0.044	-0.007	0.029	0.009	-0.011	-0.023	-0.011	-0.022	-0.228	-0.143	-0.093	-0.048	-0.066	0.167	0.016	1.000	
(18)	Ln(Employee's patent stock)	0.022	0.053	-0.002	0.051	0.017	-0.004	-0.008	-0.024	-0.039	-0.110	-0.006	-0.065	-0.002	-0.016	0.148	0.042	0.122	1.000

Table 3 – Industry agglomeration and employee's transition into entrepreneurship

	DV: Employee's transition into biotech entrepreneurship in the same region							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agglomeration level	0.0009***	0.0007***	0.0018***	0.0028***	0.0009***	0.0006***	0.0020***	0.0032***
	(0.0001)	(0.0001)	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0004)	(0.0004)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
State biotech incentives	-0.0003*	-0.0002**	-0.0004**	-0.0006*				
	(0.0001)	(0.0001)	(0.0001)	(0.0002)				
	[0.0161]	[0.0069]	[0.0022]	[0.0108]				
Women in the state legislature	0.0008	0.0004	-0.0009	-0.0012				
	(0.0009)	(0.0004)	(0.0013)	(0.0016)				
	[0.3427]	[0.2245]	[0.4874]	[0.4592]				
Cluster motion	0.0000	0.0000	0.0000	0.0000*				
	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
	[0.1209]	[0.1441]	[0.1257]	[0.0148]				
Unemployment rate	0.0023	0.0021	0.0032	0.0037				
	(0.0031)	(0.0023)	(0.0039)	(0.0042)				
	[0.4668]	[0.3628]	[0.4081]	[0.3896]				
Regional population	-0.0000	-0.0000**	-0.0000*	-0.0000				
	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
	[0.0818]	[0.0035]	[0.0269]	[0.0975]				
Proportion of female employees (region)	-0.0007	-0.0003	-0.0007	-0.0003				
	(0.0006)	(0.0003)	(0.0008)	(0.0008)				
	[0.2680]	[0.3187]	[0.3682]	[0.6738]				
Ln(Firm employees)	0.0001**	0.0003**	0.0003***	0.0003**				
	(0.0000)	(0.0001)	(0.0001)	(0.0001)				
	[0.0059]	[0.0023]	[0.0004]	[0.0098]				
Ln(Firm's patent stock)	-0.0000*	0.0000	-0.0001	0.0003				
	(0.0000)	(0.0001)	(0.0001)	(0.0002)				
	[0.0238]	[0.6669]	[0.3100]	[0.1668]				
Proportion of female senior executives (firm)	0.0001	0.0005	0.0007	0.0005				
	(0.0002)	(0.0004)	(0.0008)	(0.0007)				
	[0.6122]	[0.1901]	[0.3830]	[0.4495]				
Transition of colleagues	0.0007***	0.0006***	0.0008***	0.0008***				
	(0.0001)	(0.0001)	(0.0002)	(0.0002)				
	[0.0000]	[0.0000]	[0.0003]	[0.0002]				
Mobility of colleagues	-0.0000***	-0.0000***	-0.0000**	-0.0000***				
	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
	[0.0000]	[0.0000]	[0.0020]	[0.0009]				
Senior executive position	0.0008***	0.0008***	-0.0013	-0.0012				
	(0.0001)	(0.0001)	(0.0007)	(0.0007)				
	[0.0000]	[0.0000]	[0.0779]	[0.0942]				
Doctoral degree	0.0008*	0.0006	-0.0040*	-0.0022				
	(0.0003)	(0.0003)	(0.0019)	(0.0012)				
	[0.0173]	[0.0697]	[0.0349]	[0.0666]				
Founder experience	0.0071***	0.0099***	0.0943***	0.1859***				
	(0.0015)	(0.0019)	(0.0173)	(0.0248)				
	[0.0000]	[0.0000]	[0.0000]	[0.0000]				
Ln(Employee's patent stock)	0.0009***	0.0008***	0.0016***	0.0014***				
	(0.0002)	(0.0002)	(0.0005)	(0.0004)				
	[0.0000]	[0.0000]	[0.0009]	[0.0003]				
Region fixed effects	Yes	No	No	Yes	Yes	No	No	Yes
Firm fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Employee fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,022,996	1,022,900	988,100	988,006	1,022,996	1,022,900	988,100	988,006
Log-likelihood	2,381,076.72	2,389,719.37	2,447,767.56	2,460,195.32	2,379,626.38	2,388,228.50	2,441,111.38	2,447,937.03
R2	0.0033	0.0205	0.2698	0.2883	0.0005	0.0177	0.2599	0.2704
DV mean	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006

Notes: The table shows the relationship between agglomeration level in the region and an employee's transition into entrepreneurship. Columns (1)-(4) are with control variables and columns (5)-(8) are without control variables. Columns (4) and (8) include the full set of fixed effects. The dependent variable is an employee's transition into entrepreneurship. *Agglomeration level* is measured as the number of biotechnology employees in the region, excluding employees from the focal employee's firm. Estimates are from Linear Probability Models. Across all columns, models show a positive association between agglomeration level and transition into entrepreneurship. Refer to the text for the descriptions of the models and for the detailed definitions of the control variables. Robust standard errors clustered at the region level are shown in parentheses. P-values correspond to two-tailed tests and are shown in brackets. *p<0.05; **p<0.01; ***p<0.001

Table 4 – Industry agglomeration and employee's transition into entrepreneurship by employee gender

	DV: Employee's transition into biotech entrepreneurship in the same region							
	(1) Male	(2) Female	(3) Male	(4) Female	(5) Male	(6) Female	(7) All	(8) All
Agglomeration level	0.0040***	0.0019**	0.0034***	0.0016***	0.0035***	0.0017***	0.0011***	0.0011***
	(0.0005)	(0.0006)	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0001)	(0.0001)
	[0.0000]	[0.0012]	[0.0000]	[0.0002]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Female employee							0.0001	0.0004
							(0.0001)	(0.0003)
							[0.1593]	[0.1968]
Agglomeration level X Female employee							-0.0005***	-0.0005***
							(0.0001)	(0.0001)
							[0.0005]	[0.0003]
Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	No	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employee fixed effects	Yes	Yes	Yes	Yes	No	No	No	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employee-region fixed effects	No	No	No	No	Yes	Yes	No	No
All interaction terms	No	No	No	No	No	No	No	Yes
N	584,376	403,450	584,376	403,450	579,681	400,642	1,022,900	1,022,900
Log likelihood	1,376,634.29	1,107,274.99	1,385,004.25	1,112,811.82	1,384,278.14	1,107,839.98	2,389,829.05	2,389,892.35
R2	0.2756	0.2714	0.2961	0.2911	0.3150	0.3057	0.0207	0.0209
DV mean	0.0007	0.0003	0.0007	0.0003	0.0007	0.0003	0.0007	0.0003

Notes: The table shows the relationship between agglomeration level in the region and employee's transition into entrepreneurship by gender. Columns (1)-(6) show split sample models by gender. Columns (6) and (7) use the full sample. The dependent variable is an employee's transition into entrepreneurship. *Agglomeration level* is measured as the number of biotechnology employees in the region, excluding employees from the focal employee's firm. Estimates are from Linear Probability Models. Across columns (1)-(6), models show positive association between agglomeration level and transition into entrepreneurship for both male and female employees. Coefficients of *Agglomeration level* are statistically different between male and female employees between columns (1) and (2), (3) and (4), and (5) and (6). Coefficients for the interaction term between *Agglomeration level* and *Female employee* in columns (7)-(8) are negative and significant, suggesting that agglomeration increases the likelihood of female employee's transitioning into entrepreneurship at a lower rate than male employees. Refer to the text for the descriptions of the models and for the detailed definitions of the control variables. Robust standard errors clustered at the region level are shown in parentheses and p-values are shown in brackets. *p<0.05; **p<0.01; ***p<0.001

Table 5 – IV analysis: industry agglomeration and employees transition into entrepreneurship by employee gender

	DV: Employee's transition into biotech entrepreneurship in the same region			
	(1) Male	(2) Female	(3) Male	(4) Female
Second stage				
Instrumented agglomeration level	0.0034***	0.0016***	0.0030***	0.0013*
	(0.0005)	(0.0005)	(0.0006)	(0.0005)
	[0.0000]	[0.0007]	[0.0000]	[0.0158]
First stage				
Employment of local firms in other regions	0.2354***	0.2268***	0.2228***	0.2147***
	(0.0008)	(0.0010)	(0.0008)	(0.0010)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Controls	No	No	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Employee fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	541,224	373,503	541,224	373,503
LM test statistic	60,195.51	39,070.91	61,668.50	39,721.33
F-statistic	86,509.93	52,328.58	73,711.32	45,606.43
Log likelihood	1,258,797.54	1,024,198.50	1,263,330.25	1,027,930.00
DV mean	0.0008	0.0003	0.0008	0.0003

Notes: The table shows the relationship between the instrumented agglomeration level in the region and employee's transition into entrepreneurship by gender. Columns (1) and (3) are male employees while columns (2) and (4) only include female employees. The dependent variable is an employee's transition into entrepreneurship. Estimates are from Two-Stage Least Squares regression. Across all columns, models show a positive association between the instrumented agglomeration level and employee's transition into entrepreneurship. Coefficients of *Instrumented agglomeration level* are statistically different between column (1) and (2) and between columns (3) and (4), suggesting that there is a gendered effect of agglomeration. Refer to the text for the descriptions of the models and for the detailed definitions of the control variables. Robust standard errors are shown in parentheses and p-values are shown in brackets. *p<0.05; **p<0.01; ***p<0.001

Table 6 – Split by proportional representation of senior executives that are women in the region

	DV: Employee's transition into biotech entrepreneurship in the same region			
	Low proportion		High proportion	
	(1) Male	(2) Female	(3) Male	(4) Female
Panel A. LPM				
Agglomeration level	0.0038***	0.0011	0.0020*	0.0017
	(0.0007)	(0.0006)	(0.0009)	(0.0011)
	[0.0000]	[0.0675]	[0.0205]	[0.1196]
Controls	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Employee fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	290,319	194,270	274,288	194,288
Log Likelihood	693,437.38	527,129.96	663,538.04	567,530.06
R2	0.3179	0.3329	0.3265	0.3524
DV Mean	0.0007	0.0004	0.0007	0.0003
Panel B. 2SLS				
Instrumented agglomeration level	0.0070***	0.0024	0.0021*	0.0020**
	(0.0015)	(0.0013)	(0.0009)	(0.0006)
	[0.0000]	[0.0704]	[0.0201]	[0.0019]
First stage				
Employment of local firms in other regions	0.1584***	0.1355***	0.2837***	0.2769***
	(0.0013)	(0.0017)	(0.0022)	(0.0023)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Controls	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Employee fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	261,937	175,594	259,859	183,953
LM test statistic	18,444.92	10949.5581	27360.7224	18055.8562
F-statistic	13,989.98	6732.9064	17184.6368	14493.6474
Log likelihood	626,218.53	479,464.17	632,815.09	540,981.35
DV mean	0.0008	0.0004	0.0007	0.0003

Notes: The table shows the relationship between agglomeration level in the region and employee's transition into entrepreneurship by gender and the moderating role of the regional proportion of female senior executives. Columns (1) and (2) are regions with low regional proportion of female senior executives and columns (3) and (4) are regions with high regional proportion of female senior executives. The dependent variable is an employee's transition into entrepreneurship. *Agglomeration level* is measured as the number of biotechnology employees in the region, excluding employees from the focal employee's firm. Estimates are from Linear Probability Models for Panel A and from Two-Stage Least Squares regression for Panel B. Refer to the text for the descriptions of the models and for the detailed definitions of the control variables. Robust standard errors clustered at the region level are shown in parentheses and p-values are shown in brackets. *p<0.05; **p<0.01; ***p<0.001

Table 7 – Alternative outcomes: Mobility and transition into non-biotech entrepreneurship

	DV: Move to another biotech firm in the same region			DV: Transition into non-biotech entrepreneurship in the same region		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female
Second stage						
Instrumented agglomeration level	0.0029**	0.0049***	0.0003	0.0011	0.0017	0.0004
	(0.0011)	(0.0014)	(0.0019)	(0.0007)	(0.0010)	(0.0010)
	[0.0082]	[0.0004]	[0.8700]	[0.0828]	[0.0807]	[0.7079]
First stage						
Employment of local firms in other regions	0.2234***	0.2235***	0.2157***	0.2225***	0.2228***	0.2147***
	(0.0006)	(0.0008)	(0.0010)	(0.0006)	(0.0008)	(0.0010)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Employee fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	995,212	546,804	377,778	984,408	541,224	373,503
LM test statistic	111,673.92	62,633.54	40,430.26	109,839.56	616,68.50	39,721.33
F-statistic	132,941.91	74,908.32	46,512.99	130,911.67	73,711.32	45,606.43
Log likelihood	142,9393.15	792,920.59	540,665.43	203,6019.12	1,078,046.65	819,053.06
DV mean	0.0045	0.0044	0.0047	0.0014	0.0016	0.0011

Notes: The table shows the relationship between agglomeration level in the region and employee's moving to another biotech firm in columns (1)-(3) and employee's transition into entrepreneurship by gender in columns (4)-(6). The dependent variable is an employee's moving to another biotechnology firm in the same region for columns (1)-(3). The dependent variable is an employee's transition into non-biotechnology entrepreneurship in the same region for columns (4)-(6). *Agglomeration level* is measured as the number of biotechnology employees in the region, excluding employees from the focal employee's firm. Estimates are from Linear Probability Models. Refer to the text for the descriptions of the models and for the detailed definitions of the control variables. Robust standard errors are shown in parentheses and p-values are shown in brackets. *p<0.05; **p<0.01; ***p<0.001

Table 8 – Mechanism analysis: Split by career experience years

	DV: Employee's transition into entrepreneurship			
	Career experience years ≤ 12		Career experience years > 12	
	(1)	(2)	(3)	(4)
	Male	Female	Male	Female
Second Stage				
Instrumented agglomeration level	0.0019*	0.0014	0.0046***	0.0019*
	(0.0010)	(0.0010)	(0.0009)	(0.0009)
	[0.0474]	[0.1598]	[0.0000]	[0.0304]
First stage				
Employment of local firms in other regions	0.1893***	0.1766***	0.2291***	0.2263***
	(0.0015)	(0.0016)	(0.0011)	(0.0015)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Controls	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Employee fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	237,716	187,855	292,906	177,911
LM test statistic	19,920.42	15,239.52	35,397.29	20,594.46
F-statistic	16,769.62	12,519.22	42,656.72	22,586.83
Log likelihood	653,463.57	573,794.69	639,713.51	462,943.12
DV mean	0.0004	0.0002	0.0011	0.0005

Notes: The table shows the relationship between agglomeration level in the region and employee's transition into biotechnology entrepreneurship and the moderating role of the career experience years of employees. Columns (1) and (2) are employees with career experience years less or equal to 12 years and columns (3) and (4) are employees with career experience years more than 12 years. The dependent variable is an employee's transition into entrepreneurship. *Agglomeration level* is measured as the number of biotechnology employees in the region, excluding employees from the focal employee's firm. Estimates are from Two-Stage Least Squares regression. Refer to the text for the descriptions of the models and for the detailed definitions of the control variables. Robust standard errors clustered at the region level are shown in parentheses and p-values are shown in brackets. *p<0.05; **p<0.01; ***p<0.001

Table 9 – Mechanism analysis: Analyzing whether agglomeration increases knowledge spillovers within regions

	DV: Number of within-region cites of biotech patents		DV: Normalized within-region cites of biotech patents	
	(1)	(2)	(3)	(4)
Agglomeration level	0.6067***	0.5401***	17.0957**	16.1234**
	(0.1536)	(0.1278)	(6.5349)	(4.9864)
	[0.0001]	[0.0000]	[0.0093]	[0.0013]
Cluster motion		-0.0000		-0.0013
		(0.0001)		(0.0034)
		[0.6822]		[0.6985]
Unemployment rate		0.6716		0.9005
		(2.5396)		(3.2815)
		[0.7914]		[0.7839]
State biotech incentive		0.3247**		0.7799
		(0.1208)		(0.5930)
		[0.0072]		[0.1893]
Women in the state legislature		0.3312		-0.1482
		(1.6176)		(2.9102)
		[0.8377]		[0.9594]
Region fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	3,149	3,149	5,200	5,200
Log likelihood	-19,892.89	-19,557.73	-10,591.59	-10,581.65
Chi squared	15.60	46.71	-	-
R2	-	-	0.9376	0.9379
DV mean	94.38	94.38	1.21	1.21

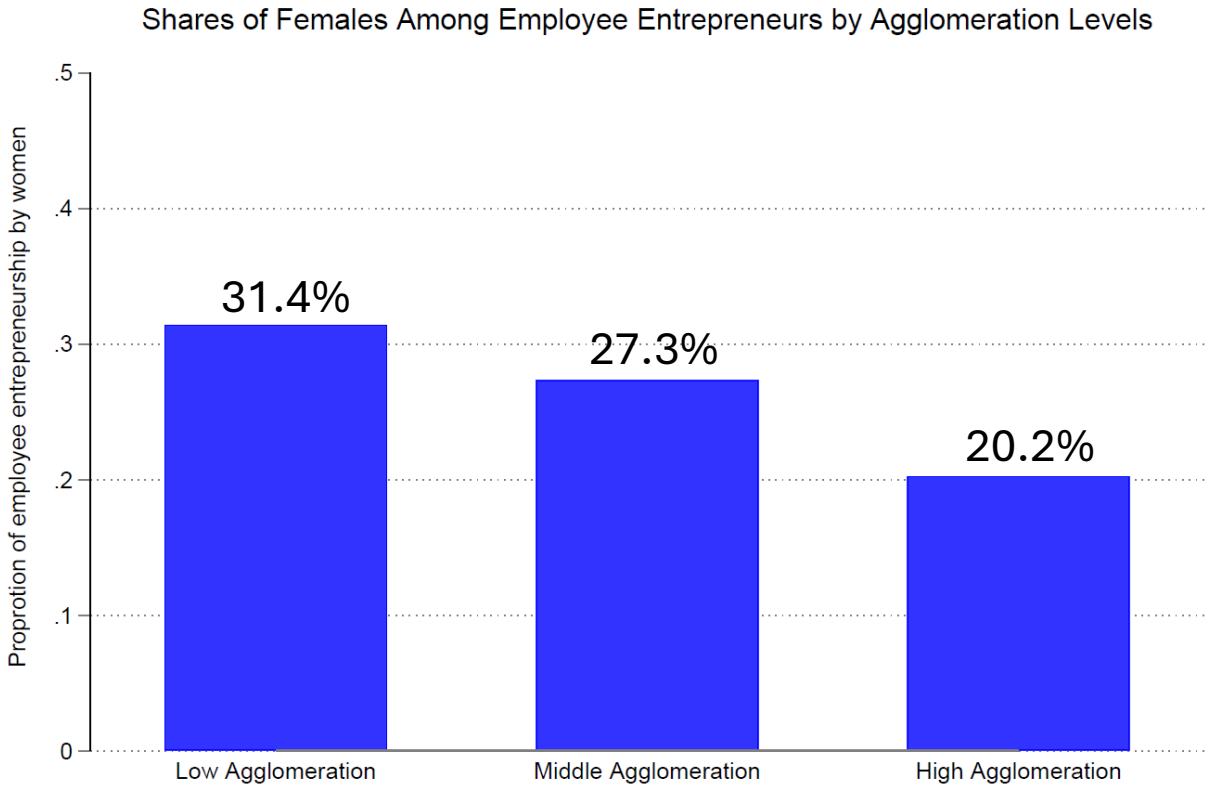
Notes: The table shows the relationship between agglomeration level in the region and number of same-region citations each year at the region level. The dependent variable is the number of within-region cites of biotech patents, excluding citations by same firms and patent examiners, in columns (1) and (2). The dependent variable in columns (3) and (4) are normalized within-region cites of biotech patents. *Agglomeration level* is measured as the number of biotechnology employees in the region. Estimates are from pseudo-maximum likelihood Poisson models in columns (1) and (2) and OLS regression models in columns (3) and (4). Refer to the text for the descriptions of the models and for the detailed definitions of the control variables. Robust standard errors clustered at the region level are shown in parentheses and p-values are shown in brackets. *p<0.05; **p<0.01; ***p<0.001

Table 10 – Alternative measures of agglomeration level

	DV: Employee's transition into biotech entrepreneurship in the same region			
	Explanatory variable: Natural log of the number of biotech employees in the region		Explanatory variable: Proportion of biotech employees in the region	
	(1) Male	(2) Female	(3) Male	(4) Female
Second stage				
Instrumented explanatory variable	0.0119***	0.0058**	0.3050***	0.1496**
	(0.0020)	(0.0021)	(0.0509)	(0.0546)
	[0.0000]	[0.0062]	[0.0000]	[0.0061]
First stage				
Employment of local firms in other regions	0.0672***	0.0564***	0.0026***	0.0022***
	(0.0012)	(0.0015)	(0.0000)	(0.0000)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Controls	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Employee fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	540,733	373,407	540,733	373,407
LM test statistic	3,808.55	1,811.10	8,531.06	4,322.57
F-statistic	3,228.02	1,479.76	6,704.27	3,398.67
Log likelihood	1,273,906.48	1,032,311.39	1,273,941.47	1,032,321.85
DV mean	0.0008	0.0003	0.0008	0.0003

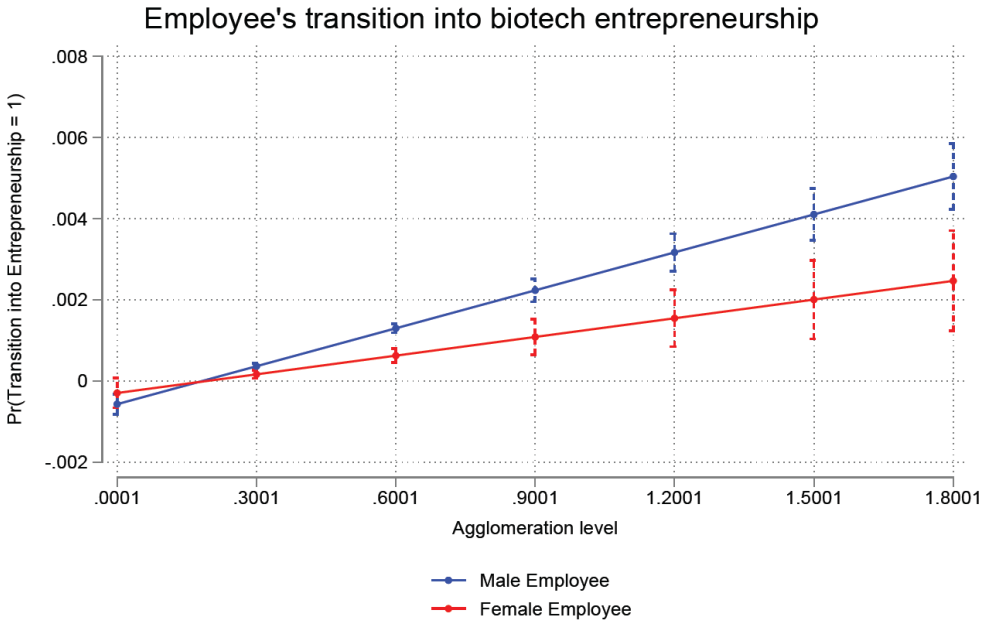
Notes: The table shows the relationship between agglomeration level in the region and employee's transition into entrepreneurship by gender with alternative measures of agglomeration level. The dependent variable is an employee's transition into entrepreneurship. *Agglomeration level* is measured as the natural log number of biotechnology employees in the region, excluding employees from the focal employee's firm, for columns (1) and (2) and measured as the proportion of U.S. biotechnology employees in the region for columns (3) and (4). Estimates are from Linear Probability Models. Refer to the text for the descriptions of the models and for the detailed definitions of the control variables. Robust standard errors are shown in parentheses and p-values are shown in brackets. *p<0.05; **p<0.01; ***p<0.001

Figure 1: Shares of female employees among employee entrepreneurs by regional agglomeration levels



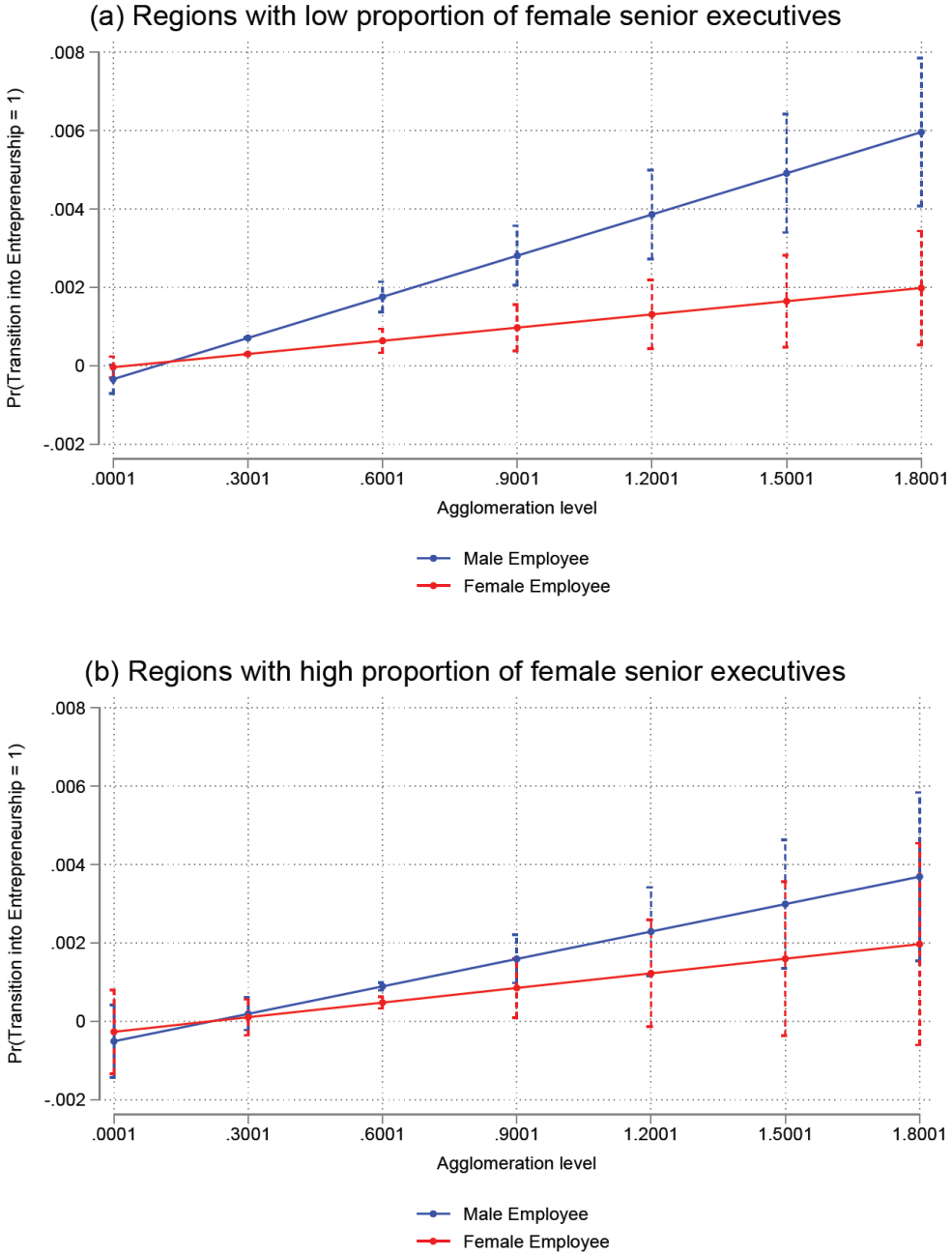
Notes: The figure above shows the proportion of female employee entrepreneurs in regions with low, middle, and high levels of agglomeration. Agglomeration level is partitioned into three terciles. The figure shows that the proportion of female employe entrepreneurs is highest in regions with low agglomeration (e.g., 31.4%) and lowest in regions with high agglomeration (e.g., 20.2%). The figure provides descriptive evidence suggesting that employee entrepreneurship compose of lower female employee participation in regions with greater levels of agglomeration.

Figure 2: Employee's transition into entrepreneurship by employee gender



Notes: The figure above is based on models in columns (3) and (4) from Table 4 and shows the predicted marginal effects of industry agglomeration for male employees and female employees. The figure shows that industry agglomeration has a positive association with both male and female employee's transition into entrepreneurship. However, slopes are statistically different from each other in most ranges, suggesting that industry agglomeration increases a female employee's transition into entrepreneurship at a lower rate.

Figure 3: Employee's transition into entrepreneurship by employee gender and regional proportion of female senior executives



Notes: Plot (a) is based on models in Table 6 columns (1) and (2) and plot (b) is based on models in Table 6 columns (3) and (4). All plots are based on linear probability models. Plot (a) documents the predicted marginal effects of industry agglomeration in regions with low proportion of female senior executives. Plot (b) shows the predicted marginal effects of industry agglomeration in regions with high proportion of female senior executives. Slopes are statistically different from each other in regions with low proportion of female senior executives, but not in regions with high proportion of female senior executives.

Chapter 3: Knowledge Spillovers Across Regions

ABSTRACT

This study examines how knowledge spillovers drive the relationship between agglomeration and firm innovation by leveraging a unique research design: a proximate industry peer's outbound relocation. We expect a firm's innovation performance to decrease because a proximate peer's relocation disrupts knowledge spillover gains. We evaluate this with data on nanotechnology firms. Contrary to our expectation, we find that a proximate peer's relocation increases a firm's innovation performance. Taking an abductive approach, we investigate the nature of this impact and find that a proximate peer's relocation creates an inter-region knowledge conduit, allowing firms increased access to knowledge from the relocated peer's new region. By showing that exit from a cluster can enhance cluster under certain circumstances, we provide novel and nuanced insights innovation into cluster dynamics.

3.1 INTRODUCTION

Scholars in strategy have long examined how geographic co-location with industry peers, a phenomenon known as "agglomeration" or "clustering," influences firm innovation. Abundant empirical evidence suggests that agglomeration increases the innovation performance of firms (e.g., Bell, 2005; Folta, Cooper & Baik, 2006; Gilbert, McDougall, & Audretsch, 2008; McCann & Folta, 2011; Delgado, Porter, & Stern, 2014; Funk, 2014; Mathias, McCann, & Whitman, 2021). The main mechanism that has been invoked for driving this relationship is knowledge spillovers between industry peers. Research finds that agglomeration increases the likelihood of alliances, employee mobility, and serendipitous encounters between firms and their employees (Saxenian, 1994; Almeida & Kogut, 1999; Reuer & Lahiri, 2014). Through these interactions, firms gain valuable knowledge from their peers, which promotes innovation.

Although extant research hypothesizes that knowledge spillovers are the driving force in the relationship between agglomeration and firm innovation, there are limitations of existing empirical approaches for isolating this mechanism. Much prior work in the literature (e.g., Feldman & Audretsch, 1999; Folta, Cooper & Baik, 2006; Gilbert, McDougall, & Audretsch, 2008; McCann & Folta, 2011) uses an across-region variation to estimate the impact of agglomeration on firm innovation (i.e., comparing firms in more agglomerated regions to those in less agglomerated regions). However, because agglomeration likely correlates with other regional differences (e.g., culture or state policies), the observed association between knowledge spillovers and innovation may be spurious. Recognizing this, some studies consider within-region variation, typically using region-fixed effects. In these studies, coefficient estimates capture how changes in innovation correlate with changes in regional agglomeration over time (e.g., Baptista & Swann, 1998; Delgado, Porter & Stern; 2014; Funk, 2014). However, because theories of agglomeration focus on increasing returns (Marshall, 1920; Krugman, 1991; Porter, 1998), if these theories are correct, then regions that grow the most will have the greatest initial levels of agglomeration. As a result, agglomeration growth will correlate with initial agglomeration levels, which raises the same concern as studies that focus on across-region variation. Hence, for testing this theory, within-region research designs provide little benefit compared to across-region research designs.

To address this challenge, we propose a novel research design wherein we examine how the relocation of geographically proximate industry peer firms to different regions affects firm innovation. This research design is less susceptible to the aforementioned concerns about increasing returns because it captures de-agglomerating. In addition, by examining the impact on companies that do not make the decision to move, we mitigate endogeneity concerns.

We apply this research design in the context of the U.S. nanotechnology industry from 1990 to 2008. Based on findings from prior literature (e.g., Baptista & Swann, 1998; Funk, 2014), our expectation is that a firm's innovation performance will decrease following a proximate industry peer's outbound relocation. Although we confirm existing findings when we employ the previously used research designs, we find that a firm's innovation performance surprisingly *increases* after a proximate industry peer relocates to a different region.

Because this result is contrary to our expectations and prior research, we undertake a number of *ex-post* analyses to better understand what might lead to this finding. In particular, we employ an abductive approach, in which we start from our counter-intuitive finding and identify plausible theoretical explanations to guide future research (King, Goldfarb, & Simcoe, 2020; Seo, Luo & Kaul, 2021).

We propose that knowledge spillovers continue between industry peers post relocation. Therefore, a proximate industry peer's outbound relocation creates an inter-region knowledge conduit between the firm and the relocating industry peer's new region - under certain conditions that we identify. Through this channel, firms absorb geographically distant knowledge, which they recombine with their knowledge stock.

3.2 BACKGROUND

Geographic agglomeration of firms creates localized externalities. Compared to firms that are relatively isolated, firms within agglomerations enjoy greater access to knowledge spillovers, specialized labor, specialized suppliers, as well as specialized institutions and regional social networks (Marshall, 1920; Porter, 1990; Saxenian, 1994). As co-location with industry peers

enable sharing of these resources, agglomerated firms are more efficient due to increasing returns to scale (Krugman, 1991). Accordingly, while performance effects may vary with the characteristics of the firm (Shaver & Flyer, 2000; Pe'er & Keil, 2013; Mathias, McCann, & Whitman, 2021), research in strategy finds that agglomerated firms generally register greater performance than more isolated ones (e.g., Decarolis & Deed, 1999; Folta, Cooper & Baik, 2006; Gilbert, McDougall, & Audretsch, 2008).

Research also shows that agglomeration externalities influence innovation. Geographic co-location of industry peers creates a fertile environment for knowledge exchange. Increased proximity to industry peers fosters chances of serendipitous interactions (Saxenian, 1994; Andrews, 2019; Roche, 2020), employee mobility (Almeida & Kogut, 1999), and R&D alliance formations (Reuer & Lahiri, 2014; McCann, Reuer & Lahiri, 2016). Because face-to-face interactions assist the transmission of tacit knowledge (Daft & Lengel, 1986; Von Hippel, 1994), geographic proximity increases formal and informal knowledge exchanges between firms. In other words, proximity to industry peers augments both the possibility and feasibility of knowledge spillovers. And because of greater access to knowledge spillovers, firms in agglomerated regions have higher innovation performance compared to firms in more isolated regions (e.g., Audretsch & Feldman, 1996; Folta, Cooper & Baik, 2006; Gilbert, McDougall, & Audretsch, 2008; Funk, 2014).

Despite the long tradition of research documenting positive associations between agglomeration and innovation, empirically isolating knowledge spillovers as the causal mechanism is challenging. To examine the impact of agglomeration on firm innovation, many studies employ research designs based on across-region variation (e.g., Feldman & Audretsch,

1996; Folta, Cooper & Baik, 2006; Gilbert, McDougall, & Audretsch, 2008; McCann & Folta, 2011). In this work, the analyses compare the innovation outcomes of firms in regions with varying levels of agglomeration. The findings typically demonstrate that firms in regions with greater agglomeration have better innovation outcomes, which is consistent with the hypothesis that knowledge spillovers from industry peers promote innovation.

Nevertheless, regions may differ in unmeasured ways that correlate with agglomeration, including cultural factors and state-level policies (Saxenian, 1994; Fallick, Fleischman & Rebitzer, 2006). This raises concerns that the documented relationship between agglomeration and innovation may be spurious. For example, Fallick and colleagues (2006) find that the unenforceability of non-compete agreements in California under state law enhances mobility and agglomeration externalities in Californian I.T. clusters. As is evident with this example, across-region designs will confound such factors unless they are explicitly controlled for in the empirical analysis.

Acknowledging this limitation, some studies employ within-region research designs, often by estimating models with region- or firm- fixed effects (e.g., Baptista & Swann, 1998; Delgado, Porter & Stern, 2014; Funk, 2014). By relying on variation in agglomeration within regions over time, this approach controls for time-invariant unobservable region characteristics, which generally mitigates the concern of across-region research designs. Nevertheless, this approach is still susceptible to concerns similar to those facing across-region research designs. Agglomeration theories propose that there are increasing returns to scale; larger clusters attract more firms and create more de novo firms (Strauss-Kahn & Vives, 2009; Delgado, Porter, & Stern, 2010). As a result, they grow at a faster rate compared to smaller clusters. This means that

cluster growth will correlate with cluster size. If growth correlates with size, then the within-region research design exhibits the same concern as the across-region research design because growth will correlate with any region characteristic that would correlate with clustering. Therefore, in the context of testing agglomeration theories, standard within-region research designs do not provide the same identification benefits that they do in many other settings.

3.2.1 A Novel Research Design to Examine Agglomeration and Innovation

We propose a novel research design that mitigates the concerns of across- and within-region research designs for testing how agglomeration affects innovation. We examine changes in firms' innovation following the geographic relocation of proximate industry peers outside the region. The logic behind this research design is that if spillovers are localized, a firm will receive fewer knowledge spillovers when a proximate industry peer relocates to another region.

Compared to the standard within-region approach (i.e., region- or firm- fixed effects), there are several advantages to this research design. First, because the outward relocation of a peer is an example of de-agglomerating, it is not subject to the same concerns facing other within-region research designs. Namely, agglomeration theories do not address outbound firm relocations. In other words, while the theory predicts that agglomerated regions will become more concentrated over time, it does not specify a relationship between the level of agglomeration and relocation. Hence, firm relocation is less susceptible to the increasing returns concern that the within-region research design faces. Second, we examine the innovation outcomes of firms that do not move. Because these firms are not the decision makers with respect to relocation (i.e., it is the relocating firm that makes this decision), this helps to mitigate

endogeneity concerns. Nevertheless, we acknowledge relocating is a choice of the firm that decides to relocate. For this reason, to validate this approach, we need to assume that the characteristics of firms that remain in a region do not cause their peers to relocate.[13]

3.3 METHODS

3.3.1 Empirical Context

We implement this research design using data on U.S.-based nanotechnology R&D firms from 1990 to 2008. This empirical setting is particularly well suited for exploring our arguments for three reasons. First, innovation is critical to the success of nanotechnology firms, and businesses in the industry tend to rely heavily on patents to protect their ideas (Zucker et al., 2007). Second, the nanotechnology industry is well recognized as a context where innovation rests on knowledge sharing and collaboration (Thursby & Thursby, 2011; Funk, 2014). Hence, potential opportunities for interactions between inventors from different firms are likely to influence knowledge spillovers and innovation. Third, nanotechnology firms are locally clustered across diverse geographic regions (Zucker & Darby, 2005), which provides us with variation we can use to study the effect of relocations of proximate industry peers.

3.3.2 Data and Sample

Our empirical analyses draw on multiple data sources. First, data on nanotechnology R&D firms come from a variety of directories and news outlets. Major sources include company directories

[13] In Appendix Table A, we report analyses that examine the likelihood of a firm's outbound relocation as a function of proximate industry peers' cumulative innovation. We do not find statistically significant results.

found in the Lux Nanotech Report (2001, 2004, 2006, 2008), the Nanotechnology Opportunity Report (2002), the Nano VIP Database (2005), Understanding Nano, BioScan, and Factiva.

Second, we collect data on patents, inventors, and citations from the U.S. Patent and Trademark Office (USPTO) PatentsView database. Patent data is widely used by researchers as a proxy for innovation. To identify relevant patents, we match our sample nanotechnology firms to patent assignee names provided by the USPTO.

Third, we identify nanotechnology patents with data from Nanobank, which is an online library of patents and publications in the nanotechnology field. Nanobank uses various sources and methods to distinguish nanotechnology patents from non-nanotechnology patents (Zucker, Darby & Fong, 2011) and has been used in prior research on the nanotechnology industry (e.g., Zucker et al., 2007; Jung & Lee, 2016).

Fourth, from the SDC Platinum Database, we collect data on alliances. Following Rothaermel & Thursby (2007), we collect all alliances by firms in 114 primary SIC industry codes that are identified as having nanotechnology firms. We identify all alliances categorized as "Research and Development Services" and "Joint Ventures" formed between firms in our sample. In total, we find 370 alliances during our study period.

Lastly, we draw upon Scopus for nanotechnology publication data. We search through authoritative journals in nanotechnology research and match employers of authors of publications to our list of nanotechnology firm names. Our final sample comprises 451 U.S.-based nanotechnology firms engaged in nanotechnology R&D between 1990 and 2008. The panel consists of 6,159 firm-year observations.

3.3.3 Variables

Dependent Variable. We measure innovation using nanotechnology patent-based indicators. Patents are commonly used to measure a firm's innovativeness (e.g., Delgado, Porter, & Stern, 2014; Funk, 2014). However, patents vary widely in their quality, so the simple count of patents assigned to a firm at a particular point in time may not accurately represent innovation performance. To account for this limitation, we operationalize innovation performance with *Patent Impact*, which is the citation-weighted count of patents (e.g., Kotha, Zheng, & George, 2011; Funk, 2014). We measure the sum of the number of citations received by nanotechnology patents applied for by firm *i* at times *t+1* and *t+2*, as the ideas underpinning a patent are generally conceived one or two years before the application is filed. Each patent is weighted by the number of citations that it received from future patents in the first five years after the patent was issued, which is the window within which most patents receive the majority of their lifetime citations (Jaffe, Trajtenberg, & Henderson, 1993; Jaffe & Trajtenberg, 2002).

Independent Variables. To compute *Proximate Industry Peer's Relocation*, we take the following steps. First, we define regions as Core-Based Statistical Areas (CBSA), which is a common approach in prior research on the U.S. context (e.g., Marquis et al., 2013; Dimitriadis et al., 2017). Second, we identify firms that relocate their headquarters and main R&D centers from one CBSA to another. In our data, we observe 69 relocations. 14.2 percent of firms relocate at least once over the course of 19 years, and five firms relocate twice. Third, to identify industry peers that are geographically proximate to the relocating firm, we compute geodesic distances between the latitude/longitude coordinates of each firm's headquarters location. Then for each outbound relocation, we identify a set of firms that are affected by the relocation using geodesic distances from the relocating firm. Because there is a significant decrease in knowledge

spillovers between organizational entities over distance (e.g., Belenzon & Schankerman, 2013; Singh & Marx, 2013; Sohn, 2021), not all firms in the region are likely to be affected by an industry peer's relocation. Firms are most likely to be influenced by knowledge from proximate industry peers when they are located within a 10-mile radius (Kolympiris, Kalaitzandonakes, & Miller, 2011). Hence, we define firms to be affected by relocations if they are located less than or equal to 10 miles from the relocating industry peer.[14]

Figure 1 illustrates the difference between proximate and non-proximate industry peers within a CBSA. Firms that are marked with small circles are located within the 10-mile radius of Nanodynamics (marked with a triangle), which is the boundary drawn by the large circle. In our study, these four firms are proximate industry peers of Nanodynamics, while other firms in the region (marked with squares) are non-proximate industry peers. Taken together, *Proximate Industry Peer's Relocation* takes a value of 1 from *t* to *t+2* if a proximate industry peer relocates to another CBSA at year *t*, and 0 if otherwise. To capture the immediate impact of the loss of knowledge spillover benefits on a firm's innovation performance, we limit the effect of outbound relocation to three years from the year of the move.[15]

Insert Figure 1 about here

Control Variables. To control for alternative mechanisms affecting a firm's innovation performance, we include the following control variables in our models. We control for *ln*(*Nano patent stock)*, defined as the natural log of the cumulative number of granted nanotechnology

[14] We examine different proximate distance ranges (e.g., within 5-miles, 15-miles, and 20-miles). We find that as distance ranges increases, the effect size decreases and its p-value increases. See Appendix Table B.

[15] We examine several different year ranges (e.g., two years, four years, and five years) for the duration of the impact of an industry peer's outbound relocation. Results are similar with different year ranges. See Appendix Table C.

patents applied for by inventors at firm *i*'s headquarters location, depreciating by 15 percent annually. Similarly, *ln(Nano paper stock)* is the natural log of the cumulative number of nanotechnology papers published by the inventors at the headquarters location, depreciating by 15 percent annually. Both *ln(Nano patent stock)* and *ln(Nano paper stock)* control for heterogeneity in the innovative capabilities of the firm. We also control for *ln(Non-nano patent stock)*, depreciating by 15 percent annually, to account for the size of the firm's non-nanotechnology portfolio, as nanotechnology inventors may also draw distant knowledge from their firm's non-nanotechnology portfolio (Zucker et al., 2007).

Firms can also source external knowledge from other firms through R&D alliances, which can subsequently enhance innovation (Ahuja, 2000; Almeida, Song, & Grant, 2002). Hence, the *Number of alliances* accounts for all R&D alliances that a firm has with nanotechnology firms in the five-year window previous to year *t*. Additionally, we build on Corredoira & Rosenkopf (2010)'s coding of inventor mobility and code the movement of nanotechnology inventors between nanotechnology R&D firms. Mobility of experienced inventors out of the firm can reduce the firm's innovative capabilities, while inward mobility of experienced inventors can result in an increase in capabilities as well as knowledge spillovers from the inventor's previous firm. *Inventor mobility out* controls for the number of experienced nanotechnology inventors leaving firm *i* at year *t*, while *Inventor mobility in* controls for the number of experienced nanotechnology inventors joining firm *i* at year *t*.[16]

To account for the geographic concentration of nanotechnology activity in the region, we control for *ln(Region's nano employment level),* which is the natural log of the number of

[16] See Appendix D for detailed description on how inventor mobility was coded.

nanotechnology patent inventors per CBSA-year. Finally, we address the possibility that regional economic conditions influence the likelihood of firm relocations and innovation. To do so, we control for local economic conditions with *Region's unemployment rate*, with data from the Local Area Unemployment Statistics program of the U.S. Bureau of Labor Statistics.

3.3.4 Estimation Strategy

We have panel data on nanotechnology firms, and our dependent variable is a count. As a result, we use pseudo-maximum likelihood Poisson models. Prior studies that examine firm innovation and knowledge flows also use this form of the Poisson model (e.g., Funk, 2014; Aggarwal, Hsu & Wu, 2020), as pseudo-maximum likelihood Poisson standard errors are robust to overdispersion. The models we estimate include firm- and year- fixed effects and take the following form:

$$E[y_{it}|x_{it}, \alpha_i] = \alpha_i e^{x'_{it}\beta}, t = 1, 2, \ldots, T, i = 1, 2, \ldots, N,$$

where y_{it} is the dependent variable for firm i at time t, x_{it} are independent and control variables, β are the coefficients, and α_i are time-invariant firm fixed effects. We report robust standard errors clustered at the zip code tabulation area level.[17] Together with the set of controls, our models rely on within-firm variation to estimate the impact of a peer's relocation on a firm's innovation performance.

[17] We clustered standard errors at the zip code area level and not at the CBSA level because of how proximate firms are assigned. Within a CBSA, there are both firms that are proximate to the relocating industry peer (i.e., within 10 miles) and firms that are not proximate to the relocating industry peer (i.e., over 10 miles). However, within a zip code area, all firms are either proximate to the relocating industry peer or not. Regardless, we try clustering standard errors at both CBSA level, and 3-digit zip code level. Results (available upon request) are nearly identical.

An assumption of our estimation strategy is that the innovation performance of proximate industry peers does not predict a focal firm's decision to relocate. To provide empirical support for this assumption, in Appendix Table A, we examine the likelihood of a firm deciding to relocate out of the region as a function of the cumulative innovation performance of proximate industry peers in the region in the prior year. These analyses do not reveal any systematic patterns associated with a firm's outbound relocation, supporting our assumption.

3.4 ANALYSES AND FINDINGS

Table 1 provides descriptive statistics. There are 962 firm-year observations associated with a proximate industry peer's outbound relocation, which corresponds to 15.6 percent of all observations. 185 firms out of 451 firms (41.02%) experienced a proximate industry peer's relocation at least once. Columns 5 and 6 include standard deviations of variables across and within firms to show that there is sufficient within-firm variation over the years. Table 2 shows a correlation matrix for key variables.

Insert Tables 1 and 2 about here

We first replicate previous findings from studies that use within-firm research designs to ensure that our data are consistent with prior research. In Table 3 M1, we measure the agglomeration level, *Region's nano industry size,* with the number of nanotechnology firms in the region. We find that an increase in the number of nanotechnology firms in a region increases

a firm's innovation performance (β = 0.042, p = 0.001). This result is consistent with prior studies.[18]

3.4.1 Main Analyses—Impact of a Proximate Industry Peer's Relocation

Table 3 M2 and M3 present our main models, which examine the effect of a proximate industry peer's outbound relocation on firm innovation. M2 is our fully specified regression model. We expect that a firm's innovation decreases when a proximate industry peer relocates to another region because outbound relocation represents de-agglomeration. However, contrary to our expectation, we do not find a negative association between a proximate industry peer's relocation and innovation performance. Rather, M2 shows that innovation increases when a proximate industry peer relocates to another region (β = 0.391, p = 0.010). The effect size is statistically and economically significant. The marginal effect of relocation on *Patent impact* is 11.58, which is about 1/9th of the within-firm standard deviation. Because *Patent impact* is measured with citation-weighted patents, ceteris paribus, a firm's citation-weighted patents increase by 11.58 following a proximate peer's relocation. In M3, we investigate whether this unexpected result is due to collinearity by running a simple regression of *Patent impact* on *Proximate industry peer's relocation* with no covariates. Collinearity between the main explanatory variable and control variables can increase the magnitude of the coefficient of the explanatory variable in the opposite direction (Kalnins, 2018). We again find a positive coefficient estimate for *Proximate industry peer's relocation* with similar magnitude and p-value to those of M2 (β = 0.346, p = 0.032).

[18] We also investigate the relationship between agglomeration and firm innovation using an across-region research design. We find that firms located in more agglomerated regions have higher innovation performance than firms in less agglomerated regions, consistent with prior research. See Appendix Table E for more details.

Results of M3 suggest that collinearity is not the main reason underlying the unexpected positive effect of relocation found in M2.

Insert Table 3 about here

3.4.2 Examining the Nature of the Unexpected Effect

To better understand the unexpected positive impact of outbound relocations, we conducted several additional analyses. In Table 4 M4, we check whether geographic proximity to the relocating peer is associated with the positive impact of relocation. If non-proximate firms (i.e., more than 10 miles away) are not affected by relocations, then the proximity to the relocating peer is important for the impact to materialize. If proximity matters, then knowledge spillovers may still be driving the unexpected impact, but in the opposite direction of our prediction. In M4, in addition to our explanatory variable *Proximate industry peer's relocation,* we add a variable, *Industry peer's relocation—more than 10 miles away*, which identifies firms in the same region that are more than 10 miles from the relocating industry peer when the relocation occurs. Hence, the omitted category in this model is firms in other regions that are not experiencing relocations. We find that outbound relocations that occur more than 10 miles away have no significant impact on firms (β = -0.081, p= 0.462), while relocations that occur within 10 miles have a positive impact (β = 0.387, p = 0.011). Because spillovers are more likely between proximate peers, the results suggest that a firm's knowledge exchange with the relocating industry peer may be the driver of this unexpected impact.[19]

[19] Similarly, in Appendix Table B, we find that the effect size of relocation coefficients decreases, and its p-value increases as distance range of proximity increases for the relocation variable (e.g., within 5-miles, 15-miles, and 20-miles).

In Table 4 M5, we distinguish relocating industry peers by whether they are important sources of nanotechnology knowledge in the region (i.e., industry peers with high innovativeness) or not (i.e., industry peers with low innovativeness). We speculate that relocations of industry peers with low innovativeness could increase a firm's innovation performance because such firms may produce unoriginal, imitative, or relatively trivial knowledge. The removal of an industry peer with low innovativeness would reduce the spillover of insignificant knowledge that could inhibit firms from developing innovative products. This could explain the increase in innovation performance following the relocation. We distinguish relocating industry peers as peers with high or low innovativeness by their contribution to their region's innovativeness in nanotechnology.[20] M5 shows that outbound relocations of both industry peers with high and low innovativeness are associated with innovation (high innovativeness peer: $\beta = 0.305$, $p = 0.016$; low innovativeness peer: $\beta = 0.334$, $p = 0.049$). This suggests that the positive impact is not driven just by the removal of knowledge from less innovative industry peers from the region.

In Table 4 M6 and M7, we use alternative definitions of relocations. In M6, we limit relocations to long-distance relocations (i.e., moving more than 60 miles from its original location). Our rationale behind this analysis is that a short distance movement by the relocated peer may not reduce the communication between the relocated peer and the firm, as the change in physical distance is relatively low. Consequently, relocation may not reduce knowledge

[20]We measure each firm's contribution to region's innovativeness as the proportion of firm's cumulative stock of nanotechnology patents to the region's cumulative stock of nanotechnology patents at year *t*, with patent stocks depreciating by 15 percent annually. If a firm's contribution during the relocation year exceeds the median value of contribution of all firms throughout the 19 years, then the relocating industry peer is coded as an industry peer with high innovativeness. If a firm contributes less than the median, then the relocating industry peer is coded as an industry peer with low innovativeness. By this procedure, 33 relocations are coded as relocations by peers with low innovativeness, while 36 relocations are coded as relocations by peers with high innovativeness.

spillovers from the relocated peer. In our data, 29 out of 69 (42.0%) outbound relocations involved the movement of less than 60 miles. M6 shows that the result is similar to prior analyses even when relocations of less than 60 miles are not coded as relocations. Additionally, the size of the marginal effect increases from 11.58 citation-weighted patents (Table 3 M2) to 17.17 ($\beta = 0.580$, $p = 0.000$), which is about $1/6^{th}$ of within firm standard deviation, when only long-distance relocations are coded as outbound relocations. In M7, we exclude relocations that move between the San Francisco-Oakland-Fremont CBSA and the San Jose-Sunnyvale-Santa Clara CBSA. These two adjacent CBSAs constitute the Bay Area and Silicon Valley and are centers of nanotechnology research in the U.S. Our exclusion of these relocations is based on our speculation that the positive impact of relocations may be driven by innovative firms in the two regions that are affected by firms moving between the two CBSAs, which constitute 26.1 percent of all relocations. Results in M7, however, show that outbound relocations of proximate industry peers increase the innovation performance of firms even when relocations between the Bay Area and the Silicon Valley are not coded as relocations ($\beta = 0.549$, $p = 0.000$).

Taken together, these additional analyses consistently show that a proximate industry peer's outbound relocation increases a firm's innovation performance. In the next section, we explore potential theoretical mechanisms for why the outbound relocation of a proximate industry peer positively impacts firm innovation.

Insert Table 4 about here

3.4.3 Plausible Theoretical Explanations

We consider two plausible theoretical explanations for our findings. The first is that when firms move, some of their employees choose not to follow the company and end up working for industry peers in the same region. The second is that the relocation of a firm from the region creates an interregional knowledge conduit because of existing ties between employees in different companies. We examine the evidence for each of these explanations.

Employee Mobility When firms make the decision to relocate to another region, employees of relocating firms do not always move with their firm (Shaver, 2018). Relocations not only affect the working life of employees but also have a significant impact on the non-working life. Hence, in deciding whether to follow their firm to a new region, employees consider various dimensions of the move, such as their attachment to the current community, attachment to the firm, the attraction of the new community, the availability of alternative job opportunities, and family reasons (Feldman & Bolino, 1998; Sagie, Krausz, & Weinstain, 2001). For example, one nanotechnology patent inventor we interviewed tells us that as soon as their West coast-based firm announced that it was relocating to the East coast, they decided to join another firm in the region because he/she preferred to stay on the West coast for family and culture. Because not all employees assess the value of following the firm higher than the value of staying in the region, relocations often result in employees leaving and joining other local firms.

We posit that hiring employees from relocating industry peers may benefit the hiring firm's innovation performance by allowing them to leverage newly hired employees' knowledge of their former employer and their capabilities. When employees join other firms, they carry the knowledge of their former employer to their new employer (Almeida & Kogut, 1999; Rosenkopf

& Almedia, 2003; Agarwal et al., 2004; Agarwal, Ganco, & Ziedonis, 2009). This knowledge not only takes the form of proprietary knowledge but also may be in the form of trade secrets or key routines that are not easily transferrable through informal encounters. In addition to providing access to knowledge, newly hired employees offer new capabilities and expertise that can complement the hiring firm's existing employees (Rao & Drazin, 2002). Hence, the knowledge and capabilities of newly hired employees can reinforce and improve existing innovation processes of hiring firms. Indeed, empirical evidence shows when firms hire employees from their industry peers, their innovation (e.g., Rao & Drazin, 2002) and firm performance (e.g., Somaya & Williamson, 2008) increase, and they are also more likely to engage in a new technology trajectory (e.g., Tzabbar, 2009). Taken together, these factors may explain why we observe the positive impact on firm innovation performance when a proximate industry peer relocates to another region.

We investigate the employee mobility explanation by directly identifying cases of inventor mobility between the relocated peer and other proximate firms in the region around the time of relocation. If mobility is driving the positive impact of the outbound relocation, then firms that do not have inventors joining from the relocated peer would not experience an increase in innovation performance. To examine this, we utilize our coding of inventor mobility between all firms in our sample and filter cases that occurred between firms in the same region and within 10 miles of distance. Among those mobility cases between proximate industry peers, we search for those that are likely to be stimulated by the firm's relocation. If inventors leave their firm around the time of relocation (i.e., two years before and after the relocation), they likely do so

because they do not want to follow their firm.[21] Hence, these mobility cases are coded as relocation-driven mobility.[22]

Table 5 presents our models investigating the employee mobility mechanism. We split samples in M8 and M9 by whether firms affected by a peer's relocation hire inventors from the relocating peer or not. In M8, we examine the impact of relocation just on firms that hired inventors. The comparison group in M8 is all firms that do not experience outbound relocations and excludes firms that do not hire inventors from the relocating industry peer. Similarly, in M9, we assess the impact of relocation just on firms that do not hire inventors from the relocating peer. The full sample is utilized in M10. Contrary to the employee mobility mechanism, results in M8 and M10 show non-significant effects of relocation on firms that hire relocated industry peer's inventors (M8: β = -0.100, p = 0.715; M10: β = -0.041, p = 0.849). By contrast, M9 and M10 show that firms that do not hire inventors from the relocating firm experience an increase in innovation performance (M9: β = 0.378, p = 0.017; M10: β = 0.404, p = 0.009). Overall, we do not find evidence that supports the employee mobility mechanism.

Insert Table 5 about here

Inter-region knowledge conduit. Our second plausible explanation focuses on the broader interpersonal relationships of employees. Within the literature on geography and innovation, an intriguing line of inquiry focuses on the interpersonal relationships of employees as drivers of knowledge spillovers between firms (e.g., Dahl & Pedersen, 2005; Breschi & Lissoni, 2009).

[21] We examine a different time range (e.g., 1 year before and after the relocation) to code inventor mobility driven by relocations. We find similar results using this alternative time range.
[22] See Appendix D for more detailed description of how mobility of inventors from relocating peers to focal firms is coded.

The geographic proximity between firms facilitates the formation of interpersonal relationships among firms' employees. For example, the physical proximity of working locations increases opportunities for serendipitous encounters as employees of different industry firms may be members of similar professional associations or go to the same gathering places (i.e., bars and restaurants) (Saxenian, 1994; Andrews, 2019). Because individual employees are active agents in the creation and spatial diffusion of knowledge (Almeida & Kogut, 1999), knowledge flows between proximate industry peers through interpersonal relationships of employees.

What happens to knowledge exchanges when a proximate industry peer relocates to another region? Research suggests that spatial distance plays a lesser role in generating conduits of knowledge flow if informal relations already exist between the two parties (e.g., Hansen & Lovas, 2004; Agrawal, Cockburn, & McHale, 2006; Bell & Zaheer, 2007). In other words, if two proximate industry peer's employees form interpersonal relationships before geographic separation, then changes in physical distance may matter less for knowledge flows. While formerly proximate employees must bear the increased costs of communicating over long distances (phone calls, transportation tickets, e-mails), the effective cost of communication does not increase significantly due to the existence of an interpersonal relationship, and therefore distance becomes less prohibitive in continuing knowledge flows (Agrawal, Cockburn, & McHale, 2006).

If interpersonal relationships continue to exist across regions, outbound relocations of a proximate industry peer allow firms to gain access to knowledge originating from the relocated peer's new region. Hence, a disruption in a firm's geography—in the form of a proximate industry peer's outbound relocation—may provide a bridge for increasing the firm's access to

distant and non-redundant knowledge from other regions. We suggest that knowledge exchanges through interpersonal relationships between proximate industry peers transform into an inter-region knowledge conduit once a proximate industry peer moves to another region.

In Table 6, we investigate our proposed mechanism of inter-region knowledge conduits by distinguishing relocations according to whether relocating peers move to more innovative or less innovative places compared to their original regions.[23] The rationale behind this split is that if knowledge exchanges continue post-relocation, their value could be shaped by the path of relocation. If a relocating peer moves to a region that is less innovative than the pre-relocation region, firms that do not move may receive knowledge that is of lower value than knowledge developed in their own region. In contrast, if a relocating peer moves to a region that is more innovative than the pre-relocation region, firms that do not move are likely to receive higher-value knowledge. Taken together, because relocation paths create a difference in the value of knowledge that firms receive, we expect the positive impact of relocation on innovation performance to be larger when a relocating peer moves to a more innovative region than when a relocating peer moves to a less innovative region.

We measure the innovativeness of regions using the cumulative stock of nanotechnology patents filed by firms in the CBSA at year *t*. *Proximate industry peer's relocation to a less innovative region* assumes a value of 1 if a proximate industry peer relocates to a CBSA with a lower cumulative stock of nanotechnology patents than the original CBSA. Similarly, *Proximate*

[23] To address the concern that interaction terms use both within and across variations (Shaver, 2019), in this study, we rely on split sampling approach and segment regression models to compare the impact of different relocations.

industry peer's relocation to a more innovative region assumes a value of 1 if the proximate industry peer relocates to a CBSA with higher cumulative stock than the pre-relocation CBSA.

The comparison group for Table 6 M11 is firms that do not experience a proximate industry peer's relocation to a more innovative region; for M12, the comparison group is firms that do not experience a peer's relocation to a less innovative region. The full sample is utilized in M13. Results show a positive and significant effect for *Proximate industry peer's relocation to a less innovative region* (M11: $\beta = 0.532$, $p = 0.001$; M13: $\beta = 0.534$, $p = 0.003$). However, for *Proximate industry peer's relocation to a more innovative region*, the coefficients do not statistically differ from zero (M12: $\beta = 0.122$, $p = 0.547$; M13: $\beta = 0.166$, $p = 0.398$). In M13, the coefficients of the two outbound relocation path variables are statistically different from one another ($p = 0.092$).[24] Overall, the results show that a particular type of proximate industry peer's relocation—relocation to a less innovative region—drives the findings of our previous analyses. Contrary to our expectation, we observe that a peer's relocation to a more innovative region does not have any significant effect on innovation performance.

Our post hoc explanation of these findings is that the relocated industry peer's employees and employees of firms that do not move require the motivation to continue exchanging knowledge across regions. In retaining relationships, deliberate and selective choice plays a salient role (Kleinbaum, 2018), as individuals may choose to minimize the costs of maintaining relationships by discontinuing ones that are less valuable (Blau, 1964). While knowledge flows

[24] Statistical significance of the difference between the two relocation path coefficients may not be very strong because of short-distance relocations (i.e., moving less than 60 miles) which only increase costs of communication marginally. In Appendix Table F, we exclude short distance relocations and distinguish relocations by paths. AM22 shows that when excluding short distance relocations, coefficients of the two outbound relocation path variables are more statistically different from one another (p=0.051).

via interpersonal relationships may lead to inter-region knowledge conduits, these flows may not continue if the cost of retaining interpersonal relationships exceeds the value attained from those relationships for relocated peers and firms that do not move.

From the perspective of employees that do not move, retention of interpersonal relationships with relocated peers will likely entail increases in communication costs, but the continuation of these ties may also yield important benefits. These employees appear to be able to source distant and non-redundant knowledge from other regions through the relocated peers, even if relocated peers move into regions that are less innovative. Hence, employees of firms that do not move may be willing to maintain long-distant relationships with their once-proximate contacts.

From the perspective of employees that relocated to a new region, however, moving to a more innovative or less innovative region may determine whether they continue to exchange knowledge with their former peers. In particular, there is likely a greater motivation for employees to retain interpersonal relationships with their former neighbors (i.e., focal firms) when their firms move to less innovative places than their pre-relocation regions. If their new region produces less advanced industry-related knowledge than their pre-relocation region, then maintaining pre-existing knowledge conduits across regions could exceed the value of just relying on local channels in the new region. By contrast, when a relocating industry peer moves to a place that is more innovative than the pre-relocation region, the relocated employees may be more motivated to build new local relationships that will help them access local knowledge spillovers. Less effort would likely be exerted towards retaining relationships with their pre-relocation neighbors, as the cost of building new local relationships would be lower than the cost

of continuing old relationships. Additionally, relocated peers would be able to source more advanced knowledge from new local relationships than from continuing relationships with former neighbors. Hence, knowledge would be less likely to flow to pre-relocation neighbors because knowledge exchanges are less likely to be continued by relocated employees. Taken together, our post hoc explanation suggests that inter-region knowledge conduits are more likely established when relocating industry peers move to less innovative regions, since relocated employees have the motivation to continue exchanging knowledge with their pre-relocation neighbors.

If inter-region knowledge conduits are established when a relocating industry peer moves to a less innovative region, as our analyses suggest, we should find that firms gain better access to knowledge from their relocated peer's new region. Table 7 shows analyses that examine whether firms use more knowledge originating from a region after a proximate industry peer's relocation to the region. The unit of analysis is the firm-region-year, and the dependent variable reports the number of patents from the region that are cited by the focal firm (i.e., backward citations of firms) at *t+1* and *t+2*. The comparison group is firm-region pairs that are not experiencing outbound relocations of proximate industry peers. To illustrate, if firm A is closely located to firm B and firm B relocates to region Z, then the pair of firm A—region Z is affected by a relocation, while other pairs of firm A—region are not affected. M14 and M15 do not display significant coefficients for a proximate industry peer's relocation.

In M16-M18, we distinguish relocations by their paths and examine the difference between relocations to less and more innovative regions. We find that *Proximate industry peer's relocation to a less innovative region* displays positive and significant coefficients (M16: β =

0.445, p = 0.003; M18: β = 0.460, p = 0.002), while in M17 and M18, *Proximate industry peer's outbound relocation to a more innovative region* does not show significant effects (M17: β = -0.050, p = 0.780; M18: β = -0.061, p = 0.731). In M19 and M20, to address the possibility that the level of knowledge production in the target region affects both the inbound relocation of industry peers and usage of the target region's patents, we include variables that account for the production of nanotechnology and other knowledge in the target region (e.g., target region's nanotechnology patent stock, nanotechnology paper stock, non-nanotechnology patent stock and nanotechnology employment level). Our main relocation variable in M19 continues to have an insignificant coefficient estimate (M19: β = 0.183, p = 0.203). Consistent with results from M18, M20 shows that the firm's citations to the relocating industry peer's new region increase when the relocated peer moved to a less innovative region (M20: β = 0.470, p = 0.002). As the dependent variable mean is 3.163, on average, relocation of an industry peer into a less innovative region is associated with the firm citing 1.9 more patents from the region (i.e., an increase of 60.0%). The coefficients for the two outbound relocation path variables are also statistically different from one another (M18: p = 0.023; M20: p = 0.017).

Overall, our results point towards the second plausible theoretical explanation, which emphasizes the importance of inter-region knowledge conduits. When industry peers relocate, firms may gain distant knowledge through this channel, and their innovation performance increases as a result. We find that the knowledge conduit is likely to be established when the relocating peer moves to a less innovative region because relocated employees are motivated to keep exchanging knowledge with their former neighbors. While the employee mobility explanation is also plausible, we do not find supporting evidence that firms hiring inventors from relocating peers benefit from relocation. Rather, we find the opposite: firms that do not hire

inventors experience increases in innovation performance following relocations of industry peers.

Insert Tables 6 and 7 about here

3.4.4 Addressing Other Explanations

To add further support to our theoretical arguments, we examine several other mechanisms that may partially explain our unexpected result. One such mechanism is that knowledge from the relocating industry peer's new region might be transferred through satellite R&D centers to other firms in its former region. In our interviews with inventors whose firms relocated, we found that some firms leave satellite R&D centers in their original location when they relocate to retain employees who do not want to follow the firm. Inventors that stay in these satellites could communicate with their colleagues in the new region and exchange knowledge internally (Alcácer & Zhao, 2012), and such knowledge from the new region could spill over to industry peers in the original location. Then, an inter-region knowledge conduit exists *within* the firm, between the relocated peer's new headquarter and the satellite R&D center. By contrast, relocations that do not leave satellite R&D centers would not lead to positive innovation performance for other firms. We test for this possibility by distinguishing outbound relocations that left satellite centers from ones that did not. In our data, 22 percent of relocating firms leave satellite R&D centers in the region. Appendix Table G AM24 and AM25 shows that relocations that do not leave satellite centers still have a positive impact on firms' innovation performance (AM24: $\beta = 0.349$, $p = 0.045$; AM25: $\beta = 0.350$, $p = 0.044$)

Another explanation concerns the possibility that the relocating industry peer shares information from firms in its prior region with its new neighbors. The rise in citations to the focal

firm's patents might be driven by the relocating industry peer's new neighbors, who start citing the firm after gaining information about their technology. If this were the case, then the increase in citation-weighted patents may be due to more firms knowing about the firm's patents and not because the firm's patents are more valuable and novel. We test for this explanation using firm-CBSA-year level data. Models across Appendix Table H show that firms in the relocating industry peer's new region are not citing more patents by focal firms in the relocating industry peer's pre-relocation region. Hence, the increase in citations to the firm's patents is not driven by more firms having information about them.

The last potential explanation is that a firm's inventors may continue to monitor the activities of the relocated peer post-relocation. Through monitoring, inventors may gain information on the knowledge and technologies of other firms in the relocated industry peer's new region. Firms can use this new source of knowledge in R&D to increase their innovation performance. Our prior analyses (e.g., Tables 6 and 7) show that this mechanism is unlikely. If inventors monitor relocating industry peers, they will concentrate on monitoring those firms that moved to more innovative regions and not firms that moved to less innovative regions. However, our results show that relocations to less innovative regions are more critical relocations that drive the overall impact of relocations.

3.5 DISCUSSION AND CONCLUSION

We began this paper by discussing the potential pitfalls of common research designs aimed at examining the relationship between agglomeration, firm innovation, and the theorized mechanism of knowledge spillovers. We proposed a novel research design—focusing on a

proximate industry peer's outbound relocation—to address the limitations of previous designs. We expected the relocation of a proximate industry peer to decrease the focal firm's innovation performance because relocation results in de-agglomeration, and focal firms are likely to experience fewer knowledge spillovers. Contrary to our expectations, we find that relocations of proximate industry peers increase a firm's innovation performance.

We explored this unexpected finding and consistently found that a firm's innovation performance increases following the relocation of an industry peer. We, therefore, proceeded with an abductive approach and investigated two plausible mechanisms that could explain this result: employees leaving relocating firms and the formation of an inter-region knowledge conduit. Our analyses point towards the inter-region knowledge conduit explanation, which suggests that interpersonal relationships between employees of focal firms and relocating peers continue to operate as knowledge conduits post-relocation. In particular, we found that the positive impact of a proximate peer's relocation on innovation performance is mainly driven by relocations to less innovative regions. Our post hoc explanation for this finding is that both employees of firms that relocate and firms that do not move have high motivation to continue exchanging knowledge when the relocating firm moves to a less innovative region. Because intra-region knowledge conduits become inter-region knowledge conduits post-relocation, knowledge spillover benefits and innovation performance of non-moving firms do not decrease.

With these findings, our study makes the following contributions. Foremost, our results suggest that attending to firm movements between regions is important for advancing research on the geography of innovation (Feldman & Audretsch, 1999; Folta, Cooper & Baik, 2006; McCann & Folta, 2011). Relocation is an overlooked phenomenon in prior research, one that

appears only indirectly through changes in local agglomeration levels. By documenting the creation of inter-region knowledge conduits and the flow of knowledge from the relocated firm's new region to the pre-relocation region, we show that it is worth considering the impact of relocation as an independent question with its own merits. At one level, these insights could expand our understanding of knowledge spillovers, because our results suggest that under certain conditions geographic distances between exchange partners do not hinder knowledge flows. Beyond that, we hope to stimulate inquiry into how inter-region knowledge conduits established through relocations can contribute to increasing knowledge flows across regions and the diversity of knowledge in regions.

Second, by documenting differences in the establishment of inter-region knowledge conduits, our findings have implications for research on industry cluster dynamics (e.g., Kim, Shaver, & Funk, 2021). We find that a proximate peer's relocation to a less innovative region benefits firms that do not move, while a proximate peer's relocation to a more innovative region does not. These two relocation paths suggest that strong and innovative regions are, in general, likely to gain from firms relocating out of their regions; whereas weak and less innovative regions generally make no gains from outbound relocations. Hence, this study's results imply that the evolution of industry clusters may potentially exacerbate economic gaps between regions because strong industry clusters get stronger even when firms leave their cluster.

Finally, our study sheds light on an unexplored aspect of agglomeration. Although firms are typically attracted to agglomerated regions by the prospect of learning from local industry peers (Strauss-Kahn & Vives, 2009), our results suggest that such regions also offer potentially significant opportunities for learning from those located in more distant geographies. These

opportunities are underwritten by the larger absolute number of outbound relocations of firms in agglomerated regions and the concomitant formation of inter-region knowledge conduits. Our study therefore suggests that some degree of local de-agglomeration of industry production (perhaps counterintuitively) increases a firm's access to knowledge spillovers and may, for that reason, ultimately help explain consistent observations of superior performance among those located in agglomerated regions.

TABLE 1 – Descriptive Statistics†

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	Mean (full sample)	Mean (relocation)††	Mean (no relocation)	S.D. (full sample)	S.D. (across firms)	S.D. (within firms)	Min (full sample)	Max (full sample)
Patent impact (t+1 and t+2)	28.396	45.119	25.300	122.976	76.706	97.207	0.000	2,652.000
Proximate industry peer's relocation	0.156	1.000	0.000	0.363	0.231	0.282	0.000	1.000
ln(Nano patent stock)	1.558	2.022	1.473	1.598	1.152	1.055	0.000	7.155
ln(Nano paper stock)	1.151	1.373	1.110	1.467	1.081	0.927	0.000	7.084
ln(Non-nano patent stock)	2.105	2.275	2.073	2.519	2.239	0.822	0.000	9.489
Number of alliances	0.320	0.378	0.309	0.986	0.673	0.655	0.000	15.000
Inventor mobility out	0.172	0.301	0.148	0.723	0.404	0.569	0.000	13.000
Inventor mobility in	0.166	0.271	0.146	0.600	0.310	0.493	0.000	8.000
Region's nano industry size	17.389	34.669	14.190	15.721	15.210	5.679	1.000	49.000
ln(Region's nano employment level)	4.595	6.481	4.246	2.330	2.020	1.211	0.000	7.992
Region's unemployment rate	0.049	0.047	0.050	0.014	0.008	0.012	0.013	0.132

†N = 6,159 for the full sample
††N = 962 for firm-years experiencing inter-region relocations

TABLE 2 – Correlations†

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	Patent impact (t+1 and t+2)	1.000										
(2)	Proximate industry peer's relocation	0.056	1.000									
(3)	ln(Nano patent stock)	0.188	0.125	1.000								
(4)	ln(Nano paper stock)	0.062	0.065	0.475	1.000							
(5)	ln(Non-nano patent stock)	0.113	0.029	0.395	0.491	1.000						
(6)	Number of alliances	0.124	0.026	0.231	0.337	0.414	1.000					
(7)	Inventor mobility out	0.172	0.077	0.298	0.351	0.397	0.435	1.000				
(8)	Inventor mobility in	0.157	0.076	0.268	0.295	0.347	0.264	0.379	1.000			
(9)	Region's nano industry size	0.072	0.473	0.149	0.105	0.032	0.053	0.053	0.095	1.000		
(10)	ln(Region's nano employment level)	0.102	0.348	0.260	0.152	0.156	0.126	0.117	0.147	0.748	1.000	
(11)	Region's unemployment rate	-0.032	-0.070	-0.048	-0.025	0.075	0.029	-0.004	0.004	0.034	0.019	1.000

†N = 6,159

TABLE 3 – Proximate industry peer's relocation and innovation performance

	M1	M2	M3
	DV: Patent Impact (t+1 and t+2)		
Region's nano industry size	0.042		
	(0.001)		
Proximate industry peer's relocation		0.391	0.346
		(0.010)	(0.032)
ln(Nano patent stock)	-0.148	-0.141	
	(0.017)	(0.028)	
ln(Nano paper stock)	0.007	0.005	
	(0.932)	(0.954)	
ln(Non-nano patent stock)	0.302	0.300	
	(0.005)	(0.005)	
Number of alliances	-0.038	-0.017	
	(0.536)	(0.792)	
Inventor mobility out	0.008	0.004	
	(0.889)	(0.933)	
Inventor mobility in	0.032	0.023	
	(0.579)	(0.717)	
ln(Region's nano employment level)	0.080	0.091	
	(0.091)	(0.058)	
Region's unemployment rate	9.628	9.991	
	(0.248)	(0.226)	
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	5,908	5,908	5,908
Log Likelihood	-121,268.872	-121,989.982	-128,242.013
Chi-Square	117.047	26.536	4.573
Degrees of Freedom	9	9	1

Notes: M1 examines the relationship between agglomeration and the focal firm's innovation performance with standard within-firm research design. M2 and M3 utilize our research design and show the relationship between a proximate industry peer's relocation and the focal firm's innovation performance. The dependent variable is the patent impact (i.e., citation-weighted patents). The comparison group in M1 is firms in other regions. The comparison group in M2 and M3 are firms not experiencing outbound relocations. *Region's nano industry size* represents the number of nanotechnology firms in the region. *Proximate industry peer's relocation* is a dummy variable equal to 1 if a proximate industry peer (i.e., within a 10-mile radius) relocated to a different region. Estimates are from pseudo-maximum likelihood Poisson models. M1 shows that our results and data are consistent with prior research. The results from M2 and M3 suggest that a focal firm's innovation performance benefit from a proximate industry peer's relocation. Refer to the text for the descriptions of the models and for the detailed definitions of the control variables. Robust standard errors are clustered at

TABLE 4 – Variations of proximate industry peer's relocation

	M4	M5	M6	M7
	DV: Patent Impact (t+1 and t+2)			
	Focal firm proximity	Large vs. small relocating peer	Relocations over 60 miles	Excluding Bay Area and Silicon Valley
Proximate industry peer's relocation	0.387		0.580	0.549
	(0.011)		(0.000)	(0.000)
Industry peer's relocation	-0.081			
– more than 10 miles away	(0.462)			
Proximate industry peer's relocation		0.305		
– high innovativeness		(0.016)		
Proximate industry peer's relocation		0.334		
– low innovativeness		(0.049)		
ln(Nano patent stock)	-0.136	-0.140	-0.142	-0.142
	(0.035)	(0.026)	(0.026)	(0.026)
ln(Nano paper stock)	0.006	0.001	-0.010	-0.007
	(0.940)	(0.989)	(0.899)	(0.932)
ln(Non-nano patent stock)	0.303	0.308	0.332	0.330
	(0.004)	(0.004)	(0.001)	(0.001)
Number of alliances	-0.017	-0.019	-0.022	-0.023
	(0.792)	(0.763)	(0.726)	(0.722)
Inventor mobility out	0.005	0.006	0.002	0.003
	(0.924)	(0.910)	(0.969)	(0.956)
Inventor mobility in	0.023	0.019	0.022	0.022
	(0.714)	(0.754)	(0.726)	(0.724)
ln(Region's nano employment level)	0.091	0.088	0.084	0.085
	(0.057)	(0.065)	(0.070)	(0.068)
Region's unemployment rate	10.135	10.323	12.731	12.636
	(0.214)	(0.207)	(0.106)	(0.109)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	5,908	5,908	5,908	5,908
Log Likelihood	-121,938.546	-121,890.617	-120,802.699	-120,994.260
Chi-Square	29.922	29.004	41.952	40.665
Degrees of Freedom	10	10	9	9

Notes: These models show variations of the relationship between a proximate industry peer's relocation and the focal firm's innovation performance. The dependent variable is the patent impact (i.e., citation-weighted patents). *Proximate industry peer's relocation* is a dummy variable equal to 1 if a proximate industry peer (i.e., within a 10-mile radius) relocated to a different region. *Industry peer's relocation – more than 10 miles away* in M4 is a dummy variable equal to 1 if a proximate industry peer that is located more than 10 miles away from the focal firm relocated to a different region. In M5, relocations are distinguished by whether the relocating industry peer's innovativeness is high or not. *Proximate industry peer's relocation – high innovativeness* is a dummy variable equal to 1 if the relocating industry peer is a high contributor to the region's citation-weighted cumulative nano patent stock. *Proximate industry peer's relocation – low innovativeness peer* is a dummy variable equal to 1 if the relocating industry peer is a low contributor to the region's citation-weighted cumulative nano patent stock. In M6, relocations that travel less than 60 miles to another region are not counted as relocations. In M7, relocations between the Bay Area (San Francisco-Oakland-Hayward CBSA) and Silicon Valley (San Jose-Sunnyvale-Santa Clara CBSA) are not counted as relocations. Estimates are from pseudo-maximum likelihood Poisson models. The results from M4 shows that a focal firm's innovation performance benefit from a proximate industry peer's relocation only if the relocating industry peer is closely located to the focal firm. M5 shows that outbound relocations of industry peers of both high and low innovativeness increase the focal firm's innovation performance. M6 shows that the exclusion of short-distance relocations consistently produces similar results, and similarly, in M7, the exclusion of relocations between the Bay Area and the Silicon Valley regions also exhibits a positive impact of relocation on patent impact. Refer to the text for the descriptions of the models and for the detailed definitions of the control variables. Robust standard errors are clustered at the focal firm's zip code area level. P-values are shown in parentheses.

TABLE 5 – Investigating employee mobility explanation

	M8	M9	M10
	DV: Patent Impact (t+1 and t+2)		
Proximate industry peer's relocation - mobility	-0.100 (0.715)		-0.041 (0.849)
Proximate industry peer's relocation - no mobility		0.378 (0.017)	0.404 (0.009)
ln(Nano patent stock)	-0.176 (0.046)	-0.123 (0.054)	-0.140 (0.030)
ln(Nano paper stock)	-0.050 (0.727)	-0.008 (0.919)	0.007 (0.933)
ln(Non-nano patent stock)	0.448 (0.000)	0.300 (0.006)	0.299 (0.005)
Number of alliances	-0.101 (0.341)	-0.024 (0.718)	-0.016 (0.803)
Inventor mobility out	-0.027 (0.679)	0.010 (0.866)	0.004 (0.933)
Inventor mobility in	0.078 (0.415)	0.020 (0.790)	0.022 (0.722)
ln(Region's nano employment level)	0.061 (0.190)	0.083 (0.075)	0.091 (0.058)
Region's unemployment rate	10.061 (0.331)	11.530 (0.162)	9.926 (0.229)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	3,477	5,781	5,908
Log Likelihood	-69,640.805	-115,961.069	-121,876.680
Chi-Square	33.093	27.349	26.472
Degrees of Freedom	9	9	10

Notes: These models investigate the employee mobility explanation. The dependent variable is the patent impact (i.e., citation-weighted patents). The comparison group in M8-M10 are firms that are not experiencing relocations. M8 examines the impact of relocation just for firms that hire inventors from the relocating industry peer. Similarly, M9 examines the impact of relocation just for firms that do not hire inventors from the relocating industry peer. The full sample is utilized in M10. Estimates are from pseudo-maximum likelihood Poisson models. *Proximate industry peer's relocation – mobility* is a dummy variable equal to 1 if a proximate industry peer relocates and the focal firm hires inventors from the relocating industry peer around the time of relocation (i.e., two years before and after the relocation). *Proximate industry peer's relocation – no mobility* is a dummy variable equal to 1 if the firm does not hire inventors from the relocating industry peer. The result from M8 and M10 display insignificant effects of relocation on firms that hire inventors. On the other hand, results from M9 and M10 show that the focal firm benefits from a proximate industry peer's relocation even if an inventor does not move from the relocating industry peer to the focal firm. These results discount the employee mobility explanation. The mobility of inventors between the relocating peer and the focal firm may not be the driving force of the positive impact of the proximate industry peer's relocation. Robust standard errors are clustered at the focal firm's zip code area level. P-values are shown in parentheses.

TABLE 6 – Investigating inter-region knowledge conduit explanation

	M11	M12	M13
	DV: Patent Impact (t+1 and t+2)		
Proximate industry peer's relocation	0.532		0.534
to a less innovative region	(0.001)		(0.003)
Proximate industry peer's relocation		0.122	0.166
to a more innovative region		(0.547)	(0.398)
ln(Nano patent stock)	-0.193	-0.124	-0.142
	(0.014)	(0.047)	(0.025)
ln(Nano paper stock)	-0.022	-0.006	0.009
	(0.824)	(0.948)	(0.912)
ln(Non-nano patent stock)	0.305	0.284	0.290
	(0.011)	(0.009)	(0.008)
Number of alliances	-0.060	-0.035	-0.019
	(0.456)	(0.605)	(0.757)
Inventor mobility out	0.012	-0.043	0.002
	(0.864)	(0.373)	(0.969)
Inventor mobility in	0.053	0.036	0.025
	(0.458)	(0.622)	(0.688)
ln(Region's nano employment level)	0.064	0.094	0.089
	(0.170)	(0.079)	(0.061)
Region's unemployment rate	5.367	10.466	9.188
	(0.526)	(0.290)	(0.261)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	4,982	5,299	5,908
Log Likelihood	-101,197.235	-110,001.176	-121,802.639
Chi-Square	27.454	26.233	26.267
Degrees of Freedom	9	9	10

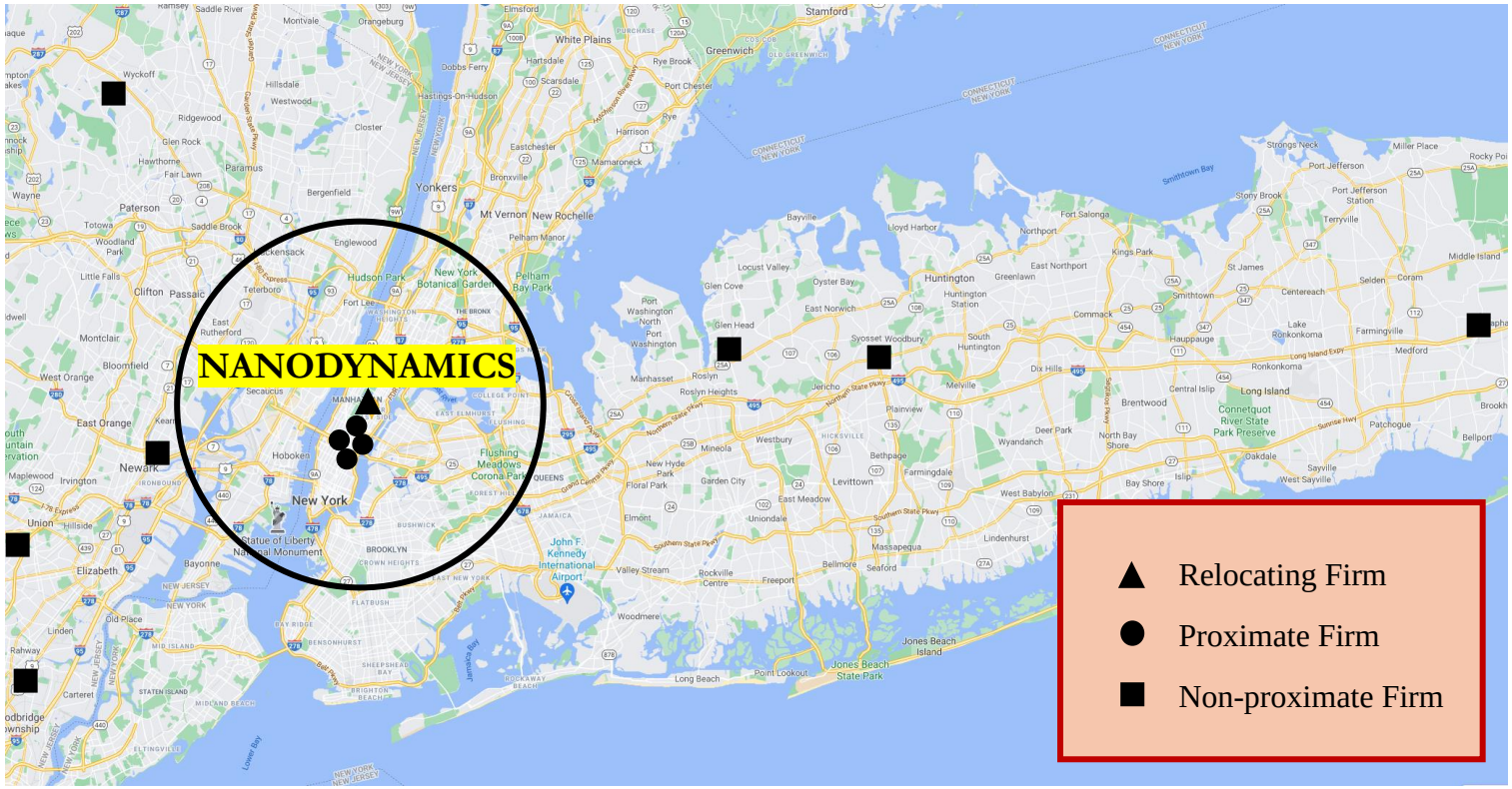
Notes: These models investigate the inter-region knowledge conduit explanation that could explain the positive association between a proximate industry peer's relocation and the focal firm's innovation performance. The dependent variable is the patent impact (i.e., citation-weighted patents). The comparison group in M11-M13 are firms not experiencing a proximate industry peer's relocation. M11 excludes firms that experience a proximate industry peer's relocation to a more innovative region, while M12 excludes firms that experience a proximate industry peer's relocation to a less innovative region. *Proximate industry peer's relocation to a less innovative region* is a dummy variable equal to 1 if a proximate industry peer relocated to a region with a lower cumulative stock of nano patents than the pre-relocation region. *Proximate industry peer's relocation to a more innovative region* is a dummy variable equal to 1 if a proximate industry peer relocated to a region with a higher cumulative stock of nano patents than the pre-relocation region. Cumulative nano patent stocks of regions are depreciated by 15% annually. Estimates are from pseudo-maximum likelihood Poisson models. Results from M13 suggest that the positive impact of a proximate industry peer's relocation on innovation performance may be driven by relocations to less innovative regions than pre-relocation regions. Refer to the text for the descriptions of the models and for the detailed definitions of the control variables. Robust standard errors are clustered at the focal firm's zip code

TABLE 7 – Examining knowledge flows from the relocated peer's new region

	M14	M15	M16	M17	M18	M19	M20
	DV: Firm's Citations of a Region's Nano Patents (t+1 and t+2)						
Proximate industry peer's relocation	0.191	0.172				0.183	
	(0.184)	(0.319)				(0.203)	
Proximate industry peer's relocation			0.445		0.460		0.470
to a less innovative region			(0.003)		(0.002)		(0.002)
Proximate industry peer's relocation				-0.050	-0.061		-0.082
to a more innovative region				(0.780)	(0.731)		(0.647)
Number of citations to nano patents	0.001		0.001	0.001	0.001	0.001	0.001
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(Nano patent stock)	0.069		0.067	0.068	0.068	0.069	0.069
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(Nano paper stock)	-0.060		-0.063	-0.059	-0.060	-0.059	-0.059
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(Non-nano patent stock)	0.192		0.192	0.193	0.193	0.191	0.192
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(Region's nano employment level)	0.022		0.021	0.022	0.021	0.022	0.021
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(Target region's nano patent stock)						0.072	0.075
						(0.000)	(0.000)
ln(Target region's nano paper stock)						-0.006	-0.007
						(0.818)	(0.794)
ln(Target region's non-nano patent stock)						0.033	0.033
						(0.231)	(0.230)
ln(Target region′s nano employment level)						0.009	0.009
						(0.179)	(0.197)
Target region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	220,022	220,022	218,932	218,903	220,022	220,022	220,022
Log Likelihood	-744,643.141	-820,752.139	-732,898.110	-738,506.469	-744,254.740	-743,642.721	-743,211.982
Chi-Square	272.708	0.995	278.293	297.696	327.455	334.784	392.979
Degrees of Freedom	6	1	6	6	7	10	11

Notes: These models show the relationship between a proximate industry peer's relocation and the focal firm's citation behavior. The unit of analysis is at the firm-region-year level, and models include all firm-region pairs where the firm cited at least one patent from a given region. The dependent variable is the number of citations that the firm makes to patents from a region (i.e., the number of backward citations by the firm to patents of the region at years t+1 and t+2). The comparison group is firm-region pairs that did not experience a proximate industry peer's relocation. M16 excludes comparison firm-region pairs that experience a proximate industry peer's relocation to a more innovative region, and M17 excludes comparison firm-region pairs that experience a proximate industry peer's relocation to a less innovative region. M19 and M20 include control variables that account for the target region's level of production of knowledge developed by nanotechnology firms. *Proximate industry peer's relocation* is a dummy variable equal to 1 if a proximate industry (i.e., within a 10-mile radius) relocated to the focal region. *Proximate industry peer's relocation to a less innovative region* is a dummy variable equal to 1 if a proximate industry peer relocated to the focal region that has a less cumulative stock of nano patents than the pre-relocation region. *Proximate industry peer's relocation to a more innovative region* is a dummy variable equal to 1 if a proximate industry peer relocated to the focal region that has more cumulative stock of nano patents than the pre-relocation region. Cumulative nano patent stocks of regions are depreciated by 15% annually. Estimates are from pseudo-maximum likelihood Poisson models. The results from M18 and M20 suggest that a focal firm cites more patents from the region when a proximate industry peer relocates into a region that is less innovative than the pre-relocation region. These results provide support for the mechanism that an inter-region knowledge transfer conduit is constructed when a proximate industry peer relocates into another region. Robust standard errors are clustered at the firm-region pair level. P-values are shown in parentheses.

FIGURE 1 – Relocating industry peer firm and geographically proximate and non-proximate firms



Notes: The figure above shows how a proximate industry peer is defined. The figure shows part of the CBSA that comprises New York City. Nanodynamics (marked as the triangle) was a Nanotechnology R&D firm in Manhattan until it relocated to Buffalo in 2005. There were 25 nano firms in this region. However, only four industry peers were within 10 miles radius of Nanodynamics, which is the boundary drawn by the large circle. These four industry peers, marked by small circles, are considered geographically proximate industry peers of Nanodynamics. However, other industry peers in the region, marked by squares, are not proximate industry peers of Nanodynamics because they are located more than 10 miles from Nanodynamics.

Chapter 4: Discussion

The purpose of this dissertation is to extend our understanding of how industry agglomeration impacts local entrepreneurship and innovation outcomes by changing the levels of knowledge spillovers. This dissertation investigates and elucidates complex dynamics of industry agglomeration that have been relatively underexplored in prior research. First, I hypothesize that local knowledge spillovers may exacerbate the gender gap in entrepreneurship in the region. Second, I utilize relocations of proximate industry peers as a research design to improve methodological identification of the knowledge spillover mechanism. Consistent with prior research, the results of this dissertation show that knowledge spillovers are critical in local entrepreneurship and innovation outcomes. More importantly, I document that contrary to expectation, de-agglomeration of industry activity could positively affect firm innovation and also present that employees may benefit differently from agglomeration by employee gender.

In this chapter, I highlight key academic and practical implications in improving our understanding of the role of knowledge spillovers within geographies on local entrepreneurship and innovation outcomes.

4.1 Academic Implications

The overall findings of this dissertation suggest that there are dynamics of industry agglomeration that are not yet well investigated by extant research. The decrease in the level of industry agglomeration (i.e., industry de-agglomeration) has not been examined as a separate research topic. It has primarily been understood just as resulting in the reduction in agglomeration externalities. Yet, the documentation of the fact that industry de-agglomeration

(i.e., outbound relocation of a proximate industry peer) can have a positive impact on local firms' innovation implies that the assumption about de-agglomeration may be inaccurate. Therefore, a key implication for researchers is that de-agglomeration, in its various forms (e.g., relocation, closure, or downsizing of firms in the region), warrants the attention of researchers in understanding how the geography of firms and industry activity affects local entrepreneurship and innovation outcomes.

In line with the above, this dissertation specifically shows that relocations of firms merit more attention than just as a factor that influences the agglomeration level. Chapter 3 shows that headquarters relocations of a proximate industry peer into another region can lead to unexpected results and new insights. Specifically, the results suggest that firms gain distant knowledge from their former neighbors after their neighbors relocate to another region. In a similar vein, though headquarters relocations are not common, relocations could enrich our understanding of the geography of firms. For example, studying the effect of inbound relocations (i.e., a firm moving into a proximate location) could also have implications for knowledge spillovers between local firms. How do firms react to another firm moving into their locality? Do all firms benefit from the newly relocating firm's knowledge? These are some questions that researchers could investigate when thinking about relocations.

Moreover, while I focus on across-region relocations in my dissertation, firms also relocate within a region. For example, in 2023, Nextern Inc., a medical device company, announced that it would relocate its headquarters from White Bear Lake to Maple Grove. Both cities are located in Minneapolis-St. Paul-Bloomington metropolitan statistical area and are about 25 miles apart. Since geographic proximity to industry peers is central to knowledge spillovers,

would the innovation performance of Nextern Inc.'s industry peers in White Bear Lake decrease following the relocation? Also, would within-region relocations increase the level of knowledge spillovers within the region since relocations of firms could lead to new interactions between employees of different firms? Investigating within-region relocations can further enhance our understanding of knowledge spillover channels between local firms and how they might change over time and distance.

Relocations can also be studied to understand the location strategy of the firm that decides to move. While researchers have long examined firms' location strategies by looking into where firms locate new facilities (Shaver & Flyer, 2000), headquarters relocations have been relatively understudied in the strategy literature. Indeed, insights from research on location strategy could be applied to understand why a firm decides to relocate to a certain location. Yet, studying relocations can offer new insights into a firm's location strategy. Relocation decisions not only involve firms choosing a new location but also concern deciding to leave the current location. Hence, the relocation decision compares the attractiveness of the new headquarters location to the attractiveness of the current location. This comparison would allow us to learn what combination of regional factors (e.g., infrastructure, corporate tax rate, access to human capital, etc.) induce firms to leave and relocate to a certain location and whether firms have different preferences in choosing a relocation destination depending on their size or the growth stage.

This dissertation also has critical implications for utilizing new research designs on studies that investigate the impact of agglomeration on local entrepreneurship and innovation. The third chapter of this dissertation develops a new research design to identify the mechanism

of agglomeration in the relationship between agglomeration and firm innovation. While the results of the study are consistent with extant research when using conventional research designs, unexpected results emerge when using a new research design. Investigating the unexpected result further abductively yields hypotheses that could be tested in future studies. This study suggests that new research designs could not only improve the identification of mechanisms but can also lead to new theoretical insights that could further extend our understanding of industry agglomeration and knowledge spillovers.

Lastly, the findings of this dissertation also suggest that the agglomeration of industry activity may have a significant influence on inequalities in economic opportunities and outcomes (e.g., the gender gap in entrepreneurship). With the exception of a couple of studies (e.g., Rosenthal & Strange, 2012), agglomeration externalities, and especially knowledge spillovers, have mainly been investigated as a positive influence on local entrepreneurship and innovation outcomes. The studies of this dissertation document facts that are consistent with the view of extant research. At the same time, this dissertation also shows that different groups of employees benefit from agglomeration at different levels, thereby enhancing the gap in entrepreneurship between the dominant group of employees and the marginalized group of employees. This finding suggests that industry agglomeration can also lead to greater inequalities in other employee opportunities and outcomes, such as innovation, productivity, and mobility between dominant and marginalized social groups, despite increasing the absolute indexes for each group.

4.2 Practical Implications

This dissertation has three critical managerial implications. First, consistent with prior research, the findings of this dissertation at the high level suggest that the location of the firm is critical for

the firm's innovation performance. To be more specific, physical distances to the same industry firms affect the level of knowledge that firms can absorb. Hence, the results can be useful in informing managers of the importance of the location of their firms' headquarters and facilities. Second, the findings suggest that firms' proximate industry peers can also be influential when they move across regions. This suggests that managers should take advantage of the neighboring firm's announcement to relocate by building connections with the neighboring firm before they leave. In particular, at the firm level, managers can develop formal relationships (e.g., R&D alliances) with the neighboring firms before they leave. The findings suggest that efforts to sustain and develop connections with the neighbor who plans to relocate can lead to greater benefits. Third, the results show that employees benefit differently from agglomeration by gender and suggest that managers can take measures to provide more opportunities for social interactions to female employees. This would not only reduce the gap in agglomeration benefits between male and female employees but also increase firms' performance overall.

The findings of this dissertation also have implications for the policymakers in local governments. Conventional wisdom is that an outbound relocation of a firm from the region leaves a significant negative economic impact. Relocations result in reduced taxes and employee layoffs in the region (e.g., Martin et al., 2014). Local governments, therefore, often develop new compensation schemes to prevent firms from relocating (Schmidt & Heitzig, 2014). This dissertation suggests that a firm leaving the region may not always result in a negative impact and that there could be secondary effects that benefit the region. Policymakers need to understand the type of positive externalities that relocations can produce and implement measures to expand those externalities.

Moreover, this dissertation also informs policymakers that industry agglomeration is associated with gender inequality in access to entrepreneurial opportunities. To ameliorate the gender inequality in entrepreneurial opportunities, local policymakers in the United States have implemented direct measures. For example, states like Minnesota have implemented angel tax credits and reserved 50% of the credit for minority- and women-owned businesses. While measures that directly target entrepreneurship funding help in providing resources and opportunities to marginalized social groups, this dissertation suggests that indirect measures are also needed. Employees from marginalized social groups systematically benefit less from agglomeration than dominant social groups. Since access to agglomeration externalities leads to economic opportunities, policymakers should try to implement measures to ensure that marginalized groups of individuals also gain equal access to agglomeration externalities. For example, according to my findings, childcare responsibilities contribute to female employees' disproportional access to agglomeration externalities. To enhance female employees' opportunities to gain knowledge and information through interactions, regional policymakers can expand daycare services such that some daycare facilities cover weekends and night times. Overall, the key implication is that policymakers can play a critical role in making information available to more marginalized people in the region.

REFERENCES

Abraham, M. (2020). Gender-role incongruity and audience-based gender bias: An examination of networking among entrepreneurs. Administrative Science Quarterly, 65(1), 151-180.

Agarwal, R., Echambadi, R., Franco, A. M., & Sarkar, M. B. (2004). Knowledge transfer through inheritance: Spin-out generation, development, and survival. *Academy of Management Journal 47*(4), 501-522.

Agarwal, R., Ganco, M., & Ziedonis, R. H. (2009). Reputations for toughness in patent enforcement: Implications for knowledge spillovers via inventor mobility. *Strategic Management Journal 30*(13), 1349-1374.

Agarwal, R., & Shah, S. K. (2014). Knowledge sources of entrepreneurship: Firm formation by academic, user and employee innovators. *Research Policy*, *43*(7), 1109-1133.

Aggarwal, V. A., Hsu, D. H., & Wu, A. (2020). Organizing knowledge production teams within firms for innovation. *Strategy Science 5*(1), 1-16.

Agrawal, A., Cockburn, I., Galasso, A., & Oettl, A. (2014). Why are some regions more innovative than others? The role of small firms in the presence of large labs. Journal of Urban Economics, 81, 149-165.

Agrawal, A., Cockburn, I., & McHale, J. (2006). Gone but not forgotten: knowledge flows, labor mobility, and enduring social relationships. *Journal of Economic Geography 6*(5), 571-591.

Ahuja, G. (2000). Collaboration networks, structural holes, and innovation: A longitudinal study. *Administrative Science Quarterly 45*(3), 425-455.

Alcácer, J., & Chung, W. (2007). Location strategies and knowledge spillovers. Management science, 53(5), 760-776.

Alcácer, J., & Zhao, M. (2012). Local R&D strategies and multilocation firms: The role of internal linkages. *Management Science 58*(4), 734-753.

Aldrich, H., & Zimmer, C. (1986). Entrepreneurship through social networks. *The art and science of entrepreneurship. Ballinger, Cambridge, MA*, *3*, 23.

Almeida, P., & Kogut, B. (1999). Localization of knowledge and the mobility of engineers in regional networks. *Management Science 45*(7), 905-917.

Almeida, P., Song, J., & Grant, R. M. (2002). Are firms superior to alliances and markets? An empirical test of cross-border knowledge building. *Organization Science 13*(2), 147-161.

Amit, R., Muller, E., & Cockburn, I. (1995). Opportunity costs and entrepreneurial activity. Journal of business venturing, 10(2), 95-106.

Andrews, M. (2019). Bar Talk: Informal Social Interactions, Alcohol Prohibition. and Invention. Working paper.

Audretsch, D. B., & Feldman, M. P. (1996). R&D spillovers and the geography of innovation and production. *The American Economic Review 86*(3), 630-640.

Baptista, R., & Swann, P. (1998). Do firms in clusters innovate more?. *Research Policy 27*(5), 525-540.

Beaman, L., Chattopadhyay, R., Duflo, E., Pande, R., & Topalova, P. (2009). Powerful women: does exposure reduce bias?. The Quarterly journal of economics, 124(4), 1497-1540.

Beaman, L., Duflo, E., Pande, R., & Topalova, P. (2012). Female leadership raises aspirations and educational attainment for girls: A policy experiment in India. science, 335(6068), 582-586.

Bell, A., Chetty, R., Jaravel, X., Petkova, N., & Van Reenen, J. (2019). Who becomes an inventor in America? The importance of exposure to innovation. The Quarterly Journal of Economics, 134(2), 647-713.
Bell, G. G. (2005). Clusters, networks, and firm innovativeness. *Strategic Management Journal 26*(3), 287-295.
Bell, G. G., & Zaheer, A. (2007). Geography, networks, and knowledge flow. Organization science, 18(6), 955-972.
Belenzon, S., & Schankerman, M. (2013). Spreading the word: Geography, policy, and knowledge spillovers. *Review of Economics and Statistics 95*(3), 884-903.
Biotechnology Innovation Organization. (2022). Measuring diversity in the biotech industry - bio.org. https://www.bio.org/sites/default/files/2022-06/261734_BIO_22_DEI_Report_P4.pdf?_hsenc=p2ANqtz-_wOtII5Pujil1RoeQTw0ojEjMkhIR6gwiTPmayXsExoFAe8SgsFgseT8B9Co3X6Qk8A7Gt
Blau, P. M. (1964). *Exchange and power in social life*. New York, NY: Wiley.
Breschi, S., & Lissoni, F. (2009). Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows. *Journal of Economic Geography 9*(4), 439-468.
Campbell, B. A., Ganco, M., Franco, A. M., & Agarwal, R. (2012). Who leaves, where to, and why worry? Employee mobility, entrepreneurship and effects on source firm performance. Strategic Management Journal, 33(1), 65-87.
Carnahan, S. (2017). Blocked but not tackled: who founds new firms when rivals dissolve?. *Strategic Management Journal*, 38(11), 2189-2212.
Castellaneta, F., Conti, R., & Kacperczyk, A. (2020). The (un) intended consequences of institutions lowering barriers to entrepreneurship: The impact on female workers. Strategic Management Journal, 41(7), 1274-1304.
Castilla, E. J., & Benard, S. (2010). The paradox of meritocracy in organizations. *Administrative science quarterly*, *55*(4), 543-676.
Cejka, M. A., & Eagly, A. H. (1999). Gender-stereotypic images of occupations correspond to the sex segregation of employment. Personality and social psychology bulletin, 25(4), 413-423.
Clough, D. R., Fang, T. P., Vissa, B., & Wu, A. (2019). Turning lead into gold: How do entrepreneurs mobilize resources to exploit opportunities?. *Academy of Management Annals*, *13*(1), 240-271.
Cohen, P. N., & Huffman, M. L. (2007). Working for the woman? Female managers and the gender wage gap. American sociological review, 72(5), 681-704.
Corredoira, R. A., & Rosenkopf, L. (2010). Should auld acquaintance be forgot? The reverse transfer of knowledge through mobility ties. *Strategic Management Journal 31*(2), 159-181.
Daft, R. L., & Lengel, R. H. (1986). Organizational information requirements, media richness and structural design. *Management Science 32*(5), 554-571.
Dahl, M. S., & Pedersen, C. Ø. (2005). Social networks in the R&D process: the case of the wireless communication industry around Aalborg, Denmark. *Journal of Engineering and Technology Management 22*(1-2), 75-92.
Dahl, M. S., & Sorenson, O. (2012). Home sweet home: Entrepreneurs' location choices and the performance of their ventures. Management science, 58(6), 1059-1071.

DeCarolis, D. M., & Deeds, D. L. (1999). The impact of stocks and flows of organizational knowledge on firm performance: An empirical investigation of the biotechnology industry. Strategic management journal, 20(10), 953-968.
Delgado, M., Porter, M. E., & Stern, S. (2010). Clusters and entrepreneurship. *Journal of Economic Geography 10*(4), 495-518.
Delgado, M., Porter, M. E., & Stern, S. (2014). Clusters, convergence, and economic performance. *Research Policy 43*(10), 1785-1799.
DeCarolis, D. M., & Deeds, D. L. (1999). The impact of stocks and flows of organizational knowledge on firm performance: An empirical investigation of the biotechnology industry. *Strategic Management Journal* 20(10), 953-968.
Dimitriadis, S., Lee, M., Ramarajan, L., & Battilana, J. (2017). Blurring the boundaries: The interplay of gender and local communities in the commercialization of social ventures. *Organization Science 28*(5), 819-839.
Eagly, A. H., & Steffen, V. J. (1984). Gender stereotypes stem from the distribution of women and men into social roles. Journal of personality and social psychology, 46(4), 735.
Eagly, A. H., & Steffen, V. J. (1986). Gender stereotypes, occupational roles, and beliefs about part-time employees. Psychology of women quarterly, 10(3), 252-262.
Elfenbein, D. W., Hamilton, B. H., & Zenger, T. R. (2010). The small firm effect and the entrepreneurial spawning of scientists and engineers. Management Science, 56(4), 659-681.
Fallick, B., Fleischman, C. A., & Rebitzer, J. B. (2006). Job-hopping in Silicon Valley: some evidence concerning the microfoundations of a high-technology cluster. *The Review of Economics and Statistics* 88(3), 472-481.
Feldman, M. P., & Audretsch, D. B. (1999). Innovation in cities:: Science-based diversity, specialization and localized competition. *European Economic Review 43*(2), 409-429.
Feldman, D. C., & Bolino, M. C. (1998). Moving on out: When are employees willing to follow their organization during corporate relocation?. *Journal of Organizational Behavior 19*(3), 275-288.
Fleming, L. (2001). Recombinant uncertainty in technological search. Management science, 47(1), 117-132.
Folta, T. B., Cooper, A. C., & Baik, Y. S. (2006). Geographic cluster size and firm performance. *Journal of Business Venturing 21*(2), 217-242.
Freedman, M. L. (2008). Job hopping, earnings dynamics, and industrial agglomeration in the software publishing industry. Journal of Urban Economics, 64(3), 590-600.
Funk, R. J. (2014). Making the most of where you are: Geography, networks, and innovation in organizations. *Academy of Management Journal 57*(1), 193-222.
Furman, J. L., Nagler, M., & Watzinger, M. (2021). Disclosure and subsequent innovation: Evidence from the patent depository library program. American Economic Journal: Economic Policy, 13(4), 239-270.
Gambardella, A., Ganco, M., & Honoré, F. (2015). Using what you know: Patented knowledge in incumbent firms and employee entrepreneurship. Organization Science, 26(2), 456-474.
Ge, C., Huang, K. W., & Png, I. P. (2016). Engineer/scientist careers: Patents, online profiles, and misclassification bias. Strategic Management Journal, 37(1), 232-253.

Gibson, D. E., & Lawrence, B. S. (2010). Women's and men's career referents: How gender composition and comparison level shape career expectations. Organization Science, 21(6), 1159-1175.
Gilbert, B. A., McDougall, P. P., & Audretsch, D. B. (2008). Clusters, knowledge spillovers and new venture performance: An empirical examination. *Journal of Business Venturing 23*(4), 405-422.
Glaeser, E. L., & Kerr, W. R. (2009). Local industrial conditions and entrepreneurship: how much of the spatial distribution can we explain?. *Journal of Economics & Management Strategy*, *18*(3), 623-663.
Granovetter, M. S. (1973). The strength of weak ties. American journal of sociology, 78(6), 1360-1380.
Guzman, J. (2019). Go west young firm: agglomeration and embeddedness in startup migrations to Silicon Valley. SSRN.
Guzman, J., & Kacperczyk, A. O. (2019). Gender gap in entrepreneurship. *Research Policy*, *48*(7), 1666-1680.
Hansen, M. T., & Løvås, B. (2004). How do multinational companies leverage technological competencies? Moving from single to interdependent explanations. *Strategic Management Journal 25*(8-9), 801-822.
Hervas-Oliver, J. L., Lleo, M., & Cervello, R. (2017). The dynamics of cluster entrepreneurship: Knowledge legacy from parents or agglomeration effects? The case of the Castellon ceramic tile district. Research Policy, 46(1), 73-92.
Huffman, M. L., Cohen, P. N., & Pearlman, J. (2010). Engendering change: Organizational dynamics and workplace gender desegregation, 1975–2005. Administrative Science Quarterly, 55(2), 255-277.
Hultin, M., & Szulkin, R. (1999). Wages and unequal access to organizational power: An empirical test of gender discrimination. Administrative Science Quarterly, 44(3), 453-472.
Ibarra, H., Carter, N. M., & Silva, C. (2010). Why men still get more promotions than women. *Harvard business review*, *88*(9), 80-85.
Jaffe, A. B., & Trajtenberg, M. (2002). *Patents, citations, and innovations: A window on the knowledge economy*. MIT press.
Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics 108*(3), 577-598.
Jennings, J. E., & Brush, C. G. (2013). Research on women entrepreneurs: challenges to (and from) the broader entrepreneurship literature?. The Academy of Management Annals, 7(1), 663-715.
Jung, H. J., & Lee, J. J. (2016). The quest for originality: A new typology of knowledge search and breakthrough inventions. *Academy of Management Journal 59*(5), 1725-1753.
Kacperczyk, A. J. (2013). Social influence and entrepreneurship: The effect of university peers on entrepreneurial entry. Organization Science, 24(3), 664-683.
Kacperczyk, A., & Marx, M. (2016). Revisiting the small-firm effect on entrepreneurship: Evidence from firm dissolutions. Organization Science, 27(4), 893-910.
Kacperczyk, O., Younkin, P., & Rocha, V. (2023). Do employees work less for female leaders? A multi-method study of entrepreneurial firms. Organization Science, 34(3), 1111-1133.

Kalnins, A. (2018). Multicollinearity: How common factors cause Type 1 errors in multivariate regression. *Strategic Management Journal 39*(8), 2362-2385.
Kalnins, A., & Williams, M. (2021). The geography of female small business survivorship: Examining the roles of proportional representation and stakeholders. *Strategic Management Journal*, *42*(7), 1247-1274.
Kanze, D., Huang, L., Conley, M. A., & Higgins, E. T. (2017). Male and female entrepreneurs get asked different questions by VCs–and it affects how much funding they get. *Harvard Business Review*, *27*.
Kanze, D., Huang, L., Conley, M. A., & Higgins, E. T. (2018). We ask men to win and women not to lose: Closing the gender gap in startup funding. *Academy of Management Journal*, *61*(2), 586-614.
Kaul, A., Ganco, M., & Raffiee, J. (2021). When subjective judgments lead to spinouts: employee entrepreneurship under uncertainty, firm-specificity, and appropriability. Academy of Management Review, (ja).
Kim, M. J., Shaver, J. M., & Funk, R. J. (2022). From mass to motion: Conceptualizing and measuring the dynamics of industry clusters. *Strategic Management Journal 43*(4), 822-846.
King, A., Goldfarb, B., & Simcoe, T. (2021). Learning from testimony on quantitative research in management. *Academy of Management Review 46*(3), 465-488.
Kleinbaum, A. M. (2018). Reorganization and tie decay choices. *Management Science*, *64*(5), 2219-2237.
Kleinbaum, A. M., Stuart, T. E., & Tushman, M. L. (2013). Discretion within constraint: Homophily and structure in a formal organization. Organization Science, 24(5), 1316-1336.
Kolympiris, C., Kalaitzandonakes, N., & Miller, D. (2011). Spatial collocation and venture capital in the U.S. biotechnology industry. *Research Policy 40*(9), 1188-1199.
Kotha, R., Zheng, Y., & George, G. (2011). Entry into new niches: The effects of firm age and the expansion of technological capabilities on innovative output and impact. *Strategic Management Journal 32*(9), 1011-1024.
Krugman, P. (1991). Increasing returns and economic geography. *Journal of Political Economy 99*(3), 483-499.
Lawson, M. A., Martin, A. E., Huda, I., & Matz, S. C. (2022). Hiring women into senior leadership positions is associated with a reduction in gender stereotypes in organizational language. *Proceedings of the National Academy of Sciences*, *119*(9), e2026443119.
Manchester, C. F., Benson, A., & Shaver, J. M. (2022). Dual careers and the willingness to consider employment in startup ventures. Strategic Management Journal.
Markussen, S., & Røed, K. (2017). The gender gap in entrepreneurship–The role of peer effects. Journal of Economic Behavior & Organization, 134, 356-373.
Marshall, A. (1920). *Principles of economics*. Eighth edition. London: MacMillan, 1920.
Marquis, C., Davis, G. F., & Glynn, M. A. (2013). Golfing alone? Corporations, elites, and nonprofit growth in 100 American communities. *Organization Science* 24(1), 39-57.
Martin, R., Muûls, M., De Preux, L. B., & Wagner, U. J. (2014). Industry compensation under relocation risk: A firm-level analysis of the EU emissions trading scheme. American Economic Review, 104(8), 2482-2508.
Marx, M. (2022). Employee non-compete agreements, gender, and entrepreneurship. *Organization Science*, *33*(5), 1756-1772.

Mathias, B. D., McCann, B. T., & Whitman, D. S. (2021). A meta-analysis of agglomeration and venture performance: Firm-level evidence. *Strategic Entrepreneurship Journal 15*(3), 430-453.
Maume Jr, D. J. (1999). Glass ceilings and glass escalators: Occupational segregation and race and sex differences in managerial promotions. Work and occupations, 26(4), 483-509.
McCann, B. T., & Folta, T. B. (2011). Performance differentials within geographic clusters. *Journal of Business Venturing 26*(1), 104-123.
McCann, B. T., Reuer, J. J., & Lahiri, N. (2016). Agglomeration and the choice between acquisitions and alliances: An information economics perspective. *Strategic Management Journal 37*(6), 1085-1106.
McClelland, D. C. (1975). Power: The inner experience. Irvington.
McDowell, J. M., Singell Jr, L. D., & Stater, M. (2006). Two to tango? Gender differences in the decisions to publish and coauthor. Economic inquiry, 44(1), 153-168.
McDowell, J. M., & Smith, J. K. (1992). The effect of gender-sorting on propensity to coauthor: Implications for academic promotion. Economic Inquiry, 30(1), 68-82.
McGinn, K. L., & Milkman, K. L. (2013). Looking up and looking out: Career mobility effects of demographic similarity among professionals. Organization Science, 24(4), 1041-1060.
Miric, M., Yin, P. L., & Fehder, D. C. (2023). Population-level evidence of the gender gap in technology entrepreneurship. *Strategy Science*, *8*(1), 62-84.
Moretti, E. (2021). The effect of high-tech clusters on the productivity of top inventors. *American Economic Review*, *111*(10), 3328-3375.
Moretti, E., & Wilson, D. J. (2014). State incentives for innovation, star scientists and jobs: Evidence from biotech. Journal of Urban Economics, 79, 20-38.
Moss-Racusin, C. A., Dovidio, J. F., Brescoll, V. L., Graham, M. J., & Handelsman, J. (2012). Science faculty's subtle gender biases favor male students. *Proceedings of the national academy of sciences*, *109*(41), 16474-16479.
Nanda, R., & Sørensen, J. B. (2010). Workplace peers and entrepreneurship. *Management Science*, 56(7), 1116-1126.
Nicolaou, N., Shane, S., Cherkas, L., Hunkin, J., & Spector, T. D. (2008). Is the tendency to engage in entrepreneurship genetic?. Management Science, 54(1), 167-179.
Pe'er, A., & Keil, T. (2013). Are all startups affected similarly by clusters? Agglomeration, competition, firm heterogeneity, and survival. *Journal of Business Venturing 28*(3), 354-372.
Porter, M.E. (1990). *The Competitive Advantage of Nations.* Free Press, New York.
Porter, M. E. (1998). Clusters and the new economics of competition. *Harvard Business Review* 76(6), 77-90.
Rao, H., & Drazin, R. (2002). Overcoming resource constraints on product innovation by recruiting talent from rivals: A study of the mutual fund industry, 1986–1994. *Academy of Management Journal* 45(3), 491-507.
Reuer, J. J., & Lahiri, N. (2014). Searching for alliance partners: Effects of geographic distance on the formation of R&D collaborations. *Organization Science 25*(1), 283-298.
Rider, C. I., Thompson, P., Kacperczyk, A., & Tåg, J. (2019). Experience and entrepreneurship: A career transition perspective. ILR Review, 72(5), 1149-1181.
Rigby, D. L., & Brown, W. M. (2015). Who benefits from agglomeration?. Regional Studies, 49(1), 28-43.

Rocha, V., & Van Praag, M. (2020). Mind the gap: The role of gender in entrepreneurial career choice and social influence by founders. *Strategic Management Journal*, *41*(5), 841-866.
Roche, M. P. (2020). Taking Innovation to the Streets: Microgeography, Physical Structure, and Innovation. *Review of Economics and Statistics 102*(5), 912-928.
Rosenkopf, L., & Almeida, P. (2003). Overcoming local search through alliances and mobility. *Management Science 49*(6), 751-766.
Rosenthal, S. S., & Strange, W. C. (2012). Female entrepreneurship, agglomeration, and a new spatial mismatch. *Review of Economics and Statistics*, *94*(3), 764-788.
Rothaermel, F. T., & Thursby, M. (2007). The nanotech versus the biotech revolution: Sources of productivity in incumbent firm research. *Research Policy 36*(6), 832-849.
Sagie, A., Krausz, M., & Weinstain, Y. (2001). To move or not to move: Factors affecting employees' actual relocation when an entire plant moves. *Journal of Occupational and Organizational Psychology* 74(3), 343-358.
Saxenian, A. (1994). *Regional Advantage: Culture and Competition in Silicon Valley and Route 128*. Harvard University Press.
Schmidt, R. C., & Heitzig, J. (2014). Carbon leakage: Grandfathering as an incentive device to avert firm relocation. Journal of Environmental Economics and Management, 67(2), 209-223.
Seo, H., Luo, J., & Kaul, A. (2021). Giving a little to many or a lot to a few? The returns to variety in corporate philanthropy. *Strategic Management Journal 42*(9), 1734-1764.
Shaffer, C. (2007). Ann Arbor community rallies in wake of Pfizer shutdown. Nature Biotechnology, 25(8), 829-831.
Shah, S. K., Agarwal, R., & Echambadi, R. (2019). Jewels in the crown: Exploring the motivations and team building processes of employee entrepreneurs. *Strategic Management Journal*, *40*(9), 1417-1452.
Shaver, J. M., & Flyer, F. (2000). Agglomeration economies, firm heterogeneity, and foreign direct investment in the United States. *Strategic Management Journal* 21(12), 1175-1193.
Shaver, J. M. (2018). *Headquarters economy: Managers, mobility, and migration*. Oxford University Press.
Shaver, J. M. (2019). Interpreting interactions in linear fixed-effect regression models: When fixed-effect estimates are no longer within-effects. *Strategy Science 4*(1), 25-40.
Singh, J., & Marx, M. (2013). Geographic constraints on knowledge spillovers: Political borders vs. spatial proximity. *Management Science* 59(9), 2056-2078.
Somaya, D., Williamson, I. O., & Lorinkova, N. (2008). Gone but not lost: The different performance impacts of employee mobility between cooperators versus competitors. *Academy of Management Journal 51*(5), 936-953.
Sohn, E. (2021). How local industry R&D shapes academic research: Evidence from the agricultural biotechnology revolution. *Organization Science* 32(3), 675-707.
Sørensen, J. B., & Fassiotto, M. A. (2011). Organizations as fonts of entrepreneurship. *Organization Science*, *22*(5), 1322-1331.
Sørensen, J. B., & Sharkey, A. J. (2014). Entrepreneurship as a mobility process. American Sociological Review, 79(2), 328-349.
Staiger, D. O., & Stock, J. H. (1994). Instrumental variables regression with weak instruments. Econometrica, 65, 557-586.

Starr, E., Balasubramanian, N., & Sakakibara, M. (2018). Screening spinouts? How noncompete enforceability affects the creation, growth, and survival of new firms. Management Science, 64(2), 552-572.

Strauss-Kahn, V., & Vives, X. (2009). Why and where do headquarters move?. *Regional Science and Urban Economics 39*(2), 168-186.

Stuart, T., & Sorenson, O. (2003). The geography of opportunity: spatial heterogeneity in founding rates and the performance of biotechnology firms. *Research policy*, *32*(2), 229-253.

Thébaud, S. (2015). Business as plan B: Institutional foundations of gender inequality in entrepreneurship across 24 industrialized countries. Administrative science quarterly, 60(4), 671-711.

Thursby, J., & Thursby, M. (2011). University-industry linkages in nanotechnology and biotechnology: evidence on collaborative patterns for new methods of inventing. *Journal of Technology Transfer 36*(6), 605-623.

Toole, Andrew A., Stefano Breschi, Ernest Miguelez, Amanda Myers, Edoardo Ferrucci, Valerio Sterzi, Charles AW DeGrazia, Francesco Lissoni, and Gianluca Tarasconi. 2009. "Progress and Potential: A Profile of Women Inventors on US Patents." In Technical Report. US Patent & Trademark Office, Office of the Chief Economist.

Tushman, M. L., & Romanelli, E. (1983). Uncertainty, social location and influence in decision making: A sociometric analysis. Management science, 29(1), 12-23.

Tzabbar, D. (2009). When does scientist recruitment affect technological repositioning?. *Academy of Management Journal 52*(5), 873-896.

Von Hippel, E. (1994). "Sticky information" and the locus of problem solving: implications for innovation. *Management Science 40*(4), 429-439.

West, J. D., Jacquet, J., King, M. M., Correll, S. J., & Bergstrom, C. T. (2013). The role of gender in scholarly authorship. PloS one, 8(7), e66212.

Zucker, L. G., & Darby, M. R. (2005). Socio-economic impact of nanoscale science: Initial results and nanobank. NBER working paper 11181.

Zucker, L. G., Darby, M. R., Furner, J., Liu, R. C., & Ma, H. (2007). Minerva unbound: Knowledge stocks, knowledge flows and new knowledge production. *Research Policy 36*(6), 850-863.

Zucker, L. G., Darby, M. R., & Fong, J. (2011). Communitywide database designs for tracking innovation impact: COMETS, STARS and Nanobank (No. w17404). National Bureau of Economic Research.

APPENDIX TABLE A – Logistic regression models of a firm's outbound relocation decision

	AM1	AM2
	DV: Outbound relocation	
	Coeff.	Marginal Effect
Innovativeness of proximate industry peers	0.000	0.000
	(0.211)	(0.217)
ln(Nano patent stock)	0.172	0.033
	(0.099)	(0.073)
ln(Nano paper stock)	-0.168	-0.032
	(0.274)	(0.345)
ln(Non-nano patent stock)	-0.270	-0.052
	(0.032)	(0.009)
Number of alliances	0.118	0.023
	(0.537)	(0.539)
Inventor mobility out	-1.336	-0.258
	(0.192)	(0.172)
Inventor mobility in	0.163	0.032
	(0.565)	(0.576)
ln(Region's nano employment level)	-0.007	-0.001
	(0.844)	(0.844)
Region's unemployment rate	21.531	4.162
	(0.152)	(0.053)
N	3,982	3,982
Log Likelihood	-266.295	
Chi-Square	138.881	
Degrees of Freedom	9	

Notes: These models show the relationship between the innovativeness of proximate industry peers in the region and the focal firm's decision to relocate. The dependent variable is the focal firm's outbound relocation. The innovativeness of proximate industry peers is the citation-weighted cumulative number of nanotechnology patents of industry peers in the region that share the same three-digit zip codes, depreciating by 15% annually. Estimates are from conditional logit models, and models are conditioned on the year. Marginal effects are calculated for AM2. The results from AM1 and AM2 show that a focal firm's decision to relocate to a different region is not a function of the innovativeness of proximate industry peers (AM1: p=0.211; AM2: p=0.217). These results provide support for our assumption that a firm's decision to relocate to a different region is exogenous to proximate firms' innovation performance. Refer to the text for the descriptions of the models and for the detailed definitions of the control variables. Robust standard errors are used. P-values are shown in parentheses.

APPENDIX TABLE B – Different distance ranges for distinguishing proximate and non-proximate firms

	AM3	AM4	AM5	AM6	AM7	AM8	AM9	AM10
	DV: Nano Patent Impact (t+1 and t+2)							
	Within 5-miles		Within 10-miles		Within 15-miles		Within 20-miles	
Proximate industry peer's relocation	0.444	0.367	0.391	0.346	0.268	0.182	0.198	0.111
	(0.003)	(0.004)	(0.010)	(0.032)	(0.091)	(0.265)	(0.105)	(0.368)
ln(Nano patent stock)	-0.140		-0.141		-0.151		-0.149	
	(0.028)		(0.028)		(0.024)		(0.023)	
ln(Nano paper stock)	0.007		0.005		0.028		0.023	
	(0.940)		(0.954)		(0.751)		(0.793)	
ln(Non-nano patent stock)	0.313		0.300		0.294		0.294	
	(0.003)		(0.005)		(0.006)		(0.006)	
Number of alliances	-0.020		-0.017		-0.017		-0.021	
	(0.747)		(0.792)		(0.792)		(0.747)	
Inventor mobility out	0.007		0.004		0.011		0.013	
	(0.902)		(0.933)		(0.845)		(0.822)	
Inventor mobility in	0.016		0.023		0.016		0.016	
	(0.800)		(0.717)		(0.806)		(0.803)	
ln(Region's nano employment level)	0.089		0.091		0.093		0.092	
	(0.057)		(0.058)		(0.054)		(0.054)	
Region's unemployment rate	10.132		9.991		10.519		10.234	
	(0.189)		(0.226)		(0.213)		(0.226)	
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,908	5,908	5,908	5,908	5,908	5,908	5,908	5,908
Log Likelihood	-121,789.557	-128,246.261	-121,989.982	-128,242.013	-122,585.666	-128,937.630	-122,820.893	-129,098.276
Chi-Square	31.218	8.441	26.536	4.573	22.685	1.245	23.779	0.809
Degrees of Freedom	9	1	9	1	9	1	9	1

Notes: These models show the relationship between a proximate industry peer's relocation and the focal firm's innovation performance with different distance ranges in defining a proximate industry peer. The dependent variable is the patent impact (i.e., citation-weighted patents). *Proximate industry peer's relocation* is a dummy variable equal to 1 if a proximate industry peer relocated to a different region. In AM3 and AM4, firms are considered proximate if they are located within a 5-miles distance. In AM5 and AM6, a 10-miles distance is used for defining proximity, which is the distance range that we use in our main analyses. In AM7 and AM8, a 15-miles distance is used, while in AM9 and AM10, a 20-miles range is used. Estimates are from pseudo-maximum likelihood Poisson models. The results show that the impact of a proximate industry peer's relocation decrease as distance ranges of proximity increase. AM10 shows that a proximate industry peer's relocation has no impact when proximity is defined to include all firms within 20-miles of the relocating industry peer. Refer to the text for the descriptions of the models and for the detailed definitions of the control variables. Robust standard errors are clustered at the focal firm's zip code area level. P-values are shown in parentheses.

APPENDIX TABLE C – Different year ranges for the duration of the impact of relocation

	AM11	AM12	AM13	AM14	AM15	AM16	AM17	AM18
	DV: Nano Patent Impact (t+1 and t+2)							
	Two years		Three years		Four years		Five years	
Proximate industry peer's relocation	0.418	0.390	0.391	0.346	0.407	0.353	0.423	0.356
	(0.003)	(0.013)	(0.010)	(0.032)	(0.015)	(0.049)	(0.019)	(0.066)
ln(Nano patent stock)	-0.139		-0.141		-0.142		-0.142	
	(0.032)		(0.028)		(0.027)		(0.025)	
ln(Nano paper stock)	0.006		0.005		0.003		0.002	
	(0.942)		(0.954)		(0.971)		(0.978)	
ln(Non-nano patent stock)	0.296		0.300		0.304		0.305	
	(0.005)		(0.005)		(0.005)		(0.005)	
Number of alliances	-0.016		-0.017		-0.020		-0.021	
	(0.796)		(0.792)		(0.755)		(0.732)	
Inventor mobility out	0.006		0.004		0.004		0.004	
	(0.905)		(0.933)		(0.946)		(0.945)	
Inventor mobility in	0.024		0.023		0.023		0.025	
	(0.693)		(0.717)		(0.713)		(0.691)	
ln(Region's nano employment level)	0.092		0.091		0.090		0.091	
	(0.054)		(0.058)		(0.062)		(0.060)	
Region's unemployment rate	10.182		9.991		9.746		9.760	
	(0.217)		(0.226)		(0.234)		(0.231)	
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,908	5,908	5,908	5,908	5,908	5,908	5,908	5,908
Log Likelihood	-121,734.924	-127,927.022	-121,989.982	-128,242.013	-121,928.562	-128,230.547	-121,886.997	-128,253.013
Chi-Square	31.213	6.165	26.536	4.573	25.220	3.875	25.249	3.374
Degrees of Freedom	9	1	9	1	9	1	9	1

Notes: These models show the relationship between a proximate industry peer's relocation and the focal firm's innovation performance with different year ranges for the duration of the impact of relocation. The dependent variable is the patent impact (i.e., citation-weighted patents). *Proximate industry peer's relocation* is a dummy variable equal to 1 if a proximate industry peer relocated to a different region. In AM11 and AM12, outbound relocation is coded for two years. In AM13 and AM14, the impact lasts for three years, which is the year range that we use in our main analyses. In AM15 and AM16, four years is used, while in AM17 and AM18, five years range is used. Estimates are from pseudo-maximum likelihood Poisson models. The results show that the impact of a proximate industry peer's relocation is relatively stable across models that use different year ranges for the duration of impact. Refer to the text for the descriptions of the models and for the detailed definitions of the control variables. Robust standard errors are clustered at the focal firm's zip code area level. P-values are shown in parentheses.

APPENDIX D: Procedures for coding inventor mobility

In this section, we share our procedures for coding inventor mobility (A) to measure our control variables of *inventor mobility out* and *inventor mobility in* and (B) to identify the mobility of inventors from the relocating industry peer to focal firms. We built our approach based on procedures used in Corredoira & Rosenkopf (2010). To demonstrate our coding procedures, we also provide five illustrative examples of our manual coding of inventor mobility from our raw data.

A. Procedures to measure *inventor mobility out* and *inventor mobility in*
   - (1) Based on patents produced by our sample firms, we identify inventors that authored at least one nanotechnology patent as a nanotechnology inventor.
   - (2) Among nanotechnology inventors, we identify inventors that authored at least two patents in two different years for one assignee firm and two patents in two different years for another assignee firm.
     i. We choose two different patents in two different years as a basis to establish that the inventor worked in the assignee firm because one patent with the firm or two patents in the same year with the firm is likely to be cases of outsourcing or collaborations.
   - (3) We exclude cases where the time difference between the last patent with the first firm and the first patent with the second firm is more than three years.
     i. If the difference exceeds three years, it becomes difficult to pinpoint years of leaving and joining firms, and inventors could have also joined and worked for other firms in between.
   - (4) We examine each case and remove cases in which inventors patent for at least two firms as a result of alliance-based collaborations, acquisitions, and parent-subsidiary or subsidiary-subsidiary relationships.
   - (5) The remaining cases are coded as mobility between nanotechnology firms.
   - (6) We calculate the number of experienced inventors leaving a firm to measure *inventor mobility out* and the number of experienced inventors joining the firm to measure *inventor mobility in.*

Case #1 – Mobility

Inventor ID	Firm	Patent year
1111	A	1996
1111	A	1997
1111	B	1997
1111	B	1998
1111	B	1998

- The inventor patents at least twice for firm A and then moves to firm B and patents at least twice, so this is coded as a case of mobility

Case #2 – No mobility

Inventor ID	Firm	Patent year
1111	A	1997
1111	A	1997
1111	B	1997
1111	B	1997
1111	B	1997

- The inventor patents at least twice for both firms A and B. The direction of mobility is difficult to discern, so this is not coded as a case of mobility

Case #3 – No mobility

Inventor ID	Firm	Patent year
1111	A	1997
1111	B	1997
1111	B	1998
1111	B	1998

- The inventor patents once for firm A, so this is not coded as a case of mobility.

Case #4 – No mobility

Inventor ID	Firm	Patent year
1111	A	1997
1111	A	1997
1111	B	1998
1111	B	1998
1111	A	1999
1111	A	1999

- The inventor patents at least twice for both firms A and B but return to firm A after two patents for firm B. There is a high possibility that this is a case of outsourcing or collaboration, so this is not coded as a case of mobility.

Case #5 – No mobility

Inventor ID	Firm	Patent year
1111	A	1992
1111	A	1993
1111	B	1998
1111	B	1998

- The inventor patents at least twice for both firms A and B, but the inventor reappears after more than three years. It becomes difficult to identify when the inventor left firm A, so this is not coded as a case of mobility.

B. Procedures to identify mobility of inventors from the relocating industry peer to focal firms
    - (1) After step (5) in the procedure above, we identify cases in which the mobility is between firms that are in the same region and within a 10-miles distance.
    - (2) Among those cases, we check for cases in which the inventor leaves the pre-mobility firm within five years of the pre-mobility firm's relocation to another region (i.e., range of two years before the relocation to two years after the relocation)
        i. We choose two years before the relocation as the starting point because relocation decisions are announced to employees well before the actual relocation.
        ii. We choose two years after the relocation as the ending point because patents include names of inventors that contributed even if they left the firm before the application was filed. For example, inventor A may have left the firm in 1999 while working on patent B, which was eventually filed in 2001.

APPENDIX TABLE E – Across-region research design

	AM19
	DV: Region's Patent Impact (t+1 and t+2) (mean)
Region's nano industry size (mean)	0.041
	(0.000)
ln(Region's nano patent stock (mean))	0.963
	(0.000)
ln(Region's nano paper stock (mean))	-0.229
	(0.025)
ln(Non-nano patent stock)	0.085
	(0.212)
ln(Region's nano employment level (mean))	-0.196
	(0.136)
Region's unemployment rate	8.046
	(0.773)
N	98
Log Likelihood	-1,500.334
Chi-Square	1,288.382
Degrees of Freedom	6

Notes: This model examines the relationship between agglomeration and the focal firm's innovation performance with standard across-region research design. The comparison group is other regions. The unit of analysis is at the region level. The dependent is the region's average patent impact (i.e., citation-weighted patents) between 1990 and 2008. To calculate the dependent variable, we aggregate the patent impact of firms located in the region to the region level, and then we take the average region-level patent impact over the years. *Region's nano industry size (mean)* represents the average number of nanotechnology firms in the region over time. Estimates are from pseudo-maximum likelihood Poisson models. AM19 shows that more agglomerated regions have higher innovation performance, consistent with prior research. Robust standard errors are used. P-values are shown in parentheses.

APPENDIX TABLE F – Long distance relocations and innovation performance

	AM20	AM21	AM22
	DV: Patent Impact (t+1 and t+2)		
Proximate industry peer's relocation	0.777		0.784
to a less innovative region	(0.000)		(0.000)
Proximate industry peer's relocation		0.310	0.315
to a more innovative region		(0.135)	(0.117)
ln(Nano patent stock)	-0.157	-0.100	-0.142
	(0.033)	(0.082)	(0.023)
ln(Nano paper stock)	-0.027	-0.014	-0.005
	(0.777)	(0.886)	(0.953)
ln(Non-nano patent stock)	0.357	0.383	0.329
	(0.001)	(0.000)	(0.001)
Number of alliances	-0.042	-0.047	-0.023
	(0.620)	(0.503)	(0.722)
Inventor mobility out	-0.007	-0.024	-0.001
	(0.919)	(0.659)	(0.984)
Inventor mobility in	0.044	0.010	0.020
	(0.559)	(0.908)	(0.756)
ln(Region's nano employment level)	0.059	0.075	0.082
	(0.164)	(0.126)	(0.073)
Region's unemployment rate	14.871	18.195	13.103
	(0.069)	(0.054)	(0.092)
Constant	2.685	2.684	2.993
	(0.588)	(0.510)	(0.521)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	5,213	4,773	5,908
Log Likelihood	-107,803.756	-91,065.279	-120,338.109
Chi-Square	45.613	38.781	46.473
Degrees of Freedom	9	9	10

Notes: These models show the relationship between a proximate industry peer's relocation and the focal firm's innovation performance. Relocations in these models are restricted to long-distance movements. In other words, short-distance movements into another region (i.e., moving less than 60 miles) are not coded as relocations. The dependent variable is the patent impact (i.e., citation-weighted patents). The comparison group in AM20-M22 are firms not experiencing outbound relocations. AM20 excludes firms that experience a proximate industry peer's relocation to a more innovative region, while AM21 excludes firms that experience a proximate industry peer's relocation to a less innovative region. *Proximate industry peer's relocation to a less innovative region* is a dummy variable equal to 1 if a proximate industry peer relocated to a region with a less cumulative stock of nano patents. *Proximate industry peer's relocation to a more innovative region* is a dummy variable equal to 1 if a proximate industry peer relocated to a region with a more cumulative stock of nano patents. Cumulative nano patent stocks of regions are depreciated 15% annually. Estimates are from pseudo-maximum likelihood Poisson models. Results across AM20-AM22 are similar to results from Table 6. Because short-distance relocations are not coded as relocations, the statistical significance of coefficients is stronger. Coefficients for the two paths in AM22 are also statistically different from one another (p=0.051). Refer to the text for the detailed definitions of the control variables. Robust standard errors are clustered at the focal firm's zip code area level. P-values are shown in parentheses.

APPENDIX TABLE G – Investigating other explanations: relocations with or without satellite R&D centers

	AM23	AM24	AM25
	DV: Patent Impact (t+1 and t+2)		
Proximate industry peer's relocation (satellites)	0.234		0.233
	(0.254)		(0.231)
Proximate industry peer's relocation (no satellites)		0.349	0.350
		(0.045)	(0.044)
ln(Nano patent stock)	-0.130	-0.143	-0.143
	(0.094)	(0.028)	(0.027)
ln(Nano paper stock)	-0.074	0.008	0.005
	(0.533)	(0.925)	(0.954)
ln(Non-nano patent stock)	0.365	0.308	0.301
	(0.002)	(0.005)	(0.005)
Number of alliances	-0.126	-0.027	-0.021
	(0.207)	(0.663)	(0.730)
Inventor mobility out	-0.044	0.004	0.005
	(0.513)	(0.944)	(0.924)
Inventor mobility in	0.088	0.022	0.022
	(0.229)	(0.724)	(0.720)
ln(Region's nano employment level)	0.055	0.089	0.088
	(0.240)	(0.062)	(0.065)
Region's unemployment rate	9.634	9.207	8.534
	(0.309)	(0.297)	(0.310)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	4,276	5,729	5,908
Log Likelihood	-89,568.163	-120,591.136	-121,924.187
Chi-Square	37.925	22.259	22.603
Degrees of Freedom	9	9	10

Notes: These models investigate whether satellite R&D centers of relocating industry peers can explain the positive association between a proximate industry peer's relocation and the focal firm's innovation performance. The dependent variable is the patent impact (i.e., citation-weighted patents). The comparison group in AM23-AM25 are firms that are not experiencing relocations. AM23 excludes firms that experience a proximate industry peer's relocation that does not leave a satellite R&D center in the region, while AM24 excludes firms that experience a proximate industry peer's relocation that does leave a satellite R&D center. The full sample is utilized in AM25. The results from AM23-AM25 show that the focal firms benefit from a proximate industry peer's relocation even if relocating industry peers do not leave a satellite R&D center. The results imply that satellite R&D centers do not explain the positive association between relocation and firm innovation. Refer to the text for the descriptions of the models and for the detailed definitions of the control variables. Robust standard errors are clustered at the focal firm's zip code area level. P-values are shown in parentheses.

APPENDIX TABLE H – Investigating other explanations: marketing mechanism

	AM26	AM27	AM28	AM29	AM30
	DV: Region's Citations of a Focal Firm's Patents (t+1 and t+2)				
Proximate industry peer's relocation	0.128	0.029			
	(0.442)	(0.911)			
Proximate industry peer's relocation to a less innovative region			0.123		0.119
			(0.531)		(0.541)
Proximate industry peer's relocation to a more innovative region				0.066	0.042
				(0.729)	(0.823)
Number of citations to nano patents	0.005		0.005	0.005	0.005
	(0.000)		(0.000)	(0.000)	(0.000)
ln(Target firm's nano patent stock)	0.062		0.063	0.062	0.062
	(0.000)		(0.000)	(0.000)	(0.000)
ln(Target firm's nano paper stock)	0.041		0.042	0.012	0.041
	(0.357)		(0.369)	(0.770)	(0.356)
ln(Target firm's non-nano patent stock)	0.344		0.346	0.344	0.344
	(0.000)		(0.000)	(0.000)	(0.000)
ln(Target firm's region's nano employment level)	0.012		0.010	0.012	0.012
	(0.065)		(0.112)	(0.055)	(0.065)
ln(Region's nano patent stock)	0.087		0.086	0.091	0.087
	(0.030)		(0.032)	(0.025)	(0.029)
ln(Region's nano paper stock)	0.140		0.140	0.111	0.140
	(0.005)		(0.005)	(0.020)	(0.005)
ln(Region's non-nano patent stock)	0.353		0.354	0.382	0.354
	(0.000)		(0.000)	(0.000)	(0.000)
ln(Region's nano employment level)	0.009		0.010	0.009	0.009
	(0.230)		(0.208)	(0.250)	(0.222)
Region fixed effects	Yes	Yes	Yes	Yes	Yes
Target Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N	43,007	43,007	42,242	42,368	43,007
Log Likelihood	-159,298.157	-230,465.694	-155,326.944	-153,570.601	-159,315.162
Chi-Square	484.567	0.013	485.874	472.237	484.810
Degrees of Freedom	10	1	10	10	11

Notes: These models show the relationship between a proximate industry peer's relocation and the citation behavior of the relocated peer's new region. The unit of analysis is at the firm-region-year level, and all firm-region pairs where the region cited at least one patent from a given firm are included. The comparison group is firm-region pairs that did not experience a proximate industry peer's relocation. The dependent variable is the number of citations that a region makes to patents from the focal firm (i.e., the number of backward citations by the region to patents of the focal firm at years t+1 and t+2). AM28 excludes firm-region pairs in which a firm's proximate industry peer's relocation to the region is characterized as a relocation to a more innovative region, and similarly, AM29 excludes firm-region pairs in which a firm's proximate industry peer's relocation to the region is characterized as a relocation to a less innovative region. *Proximate industry peer's relocation* is a dummy variable equal to 1 if a proximate industry peer (i.e., within a 10-mile radius) relocated to the focal region. *Proximate industry peer's relocation to a less innovative region* is a dummy variable equal to 1 if a proximate industry peer relocated to the focal region that has a lower cumulative stock of nano patents than the pre-relocation region. *Proximate industry peer's relocation to a more innovative region* is a dummy variable equal to 1 if a proximate industry peer relocated to the focal region that has a higher cumulative stock of nano patents than the pre-relocation region. Cumulative nano patent stocks of regions are depreciated by 15% annually. Estimates are from pseudo-maximum likelihood Poisson models. The results from AM26 and AM27 suggest that a focal region does not cite more from the focal firm following the focal firm's proximate industry peer's relocation into the region. AM28-AM30 show that results are consistent regardless of whether the proximate industry peer relocated to a less or to more innovative region. Refer to the text for the descriptions of the models and for the detailed definitions of the control variables. Robust standard errors are clustered at the firm-region level. P-values are shown in parentheses.