From Mass to Motion: The Temporal Dynamics of Industry Clusters

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To my family,

for always loving, supporting, and believing in me.

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ABSTRACT

This dissertation zooms in an underexplored phenomenon that I refer to as *the temporal dynamics of industry clusters*: concentration levels of industry activity in a region change over time and patterns of growth do not necessarily follow life cycle stages or larger industry- or region-wide trends. Despite extensive work on cluster size (or "mass"), there has been little attention paid to their temporal dynamics (or "motion"). I propose that understanding cluster dynamics is important, because clusters are seldom stable, and cluster dynamics may have strategic implications not accounted for in existing approaches. In the first essay of my dissertation (Chapter 2), I build a framework for characterizing cluster temporal dynamics, develop a novel empirical technique that characterizes the dynamics, and document the prevalence of the phenomenon. The second essay (Chapter 3) builds on the first chapter framework and examines how cluster dynamics influence the nature of technology creation. I find evidence that innovation by firms in clusters experiencing greater sustained growth is likely to be more disruptive relative to innovation by firms in clusters of comparable size that are experiencing stable or declining periods. I also find that cluster dynamics influence innovation, at least in part, because of cross-cluster employee mobility, which has rarely been discussed as a key mechanism by which clusters influence firm innovation. In the third essay (Chapter 4), I conduct a qualitative study on cluster temporal dynamics based on interviews and historical case studies, unpacking the phenomenon of the temporal dynamics of the medical device industry in the Minneapolis-St. Paul region.

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Chapter 1: Introduction

Researchers in strategy have long recognized that firms benefit from locating in industry clusters—regions that have the disproportional amount of particular industry activity. For example, relative to more geographically isolated firms, those in bigger clusters have easier and greater access to resources, including knowledge from neighboring firms (Alcácer and Chung, 2007; Alcácer and Zhao, 2012; Flyer and Shaver, 2003; Shaver and Flyer, 2000), specialized labor markets (David and Rosenbloom, 1990; Krugman, 1991), and specialized input markets (Carlton, 1983; Rosenthal and Strange, 2003). Clustered firms can also form and leverage social ties more easily (Sorenson and Audia, 2000; Stuart and Sorenson, 2003) and benefit from heightened demand (Chung and Kalnins, 2001; Hotelling, 1929). These positive externalities may result in a greater capacity for innovation (Baptista and Swann, 1998; Bell, 2005) and better economic performance (Decarolis and Deeds, 1999; Tallman *et al.*, 2004).

Although scholars have made significant progress in understanding the importance of cluster membership for firm strategy and the mechanisms through which cluster membership affects firms, the approach taken by existing studies is limited. Specifically, the existing approach tends to focus on *cluster mass* (i.e., levels of geographic concentration) while paying comparatively little attention to an aspect of clusters, which clearly exists and may have strategic implications for firms: *cluster motion* (i.e., the temporal dynamics of clusters—changes in geographic concentration levels over time). While underexplored, cluster motion is potentially important for a more complete understanding of how clusters affect firm outcomes for two reasons.

First, clusters are dynamics, meaning that the concentration of actors within particular industry clusters is seldom stable and may move in ways that run counter to industry-wide or region-wide trends. For example, even after a long and steady growth, clusters can shrink dramatically as steel industry clusters in the Rust Belt showed. Moreover, while some of them keep shrinking, some can rebound after a long setback (e.g., Pittsburgh) or transition very smoothly without any setbacks (e.g., the Minneapolis-St.Paul area).

Not only across regions, but variance also exists within a region across different industries. For example, from the 1950s to the early 1970s, before the rise of Silicon Valley, Minneapolis-St. Paul was home to a large concentration of firms in the computer manufacturing industry (e.g., Control Data, ERA, Cray Research, Honeywell) (Misa, 2013). In subsequent decades, although the U.S. computer industry grew as a whole, Minneapolis-St. Paul's computer industry shrank as many firms relocated to Silicon Valley and Boston's Route 128 region. And, while the local computer industry was shrinking, Minneapolis-St. Paul was experiencing an increase in the concentration of other industries, particularly the medical device sector.

Second, cluster motion may have strategic implications that are not accounted for in existing approaches, which focus on cluster mass, but that may nevertheless influence the relationship between cluster membership and firm outcomes. On the one hand, cluster mass informs levels of concentration of local firms, which determine the *magnitude* of externalities, for instance, the size of a pool of labor, local knowledge, and suppliers. On the other hand, cluster motion not only informs changes in the magnitude of externalities but implies the *nature* of externalities. This is because it reflects how firms, workers, or other industry actors have been flowing across cluster boundaries. These flows, in turn, may determine the nature of externalities—for example, the novelty and diversity of local knowledge. To see this, consider two clusters—A and B—that are identical in size but differ in their recent temporal trends, such that concentration is increasing in A but stable in B. By considering only the levels of concentration at time t, A and B cannot be differentiated—they are identical in terms of the magnitude of externalities. However, the nature of the externalities potentially differs in A and B due to their different temporal trends. Specifically, an increase in concentration levels (e.g., the disproportional amount of focal industry employees) in A implies that new employees entered A from outside its geographical or industrial boundaries unless nation-wide employee population of focal industry and general population of each region decrease[1]. As a result, firms in cluster A might have access to more diverse and distant knowledge that might put firms in A at a competitive advantage over those in B.

Within this context, I suggest broadening a focus from mass to include *motion* for a more complete understanding of the relationship between clusters and firm outcomes. For this purpose, in this dissertation, I develop a cluster motion approach—which will be a framework for the study of cluster temporal dynamics—and by adopting the approach, I empirically examine how cluster temporal dynamics affect firm outcomes.

1.1 Outline of the dissertation chapters

Chapter 2 of my dissertation proposes a measure of cluster motion and documents

[1] In many high tech industries and Metropolitan Statistical Areas in the United States, which are a research context of this research as well as many existing studies on industry clusters, nation-wide employee population of focal industry and general population of each region have not decreased over the last fifty years.

observations about the temporal dynamics of clusters. Specifically, I identify several fundamental features of cluster dynamics based on previous studies scattered across different fields—including the strategy, economics, and geography—and propose a novel empirical technique that systematically measures cluster dynamics. Applying the proposed technique to the U.S. Census Bureau's County Business Pattern (CBP) database on the computer and semiconductor industries between 1974 to 2016, I document several empirical observations about cluster temporal dynamics: (1) concentration levels changed over time in many industry clusters; (2) concentration changes vary across clusters and within clusters over time (i.e., some clusters show periods of increasing and decreasing concentration); (3) the patterns of change vary not only across regions in the same industry but also across industries within the same region. Collectively, these observations help to establish the dynamic nature of industry clusters.

In Chapter 3, using the measure developed in Chapter 2, I further investigate the effects of cluster dynamics—in particular, concentration trends (i.e., the growth rates of concentration)—on firm outcomes by developing and testing hypotheses. Specifically, I examine how cluster dynamics affect firms' technological innovation—particularly, the degree to which innovation disrupts existing streams of technology and establishes new streams. I argue that firms in clusters experiencing a period of sustained growth will be more likely to generate disruptive innovation relative to firms in clusters of comparable size that are experiencing stable or declining periods. This is because a period of sustained growth implies the influx of employees, and the subsequent changes in relevant organizations in the local ecosystem will help cluster firms access distant knowledge and facilitate understanding and application of this knowledge.

Existing studies' cluster *mass* approach can hardly provide a clear answer to this research question. This is because the existing approach simply assumes the nature of agglomeration externalities to be similar in clusters of comparable size, regardless of the temporal trends that the clusters are experiencing. In other words, the cluster mass approach takes little account of possibilities that nature may vary depending on whether the clusters are experiencing a period of sustained growth, decline, or stability. This might be a reason why existing literature finds conflicting evidence on whether a larger concentration exhibits higher levels of firm innovativeness (e.g., Bell, 2005; Ozer and Zhang, 2015).

I empirically test my argument in the context of the U.S. medical device industry from 1974 to 2016, using data on employment from the U.S. Census Bureau's CBP database and data on utility patents granted by the U.S. Patent and Trademark Office (USPTO). My findings support my argument that firms in clusters experiencing sustained growth are likely to produce more disruptive innovation than those in clusters of comparable size experiencing stable or declining periods.

In addition, I further investigate the underlying mechanism behind the relationship between cluster trends and disruptive innovation. Consistent with my argument, the empirical evidence demonstrates that cross-cluster resource mobility is a mechanism. Yet, interestingly, cross-*industry* resource mobility is found to be a mechanism, whereas cross-*geography* mobility is not. Specifically, I find that firms in growing clusters create technologies based more on knowledge from different industries than firms in stable or declining clusters; I find no statistically significant evidence of a higher tendency of firms in growing clusters to base more on different regions. Moreover, I also examine the mechanism by seeing if there are heterogeneous effects on entrepreneurial firms versus large established firms and ruling out the competition effects explanation.

In Chapter 4, I conduct a qualitative study on cluster temporal dynamics based on interviews and historical case studies. In this mini case study, I unpack the phenomenon of the temporal dynamics of the medical device industry in the Minneapolis-St. Paul region. The area is one of the largest medical device clusters in the US. I demonstrate whether and how resources—financial resources, employees, and relevant organizations—were flowing from the outside local medical device industry boundary during a period of sustained growth in the local medical device industry. One of the major sources of resource inflows is the local computer industry. Since Minneapolis-St. Paul was a computer industry hub before the emergence of a medical device cluster, there were a lot of resources and industry activities that were specialized in the computer industry. However, during a period of growth in the local medical device industry, those resources and activities shift their attention from the computers to the medical devices. Furthermore, this transition contributed to innovation in the medical device industry.

1.2. Contributions

This research contributes to the existing literature in several ways. First, this study transforms academic approaches to studying clusters: broadening from a *cluster mass* to include a *cluster motion* approach. This will enrich the understanding of the relationships between industry clusters and firm outcomes. Second, the implications of cluster motion may help resolve conflicting findings within longstanding debates—whether higher industry concentration facilitates or deters disruptive innovation. Considering cluster motion in addition to cluster mass may provide clear evidence on the role of clusters in innovation. Third, the proposed empirical technique and the documented phenomenon will further facilitate more theory developments. According to Merton's (1987), the first step in theory building is "establishing that the phenomenon actually exists, that it is enough of regularity to require and to allow explanation." Thus, with the proposed technique and documented observations about cluster dynamics, in the future, researchers will be able to establish the regularity of clustery dynamics in a variety of contexts, which becomes a fundamental foundation for theorizing cluster dynamics in strategy research. Furthermore, the proposed measure will allow researchers to examine the effect of cluster temporal dynamics on firms via quantitative studies using large samples.

Chapter 2: Conceptualizing and Measuring Cluster Temporal Dynamics

In this chapter, I develop a cluster motion approach. First, I offer a synthesis of the small body of existing literature in strategy on this topic. Although this literature offers valuable insights, it tends to be scattered across subfields, which limits the development of sustained research attention. Second, building on this groundwork, I identify several fundamental features of cluster temporal dynamics and propose a novel technique for measuring them. Third, applying the proposed technique to U.S. Census data on the computer and semiconductor industries, I document wide variation in cluster mass over time, both within and across regions. Moreover, I assess the validity of the proposed measure, *cluster motion* ($\boldsymbol{C_{Motion}}$). Specifically, I examine whether the output of the measure is consistent with intuition and known trends from economic history, whether there is sufficient variance in $\boldsymbol{C_{Motion}}$, and whether $\boldsymbol{C_{Motion}}$ is different from a measure of cluster *mass*.

2.1. Literature Review

2.1.1. Industry Clusters

An industry cluster is defined as a geographical concentration of firms within an industry. Locating with high industry agglomeration can generate external economies, including a knowledge spillover, specialized labor pool, specialized input markets, and greater demand (Marshall, 1920). Researchers in strategic management have long recognized these positive externalities, and they classify the externalities into two categories: the supply side and the demand side (e.g., Alcácer & Chung, 2014; Canina, Enz, & Harrison, 2005; McCann & Folta, 2008; Pe'er, Vertinsky, & Keil, 2016).

On the supply side, firms in clusters contribute to co-locating firms' production efficiency. Shaver and Flyer (2000) suggest that firms that locate in industry clusters can improve their productivity by accessing the neighboring firms' superior resources. The resources include technological knowledge, human capital, training programs, suppliers, and distributors. In the geographic clustering of industries, knowledge is more easily and frequently transferred (Alcácer & Chung, 2007; Flyer & Shaver, 2003; Saxenian, 1994; Tallman et al., 2004) and a labor market with specialized skills is created (David & Rosenbloom, 1990; Helsley & Strange, 1991; Krugman, 1991). In addition, there are more specialized inputs available, such as suppliers, facilities, or research tools, and the production of inputs may be more efficient in bigger clusters (Carlton, 1983; Folta, Cooper, & Baik, 2006; Rosenthal & Strange, 2003). On the demand side, the spatial concentration of industries increases demand because it reduces consumers' search costs, including costs of discovering and evaluating the offerings of firms (Chung & Kalnins, 2001; Hotelling, 1929; Stahl, 1982).

Based on an understanding of the externalities of industry clusters, researchers have examined how these externalities affect firms, especially firms' survival and founding. High survival and founding rates of clustered firms have been discussed as major mechanisms behind how industry clusters can persist (McCann & Folta, 2008; Sorenson & Audia, 2000; Wang et al., 2014). Regarding survival, researchers argue that externalities from geographic concentration enable clustered firms to perform better and hence survive longer than those in isolated areas. For example, clustering activities facilitate knowledge spillovers, which help firms generate more innovations (Baptista &

Swann, 1998; Bell, 2005; Delgado et al., 2014; Funk, 2014). There are also empirical findings that show firms in clusters have better economic performance than less clustered firms (Beadry & Swann, 2001; Decarolis & Deeds, 1999; Tallman et al., 2004). In addition to survival, firms' founding rates also appear to be influenced by agglomeration. That is, firms are more likely to locate in regions with higher levels of similar industry activities (Head, Ries, & Swenson, 1995; Kalnins & Chung, 2004; Rosenthal & Strange, 2003). In particular, entrepreneurs tend to create their ventures in clusters because they may obtain and leverage social ties more easily in the clusters (Sorenson & Audia, 2000; Stuart & Sorenson, 2003).

Although there are empirical findings that show such positive impact of spatial concentration on firm survival and founding, clustering does not necessarily improve firm performance or increase firm founding rates (Alcácer & Chung, 2007; Shaver & Flyer, 2000; Sorenson & Audia, 2000). This is because clustering also generates negative externalities, meaning that greater competition and other factors created by clustering may generate challenges for firms in clusters. As both positive and negative externalities exist, performance and founding implications can be different depending on firm heterogeneity. For example, firms with superior resources such as technology or human capital are less likely to locate in clusters because they gain little while contributing to externalities co-locating competitors benefit from (Alcácer & Chung, 2007; Shaver & Flyer, 2000). There are also empirical findings that clustered firms have lower survival rates (e.g., Baum & Mezias, 1992; Folta et al., 2006; Shaver & Flyer, 2000; Sorenson & Audia, 2000).

Recognizing both the positive and negative externalities of industry clusters, researchers have also explored appropriate organizational designs with which many of the negative externalities can be overcome. For example, Funk (2014) suggests that a cohesive intra-organizational network can help firms overcome one of the challenges a clustered firm would face, which is to process a large amount of knowledge inflow from co-locating firms. This is because, with cohesive networks, individuals are better able to identify the value of knowledge as their colleagues help. Similarly, Alcácer and Zhao (2012) suggest that firms with strong networks of internal linkages would reduce the risk of knowledge leakage to co-locating competitors as they can closely monitor and control local innovation.

As this review demonstrates, previous literature enhances the understanding of the importance of cluster membership for firm strategies and mechanisms through which cluster membership affects firms. However, the approach taken by existing work, both theoretically and empirically, tends to focus on cluster mass (i.e., concentration levels in clusters) rather than cluster motion or cluster temporal dynamics (i.e., changes in concentration levels over time).

From a theoretical standpoint, scholars tend to develop propositions with a focus on local concentration levels at a given point in time. For example, previous research predicts that firms in bigger clusters generate more innovations than those in smaller clusters. However, this research does not consider if the focal clusters are experiencing an upward or downward trend (Baptista and Swann, 1998).

Empirically, many existing studies rely on cross-sectional variation to examine cluster effects. Specifically, these studies examine how variation in mass among clusters explains firm heterogeneity (e.g., Bell, 2005; Decarolis and Deeds, 1999). To the extent that studies leverage cluster data over time (e.g., Alcácer and Chung, 2014; Pe'er, Vertinsky, and Keil, 2016), the empirical approaches control for cluster heterogeneity and isolate the effects of cluster mass on firms. Although longitudinal in the sense that they leverage panel data, as noted by Greve and Goldeng (2004) and Certo and Semadeni (2006), these types of models are designed to study differences in a variable (e.g., cluster mass) not to explicitly test propositions with reference to temporal process (e.g., cluster motion).

2.1.2. Temporal Dynamics of Industry Clusters

While mainstream work in strategy tends to focus on the implications of cluster mass, a small number of studies acknowledge and consider cluster temporal dynamics. For example, Klepper and colleagues [Klepper (2007); Cheyre, Klepper, and Veloso (2015)] examine how spinoff rates of firms differ depending on patterns of change in concentration. In one study, Klepper (2007) divides the time series of the Detroit automobile industry cluster into two distinct trends, one of increasing and one of decreasing concentration. He finds that the probability of Detroit firms spawning a spinoff becomes significantly lower after 1916, in which the trend shifted from an increase to a decrease.

Pouder and St. John (1996) propose a conceptual model that describes the evolutionary phases of cluster growth. They argue that clusters evolve following a sequence of phases (i.e., through origination, convergence, and then failure). According to this model, when clusters originate, member firms are expected to grow faster than the industry-wide rate because of agglomeration economies. By contrast, as clusters evolve over time (i.e., through the convergence and failure phases), the marginal benefits for firms decrease due to congestion costs and a homogeneous macro culture. A few researchers have applied this evolutionary phase model. For example, Wang, Madhok, and Li (2014) divide the Ontario wine industry into two temporal phases—the origination phase and the convergence phase—and find that these phases are associated with firm founding and survival rates. In addition, Folta, Cooper, and Baik (2006) demonstrate that in the U.S. biotechnology industry, the evolutionary phases of clusters also have an influence over firm performance.

In summary, prior research in strategy offers a useful foundation for the study of cluster temporal dynamics. However, in addition to there being few studies, existing work tends to appear across various subfields of strategy, which hampers the cumulation of research findings. Moreover, existing work has generally been case study-based, and consequently, has limited generalizability.

In addition to strategy scholars, economic geographers also study cluster dynamics. Unlike strategy researchers, economic geographers tend to focus on clusters as interesting phenomena in their own right and are less interested in the implications of clusters for firms. I can classify research in economic geography on cluster dynamics into three general approaches. The first approach argues that industry clusters have a path-dependent nature, meaning that clusters become locked-in as they age (e.g., Boschma, 2004; Cooke and Morgan, 1998; Hassink, 2005). The second approach suggests that clusters go through life cycle stages, which consist of emerging, growing, sustaining, and declining stages (Enright, 2003; Menzel and Fornahl, 2009; Tichy, 1998). The third approach, which argues against the life cycle model, suggests that clusters evolve differently due to the episodic interactions of nested systems (Isaksen, 2015; Martin and

Sunley, 2011). Collectively, this body of work emphasizes that clusters change over time and that patterns of change can be the same or different among clusters.

2.2. Measuring the Temporal Dynamics of Industry Clusters

2.2.1. Fundamental Characteristics of Cluster Temporal Dynamics

I suspect that the limited research on cluster temporal dynamics is due, in part, to a lack of tools for systematically measuring how the geographic concentration of industries changes over time. To remedy this, I propose a novel empirical technique that characterizes cluster temporal dynamics and that therefore may open avenues for research.

Before proposing a measure, I draw on the previous literature in strategy and economic geography discussed above to identify four fundamental characteristics of cluster temporal dynamics. These features help to guide the measure development; a valid measure should be able to capture the core properties of dynamics that previous work has discovered.

First, a single cluster's time series (i.e., how concentration levels change over time) can be segmented into multiple distinct trends. Pouder and St. John (1996) and life cycle approach scholars argue that clusters follow multiple life cycle stages. In addition, Klepper (2007) and adaptive cycle theorists suggest that the patterns of change in concentration may shift dramatically over time. The arguments of both studies suggest the existence of one or more trends in a single cluster.

Second, industry clusters have their own unique paths; such that different geographic regions in the same industry may go through different sequences of concentration trends. Put another way, within an industry, not all regions necessarily follow the same course (i.e., the pattern of change). This view has been suggested by adaptive approach scholars and Klepper (2007), along with other researchers, including Saxenian (1994) and Delgado, Porter, and Stern (2010). For example, Saxenian (1994) compares the computer industry evolution in two regions, Boston and Silicon Valley, and describes why they evolved differently from each other.

Third, industry clusters are subject to change qualitatively (i.e., in terms of whether concentration levels are increasing, decreasing, or stable over time). Klepper (2007), for example, identifies increasing and decreasing concentration trends and finds that Detroit firms exhibit different spinoff rates depending on these trends.

Fourth, industry clusters are subject to change quantitatively (i.e., in terms of how much concentration is increasing or decreasing). Cheyre, Klepper, and Veloso (2015), for example, compare the spinoff rates of firms before and after 1975, the year in which the growth trend of the semiconductor industry in Silicon Valley shifted from a gradual increase to a rapid increase. Similarly, Wang, Madhok, and Li (2014) also identify a gradual and rapid increase and find that these two types of increase show different rates of firm survival.

Although I do not claim that this is an exhaustive list of the fundamental properties of cluster dynamics, prior work suggests that these four features offer a useful starting point for developing a measurement framework.

2.2.2. Measure Development

Calculating the measure of cluster dynamics consists of three steps: (1) measuring concentration levels of clusters, (2) identifying trends in concentration levels, and (3) quantifying characteristics of the trends.

Step 1: Identifying clusters using Monte Carlo simulations

The first step is to measure the degree of local concentration and identify clusters. Following Alcácer and Zhao (2016), I identify clusters based on the type of economic activity, the unit of geography, and the threshold of concentration required to label a location as a cluster. In other words, a location is identified as an industry cluster when the degree to which a type of economic activity (e.g., the number of firms) in an industry is concentrated within a geographic boundary (e.g., Metropolitan Statistical Areas) exceeds a threshold.

I compute this threshold by adopting the logic of Ellison and Glaeser's (1997) "dartboard approach." The logic of this approach is that, without agglomeration, a geographic concentration of economic activity should be determined by randomly throwing darts at a map. The size of each geographic region can be weighed by different criteria (e.g., population size, area) according to the needs of the analysis. Locations with economic activity in excess of this dartboard threshold are considered clusters, and the extent of the difference between the actual activity and the threshold is considered the degree of concentration. Because the degree of concentration needs to be comparable across different years and locations, I normalize the concentration by using a z-score method with the Monte Carlo simulation.

Specifically, the main steps are the following:

1. Add up the value of economic activities (e.g., the number of firms) of all regions by industry and year, resulting in the industry-year level total.
2. Randomly distribute the industry-year level total over a map and check the value (e.g., count the number of firms) assigned to each region. This synthetic instance

(i.e., random throw) is created and repeated through the Monte Carlo simulation.

3. Calculate the region-industry-year level average and standard deviation of the assigned values (e.g., the number of firms assigned to a region) obtained from synthetic instances.
4. Using the average and distribution, calculate a z-score;

$$z = \frac{obs - exp}{\sigma}$$

where obs is the value of economic activity in a given region, industry, and year, observed from the data. exp and σ are the mean and standard deviation, respectively, which was calculated from the randomized simulations.

Following the steps above, I obtain the region-industry-year level z-scores, which capture how much the degree of concentration exceeds a threshold. I use the z-scores as input in the following analyses.

Step 2: Time-series segmentation using the Bai-Perron test

To identify (potentially multiple) distinct trends for each cluster, I find breaks in the time series of concentration levels (i.e., the z-scores) by using structural break analysis. Structural break analysis estimates a linear regression model of structural changes or unexpected shifts in a time series. As a test for the structural breaks, I use the Bai-Perron test. This test estimates the number of breaks—which divide a linear regression into multiple regimes—and unknown break dates (Bai and Perron, 1998, 2003). In particular, the general logic of the test is to find a global minimizer for the sum of squared residuals.

A pure structural change model with the linear regression with ***m*** breaks (***m+1*** regimes) is given by:

$$y_t = z'_t\delta_j + u_t$$

where $t = T_{j-1} + 1, \ldots, T_j$ for $j = 1, \ldots, m + 1$. z_t are vectors of covariates, in which coefficients are allowed to change across regimes. The break point estimators $(T_1, T_2, \ldots, T_m)$ are computed based on the principle of dynamic programming that allows the computation of estimates of the break points as global minimizers of the sum of squared residuals. The regression parameter estimates are the estimates associated with *m*-partition $\{\hat{T}_j\}$, that is, $\hat{\beta} = \hat{\beta}(\{\hat{T}_j\})$.

Bai and Perron (1998) suggest three statistics to identify the break points: the $supF_T(k)$ test, the double maximum tests (UD_{max} test, WD_{max} test), and the $supF_T(l+1|l)$ test. First, the $supF_T(k)$ test estimates the long-run relationship with multiple structural breaks *k*. The null hypothesis is that "there is no structural break (*m*=0)," and the alternative hypothesis is that "there exist a fixed (arbitrary) number of breaks (*m*=*k*)." A test statistic is estimated using:

$$supF_T(k) = F_T(\hat{\lambda}_1, \ldots, \hat{\lambda}_k; q) = \frac{1}{T}\left(\frac{T-(k+1)q-p}{kq}\right)\hat{\delta}'R'(R\hat{V}(\hat{\delta})R')^{-1}R\hat{\delta}$$

where $T_i = [T\lambda_i]$ (i=*1,…k*) and $(R\delta)' = (\delta_1 - \delta_2, \ldots, \delta_k - \delta_{k+1})$.

Second, the aim of the double maximum tests is also to test whether there exist one or more structural breaks in a time series. The null hypothesis is that "there is no structural break" and the alternative hypothesis is that "there is an unknown number of breaks given some upper bound *M*." The first test is an equal weighed version, UD_{max} test:

$$UD_{max}F_T(M, q) = max_{1 \le m \le M} F_T(\hat{\lambda}_1, \ldots, \hat{\lambda}_m; q),$$

where $\hat{\lambda}_1 = \frac{\hat{T}_j}{T}$ $(j = 1 \ldots . m)$. The other test is the WD_{max} test, which uses weights that depend on the number of regressors, and the significance level of the test:

$$WD_{max}F_T(M,q) = \ max_{1\leq m\leq M}\frac{c(q,\alpha,1)}{c(q,\alpha,m)}F_T\big(\hat{\lambda}_1,\dots,\hat{\lambda}_m;q\big),$$

where $c(q,\alpha,1)$ is the asymptotic critical value of the test $F_T(M,q)$ for a significance level α.

Finally, the last test is the $supF_T(l+1|l)$ test. While the previous two tests focus on testing the existence of one or more breaks, this sequential F test is for estimating the number and dates (years) of breaks. Specifically, the $supF_T(l+1|l)$ test considers the null hypothesis of l structural breaks against the alternative hypothesis that an additional break exists. More precisely, the test is defined by:

$$F_T\ (l+1|l) = \Big\{S_T\big(\widehat{T}_1,\dots,\widehat{T}_l\big) - \min_{1\leq i\leq l+1}\inf_{\tau\epsilon\Lambda_{i,\eta}} S_T\big(\widehat{T}_1,\dots,\widehat{T}_{i-1},\tau,\widehat{T}_\iota,\dots,\widehat{T}_l\big)\Big\}/\hat{\sigma}^2,$$

where $\Lambda_{i,\eta} = \{\tau;\hat{T}_{i-1} + (\hat{T}_i - \hat{T}_{i-1})\eta \leq \tau \leq \hat{T}_i - (\hat{T}_i - \hat{T}_{i-1})\eta\}$.

Through these F tests, I can obtain the information on the number and dates of structural breaks. Given this information, I divide the time series of an industry cluster into multiple segments. As the structural breaks refer to the points at which the patterns of change in concentration levels shift, I consider each segment "a concentration trend."

Step 3: A regression analysis for each concentration trend

By running a regression analysis for a given concentration trend—a segment as identified in *Step 2*—I quantify the direction and magnitude of change in concentration levels in the trend. Specifically, the regression coefficient estimate from the analysis informs the direction and magnitude of change in the trend. I store the values of the coefficient estimates as the values of the proposed measure of cluster temporal dynamics, which is denoted by C_{Motion}. Thus, C_{Motion} tells us, for each cluster trend, the degree to which concentration levels have been changing. The sign of C_{Motion} (i.e., positive or negative) indicates whether the cluster has been concentrating or dissipating; the absolute value of C_{Motion} implies how rapidly the cluster has been concentrating or dissipating.

2.3. Assessing the Measure

In this section, by applying the proposed technique to data[2], I assess the validity of the measure, C_{Motion}. Specifically, I examine (1) whether the measure output accords with intuition and known trends from economic history, (2) whether there exists variance in C_{Motion}, and (3) whether C_{Motion} is distinctive from cluster mass. Following these assessments of validity, I explore whether the measure relates to a central question in strategy research on industry clusters—is clustering associated with greater localized knowledge spillovers?

2.3.1. Initial validity check

2.3.1.1. Data and sample

I calculate C_{Motion} for United States metropolitan areas in two high technology industries: the semiconductor industry and the computer industry[3]. The activities of these industries are geographically concentrated in the United States and have been studied extensively in prior work in strategy (e.g., Almeida, 1996; Eisenhardt and Schoonhoven, 1990; Lavie, 2007). To define economic activity, I use the number of business establishments for the respective industries. To define geographical boundaries, I use the

[2] Upon publication, I will make code and data for calculating C_{Motion} publicly available to allow replication of the analysis and to facilitate future research.
[3] The computer industry includes both the computer hardware (manufacturing) and software industries.

Metropolitan Statistical Area (MSA), which reflects the spatial distribution of firms more accurately than other predetermined geographic units, such as states or counties.

I establish a dataset—which captures the number of business establishments at the MSA-industry-year level for the semiconductor and computer industries—based on the County Business Pattern (CBP) data from the U.S. Census Bureau and the National Historical Geographic Information System. The CBP data provides subnational economic data, including the number of business establishments at detailed geography and industry levels. Existing studies have used these data extensively (e.g., Delgado, Porter, and Stern, 2014; Porter, 2003).

The dataset spans 43 years (from 1974 to 2016). Using this 43-year time series is of great benefit because I can capture meaningful trends using a long time series. However, using data over such a long window also creates challenges because industry classification codes and geographical units and boundaries change over time. I address this issue by creating crosswalks for different versions of industry classification codes and for geographical units and boundaries.

The primary industry classification code I use is the four-digit Standard Industrial Classification (SIC). The SIC was updated five times during the sample period, resulting in six different versions (1972 SIC, 1987 SIC, 1997 NAICS, 2002 NAICS, 2007 NAICS, and 2012 NAICS). Using concordances from the NBER-CES Manufacturing Industry Database and the U.S. Census Bureau, I convert all versions of code into 1987 SIC.[4]

[4] I use 1987 SIC as the primary version for two reasons. First, SIC codes are more aggregated and cover more years in this data than the North American Industry Classification System (NAICS). Second, there was a substantial update in 1987 SIC, and the NAICS was created based on the 1987 SIC.

The geographical unit in the CBP data is the county, so I map counties to MSAs. An MSA is an aggregate of multiple counties, but some counties have experienced changes in their boundaries. Because the degree of geographic concentration is susceptible to changes in geographical boundaries, I account for these boundary changes. Specifically, I look carefully at the changes, which were announced by the U.S. Census Bureau, through the comparison of the shape files of county boundaries across time. As a result, I convert 1,231 counties into 375 MSAs, after excluding Alaska, Hawaii, and Puerto Rico[5].

2.3.1.2. Examples of C_{Motion} calculation

Utilizing the dataset, I calculate C_{Motion} following the three steps described in the measure development section.

Step1: I calculate z-scores for all 375 MSAs in the semiconductor and computer industries, respectively. First, I add up the number of establishments in the respective industries in all MSAs by year, resulting in the industry-year level totals. Using Monte Carlo simulations, I then randomly distribute the firms that make up the industry-year level total over a map; the size of each MSA is proportional to its population size. I repeat this process 100 times and then calculate the mean and standard deviation of the number of firms obtained from the 100 synthetic iterations at the MSA-industry-year level. Using these two calculated values (i.e., the mean and standard deviation) and the observed value from the data, I calculate a z-score, which represents the extent to which the degree of concentration in a focal MSA exceeds a threshold value (i.e., what would be expected by

[5] Further information about the crosswalk for the regional boundary is available upon request.

chance).

In Figure 2.1, I give an overview of the z-scores for both industries using heat maps. Here, the goal is to demonstrate that MSA z-scores change over time and that the patterns of change in z-scores for specific industry clusters do not always align with industry-wide trends or region-wide trends. Figures 1a and 1b plot the z-scores for the top five percent of regions[6] (i.e., 20 MSAs) with the largest mean of z-scores from 1974 to 2016 in the computer and semiconductor industries, respectively. On the Y-axis, I list the regions ranked from the first to the 20th in order from top to bottom. On the X-axis, I list the years. Cells represent the values of z-scores as colors[7] so that darker cells represent higher z-scores (i.e., higher concentrations). Thus, each row displays how the z-scores of a given region change over time. In other words, by observing cells in a row, I can understand how the concentration of local industry activity changed between 1974 and 2016.

---Insert Figure 2.1 here---

From the changing colors in the heat maps for both industries, I demonstrate the existence of temporal dynamics in most clusters. I also find that even for z-scores within the same industry, the patterns of change vary among regions. For example, in the

[6] Specifically, for all 375 MSAs in each industry, I calculated the mean of z-scores over the years when their z-scores are positive (i.e., during the period of time when the focal region is identified as a cluster). I then selected the top 20 MSAs with the largest mean of z-scores for each industry. These large clusters were selected among the MSAs, in which annual average numbers of firms are at least greater than five during the years when their z-scores are positive.

[7] For each industry, I divide the 20 regions into two groups: 1) the top 10 regions and 2) the next 10 regions. These groups use different value scales for determining cell coloring because the z-scores are greatly different between the two groups. The use of different color schemes makes the within-region variations visually clearer. I provide the color schemes next to the heat maps.

computer industry (Figure 2.1a), the top five regions share a common pattern: an increase in z-scores until the mid-1990s. However, the z-scores in New York-Newark-Jersey City and Boston-Cambridge-Newton begin to decrease in the early 2000s and then return to their original values, while those in the top three regions do not. In addition, unlike those in the top five regions, the z-scores in Los Angeles-Long Beach-Anaheim are very high for the first 15 years and then begin to drop rapidly. San Diego-Carlsbad also shows a decrease in z-scores in the early 1990s, but unlike Los Angeles-Long Beach-Anaheim, its z-scores rebound and grow rapidly from 2000 onward.

The semiconductor industry (Figure 2.1b) also shows different patterns of change among regions. For example, the patterns of change in Los Angeles-Long Beach-Anaheim and Colorado Springs appear as mirror images of each other. The z-scores in Los Angeles-Long Beach-Anaheim decrease in the late 1980s and rebound in the early 2000s, whereas those in Colorado Springs rapidly grow in the late 1980s and drop in the early 2000s.

I also find that the patterns of change are different between industries within the same geographic boundary. For example, in New York-Newark-Jersey City, the z-scores of the computer industry stay low until the early 1990s when they begin to gradually increase, while those of the semiconductor industry display a steep decrease until 1990 and stay low thereafter.

Step 2: To identify concentration trends for each MSA, I implement a structural break analysis, following the approach described above. This analysis reports the number of distinct concentration trends identified in each MSA during a 43-year study window, including information on the years when each trend begins and ends.

To illustrate more specifically how the proposed method works, I choose one of the top 20 largest clusters for each industry, within which there exist multiple concentration trends. The selected MSAs are 1) San Diego-Carlsbad in California for the computer industry and 2) New York-Newark-Jersey City in the states of New York, New Jersey, and Pennsylvania for the semiconductor industry. Figure 2.2 shows the z-scores of these areas from 1974 to 2016, which are segmented into multiple concentration trends by the structural break analysis. Table 2.1 presents the detailed test results.

---Insert Figure 2.2 and Table 2.1 here---

Table 2.1 reports the results of the Bai-Perron test, which consists of the $supF_T(k)$ test, the double maximum tests (UD_{max} test and WD_{max} test), and the sequential $supF_T(\ell + 1|\ell)$ test. I find that for both MSAs (Tables 1a and 1b, respectively) the test values obtained from the first two tests are greater than the critical values at the five percent significance level. This means that I can reject the null hypothesis that there is no structural break in either time series. In other words, both industries have experienced two or more trends during the sample period.

From the sequential $supF_T(\ell + 1|\ell)$ test, I can estimate how many structural breaks exist and when they occur. In San Diego-Carlsbad, the value of the $supF_T(2|1)$ test (190.057) is greater than the critical value at the five percent significance level (11.47). Yet, the $supF_T(3|2)$ test value is 10.794, which is smaller than the critical value (12.95). These results reveal two structural breaks in this region. The test reports that these breaks occurred in 1985 and 1999, implying that the region has experienced three trends: the first trend from 1975 to 1985, the second from 1985 to 1999, the third from 1999 to 2016. The test results for New York-Newark-Jersey City (Table 2.1b) report the existence of three breaks since the values of the $supF_T(2|1)$ and $supF_T(3|2)$ tests (55.466 and 26.405, respectively) are greater than the critical values while the $supF_T(4|3)$ test value (10.961) is smaller than its critical value. The years of breaks are 1990, 1997, and 2008.

Step 3: For each concentration trend, I run a regression analysis. The values of the regression coefficient estimates, which represent the direction and magnitude of change, are the values of C_{Motion}. Table 2.2 reports the coefficient estimates with their standard errors and p-values. Specifically, the results in Table 2.2a imply that the computer industry in San Diego-Carlsbad experiences an increasing concentration trend (β= 0.343, p = 0.001) from 1974 to 1985, followed by a decreasing trend (β= -0.490, p = 0.000). From 1999 onward, the industry experiences a sharp increase (β= 0.707, p = 0.000) until 2016.

In Table 2.2b, the results report that the semiconductor industry in New York-Newark-Jersey City experiences a decreasing concentration trend from 1975 to 1990 (β= -0.195, p = 0.000). Then, the extent of a decrease becomes bigger (β= -0.651, p = 0.000) until 1997. This shows that the proposed measure is able to capture not just shifts from an increase to a decrease or vice versa, but also shifts in the magnitude of increase or decrease. The region then experiences a slight increase followed by a decrease until 2016, but these changes are not great in size (β= 0.085 and -0.105), and the decreasing trend from 2008 to 2016 is not statistically significant at the five percent level (p = 0.072). In other words, no strong upward or downward concentration trend is detected for this period.

---Insert Table 2.2 here---

These examples demonstrate that the proposed technique helps to reveal how clusters change over time. Without segmentation, I would ignore or underestimate the temporal dynamics. To demonstrate this, I report the results of the approach without segmentation (i.e., running a regression for an entire time series) in the last rows in Tables 2.2a and 2.2b. For example, in Table 2a, the regression coefficient estimate suggests that this region has experienced one trend of a moderate increase (β= 0.321, p = 0.000) over 43 years. However, this conceals a trend of a decrease from 1985 to 1999 and underestimates the magnitude of change from 1999 to 2016.

2.3.1.3. Does C_{Motion} output accord with intuition and known trends from economic history?

As a first step to check the face validity of the measure, I investigate whether results using the cluster motion approach are consistent with visually apparent trends from time series graphs and with the history of the local industry.

Beginning with the graph in Figure 2.2a, there is clear visual evidence of a break in the late 1990s, at which point the trend changes from a decrease to a sharp increase in concentration. This is consistent with the history of the computer industry in San Diego-Carlsbad. Since Qualcomm was established in 1985, the wireless communication industry and the semiconductor industry in this area have grown rapidly (Cortright and Mayer, 2001), implying that many local resources have moved into those industries. As a result, the local concentration of the other industries, including the computer industry, consequently decreased during the late 1980s. However, from the late 1990s, this downward trend shifted to a steep increase, led by a few anchoring firms in the computer industry. For example, Websense Inc., a security software firm established in 1994, grew fast during the late 1990s and successfully went public with an IPO in 2000. In addition, ESET, an established IT security firm in Slovakia, created the U.S. headquarter in San Diego in 1999. Both Websense and ESET kept growing rapidly even after the burst of the dot-com bubble (Contu and Cheung, 2011; Lemos, 2013), during which many U.S. firms in the computer industry shut down. This resulted in a trend of increasing concentration of the industry in this area. These breaks, discovered from the time series graph and also the history of the region, are consistent with the outputs of the measurement, as the Bai-Perron test reports a break in 1999, and the regression analysis suggests a decrease before the break and a subsequent rapid increase.

Similarly, in Figure 2.2b, the existence of a break in the late 1990s is visually apparent, at which point the trend shifts from a steep decrease to an increase, albeit a moderate one. This is also consistent with the history of the semiconductor industry in New York-Newark-Jersey City, which was the original center of the U.S. semiconductor industry. The region's early leadership in this industry was cemented in the early 1950s by the presence of several leading firms, including Bell Labs and Germanium Products Corp (Morris, 1990). However, the degree of local concentration decreased as many of the leading firms relocated to other areas, such as California and Colorado. Moreover, as several leading firms in other areas (e.g., Fairchild in California, Texas Instruments in Texas) grew fast, many firms, even prominent Japanese manufacturers, entered these areas. As a result, this accelerated an upward trend in California and Texas and a decreasing concentration trend in New York-Newark-Jersey City. From the late 1990s, however, industry activity in California and Texas began to decrease because many of the local facilities relocated to Asian countries. In consequence, New York-Newark-Jersey

City's trend of a steep decrease, shown in the 1980s, stopped. The proposed measurement technique well captures these over-time changes—the statistical test results report a break in 1997 and suggest a sharp decrease before the break followed by a slight increase.

These examples offer strong support that the output of the measure, C_{Motion}, accords with intuition and known trends from economic history

2.3.1.4. Is there sufficient variance in $\mathbf{C_{Motion}}$?

To further establish the validity of the measure, I also need to demonstrate the nature of variance in C_{Motion}. The purpose of developing this measure is to facilitate future empirical research on cluster dynamics; thus, it is important that I can observe the meaningful variance in C_{Motion}.

I present descriptive statistics (Table 2.3) and density plots (Figure 2.3). As shown in Table 2.3, the values of C_{Motion} for the computer industry range from -1.938 to 5.545, with a mean and standard deviation of -0.072 and 0.396, respectively. In the semiconductor industry, the values of C_{Motion} range from -1.317 to 2.463, with a mean and standard deviation of 0.0003 and 0.133, respectively.

---Insert Table 2.3 and Figure 2.3 here---

I also examine the variance by reducing a sample to the top five percent of regions (i.e., 20 MSAs) with the largest mean of z-scores for the respective industries. Two considerations led to examine this subsample. First, in strategy and economic geography, researchers are mainly interested in studying the large-sized clusters, rather than all regions. Second, focusing on larger regions helps evaluate the potential concern that the observed variance comes from the outliers of small-sized regions. As shown in the second column of Table 2.3, I continue to find substantial variance when the sample is confined to the large-sized clusters, while the range of C_{Motion} values remains highly consistent with the full sample. Specifically, the standard deviations are 1.381 for the computer industry and 0.455 for the semiconductor industry.

Figures 3a and 3b visualize these different distributions through density plots. From the figures, I generally see that C_{Motion} values for all regions are highly concentrated around zero whereas the values for the top 20 regions are dispersed. This implies that—perhaps unsurprisingly—for both industries, large-sized clusters are more dynamic—that is, the degree of concentration changes more dramatically—than many small-sized regions, and that their patterns of change vary.

To examine whether the variance in C_{Motion} is sufficient to be a useful measure, I compare the variance in C_{Motion} to the variance in the measure of concentration levels (measured by the z-score; denoted by C_{Mass}), which is a quantity that has been used widely in previous literature. I can conclude that C_{Motion} has sufficient variance if the value for variance in C_{Motion} is similar to or greater than the variance in C_{Mass}. Because C_{Motion} and C_{Mass} use different units and have widely different means, I examine two relative measures of variation: the coefficient of variation (the standard deviation divided by the mean) and the coefficient of quartile variation (the difference between the first and third quartiles divided by the sum of those quartiles). As shown in Table 2.4, the coefficient of variation in C_{Motion} is *greater* than C_{Mass}.

---Insert Table 2.4 here---

While the statistics in Tables 3 and 4 and the density distributions in Figure 2.3 allow examining how much the values of C_{Motion} are dispersed, they do not offer insight into the how the distributions vary across clusters. Figure 2.4 displays ridge plots that visualize the respective distributions of C_{Motion} for the top 20 largest clusters, which are listed on the Y-axis in order of variance from largest to smallest. These plots allow seeing within-cluster variance as well as between-cluster variance at a glance.

---Insert Figure 2.4 here---

First, the ridge plots show the existence of variance in C_{Motion} within individual industry clusters. While the density distributions in Figure 2.3, which aggregate the distributions of all regions, display the unimodal distributions, the ridge plots in Figure 2.4 show that many clusters have bimodal or trimodal distributions. This means that the values of C_{Motion} are dispersed rather than being concentrated in one value, implying that many clusters have experienced more than one trend over the sample period.

Second, I find evidence of variance across regions in the same industry, based on the fact that many of the distribution plots of the top 20 largest clusters in a given industry look quite different from each other.

Third, the ridge plots show that there is variance across industries even within the same region. For example, in the semiconductor industry, C_{Motion} for San Jose-Sunnyvale-Santa Clara in California shows the widest range among the top 20 regions, ranging from -0.723 to 2.086. Specifically, although not shown in Figure 2.4, a structural break analysis and regression analysis report that this area has experienced four different trends with respect to semiconductor industry activities: an increase until 1987 (C_{Motion}: 2.086), another smaller increase until 1988 (C_{Motion}: 1.862), and a decrease until 2006 (C_{Motion}: -0.723). This pattern differs from those that area experienced with respect to the computer industry: an increase until 1983 (C_{Motion}: 3.047), another smaller increase until 1990 (C_{Motion}: 1.816), a bigger increase until 1996 (C_{Motion}:3.29), and a small increase after 1996 (C_{Motion}:0.055). While the area has experienced both increasing and decreasing concentration as a semiconductor industry cluster, San Jose-Sunnyvale-Santa Clara has experienced only increasing trends as a computer industry cluster.

In summary, I demonstrate variance in C_{Motion} generally, and specifically, within industry clusters, across regions in the same industry, and across industries in the same region.

2.3.1.5. Is C_{Motion} different from C_{Mass}?

Although I show evidence of variance in C_{Motion}, the measure is of limited value if it correlates highly with concentration levels. Accordingly, I examine the discriminant validity of C_{Motion} against the concentration levels measure, C_{Mass}.

I calculate the correlation between C_{Motion} and C_{Mass} and its confidence interval. If the interval does not include 1.0, discriminant validity is demonstrated (Anderson and Gerbing, 1988). As seen in the first column in Table 2.5, the confidence interval for the correlation in the computer industry ranges from 0.465 to 0.489; the interval for the semiconductor industry ranges from 0.204 to 0.234, neither of which span 1.0. Rather, the values of the intervals are less than 0.5. I also calculate the confidence intervals of correlation for the top 20 largest clusters. I see that the correlations become smaller when I confine the sample. Specifically, the confidence interval for the correlation in the computer industry ranges from 0.281 to 0.4, and the confidence interval in the semiconductor industry ranges from 0.144 to 0.273.

These results suggest that C_{Motion} is distinct from C_{Mass}, implying that cluster motion captures certain characteristics that cluster mass does not.

---Insert Table 2.5 here---

2.4. Conclusion

Strategy scholars have made significant progress in understanding the importance of industry clusters for firms. However, they have paid little attention to the temporal dynamics of clusters. Changes in cluster concentration—cluster motion—may have strategic implications that are not accounted for by cluster mass approaches, but may influence the relationship between clusters and firm outcomes.

Within this context, I develop a framework for understanding cluster temporal dynamics by proposing a novel measure, C_{Motion}. In generating this measure, I document that clusters are best viewed as dynamic entities. Specifically, I find that many clusters experience more than one concentration trend. In addition, the analyses in this study show patterns of cluster change that vary across industries in the same region as well as across regions in the same industry. I confirm the validity of the proposed measure by showing that C_{Motion} identifies temporal trends that align with qualitative accounts from economic history, has a significant variance, and is distinct from cluster mass.

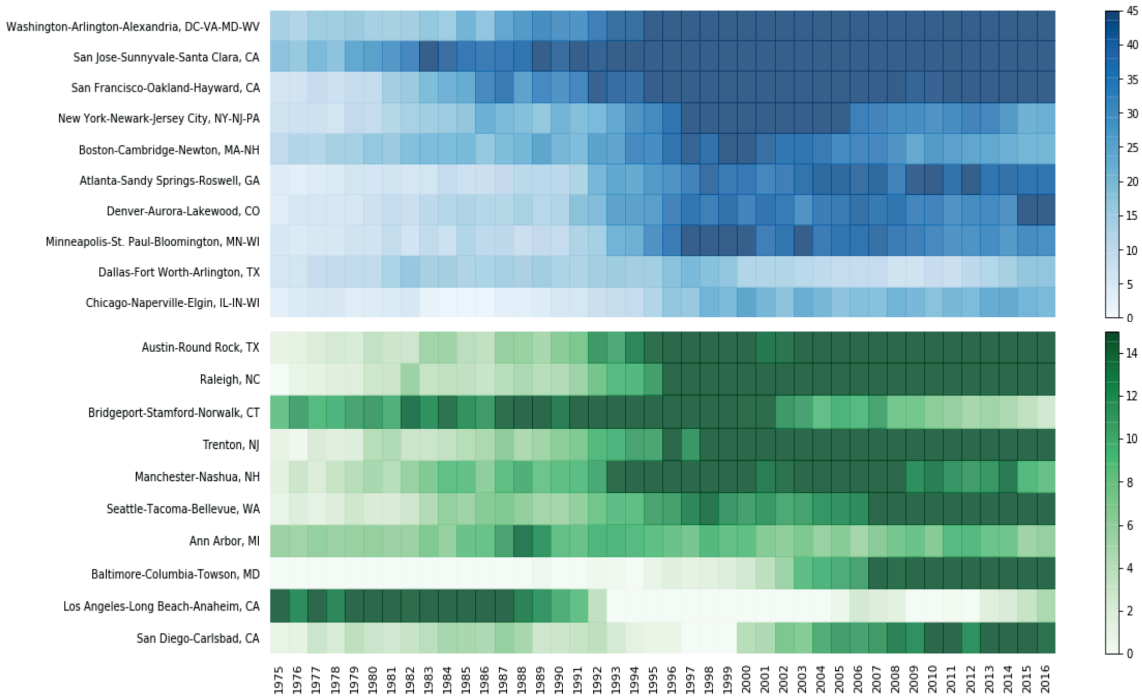
This study contributes to the existing literature on industry clusters in several ways. First, this study enriches the understanding of the relationships between industry clusters and firm outcomes by considering the temporal dynamics of clusters, which have been largely overlooked in the existing strategy literature. Second, I synthesize scholarship in disconnected areas—economic geography and strategy—to guide the formation of the measure and expand the reach of cluster literature in strategy. Third, the proposed empirical technique allows researchers to examine the effect of cluster temporal dynamics on firms via quantitative studies using large samples.

The proposed measure of cluster temporal dynamics, C_{Motion}, has attractive features. First, I find evidence that C_{Motion} is advantageous over alternative empirical approaches. For example, because C_{Motion} quantifies cluster dynamics, researchers can generalize findings using large samples, which is difficult using case study-based qualitative approaches (e.g., Saxenian, 1994; Wang *et al.*, 2014). Also, C_{Motion} does not assume that a single characteristic of clusters, such as cluster age, can capture the temporal dynamics of focal clusters, while this is the case for the quantitative approaches relying on proxies (e.g., Folta *et al.*, 2006; McCann and Folta, 2011). Second, the approach normalizes the degree of industry concentration by using the logic of the dartboard approach, making it easy to compare concentration levels across years and locations. Third, the proposed measurement is flexible in that researchers can tailor according to the needs of the analysis. For example, researchers can determine the type of economic activity and the criteria by which to weigh the size of each region.

I acknowledge the limitations of the proposed measure. Specifically, the measure requires a span of data long enough to observe meaningful trends. Also, the approach uses a predetermined geographic unit, MSA, but actual economic activity might not necessarily follow this predetermined boundary. In this regard, future research could use alternative ways to identify cluster boundaries organically, such as the density-based cluster identification method (Alcácer and Zhao, 2016; Wang and Zhao, 2018).

Although not without limitations, I believe that the proposed approach can help expand research in multiple areas. Future work could use this measure to study the effects of cluster temporal dynamics on various outcomes that are affected by industry concentration (e.g., firm survival rates, spin-off rates). These investigations might help resolve the limitations of existing literature, in particular, conflicting findings that have caused longstanding debates—for example, whether higher industry concentration improves or deters firm innovation (e.g., Bell, 2005; Ozer and Zhang, 2015). Furthermore, improved understanding of cluster dynamics enabled by the proposed approach might help resolve the political and sociological issues relevant to clusters, such as the great divergence (Pomeranz, 2000) or inequality (Massey and Eggers, 1990). Researchers could also use this approach to measure the temporal dynamics of various concepts of interest to them (e.g., firm performance, network centrality). By proposing a systematic empirical technique, this study sets the stage for the further theoretical and empirical exploration of the effects of cluster temporal dynamics and various concepts.

(a) The computer industry



(b) The semiconductor industry

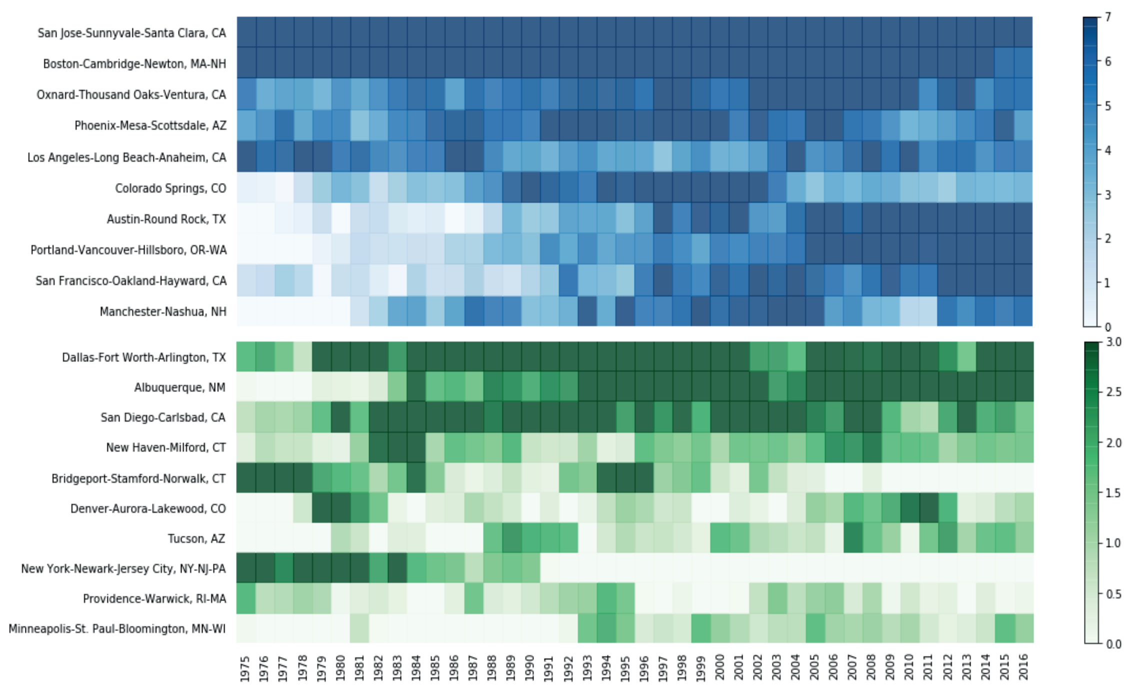
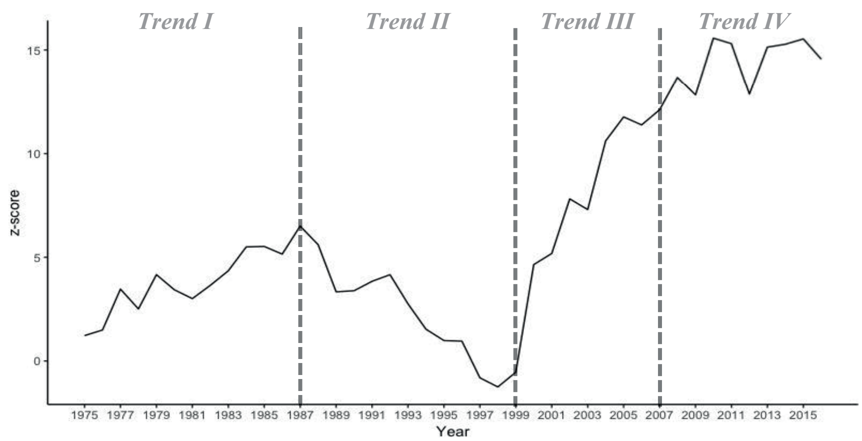


Figure 2. 1. The heat maps of the degree of a concentration in the MSAs in the United States

(a) The computer industry in San Diego-Carlsbad, CA



(b) The semiconductor industry in New York-Newark-Jersey City, NY-NJ-PA

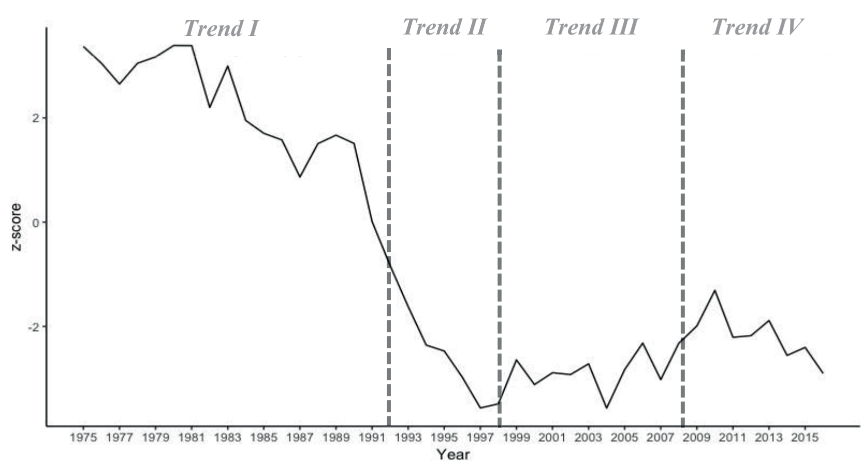
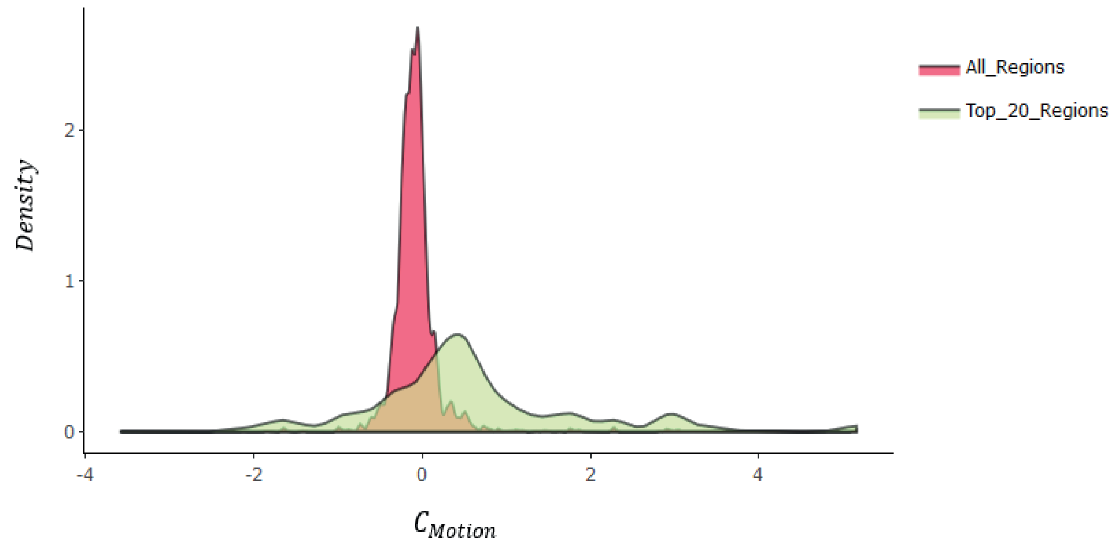


Figure 2. 2. The identification of distinct concentration trends

(a) The computer industry



(b) The semiconductor industry

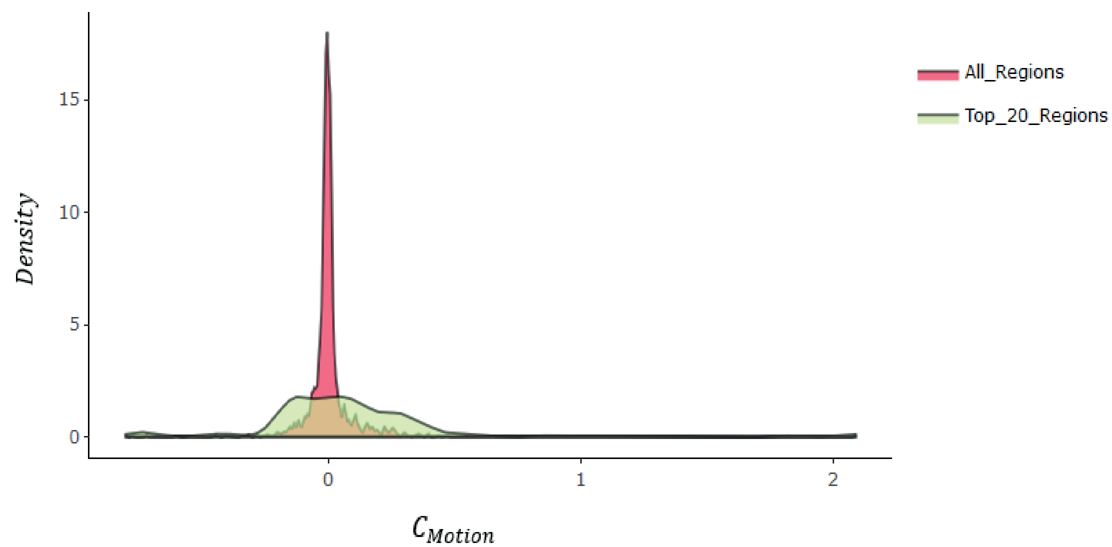
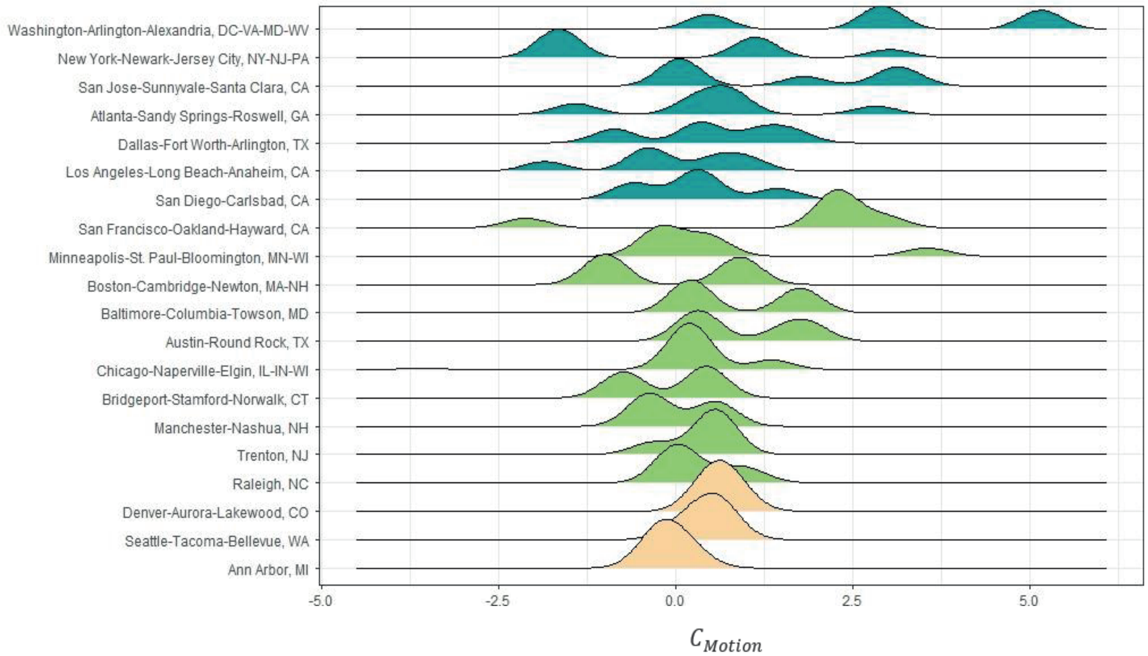


Figure 2. 3. The density distributions of C_{Motion}

(a) The computer industry



(b) The semiconductor industry

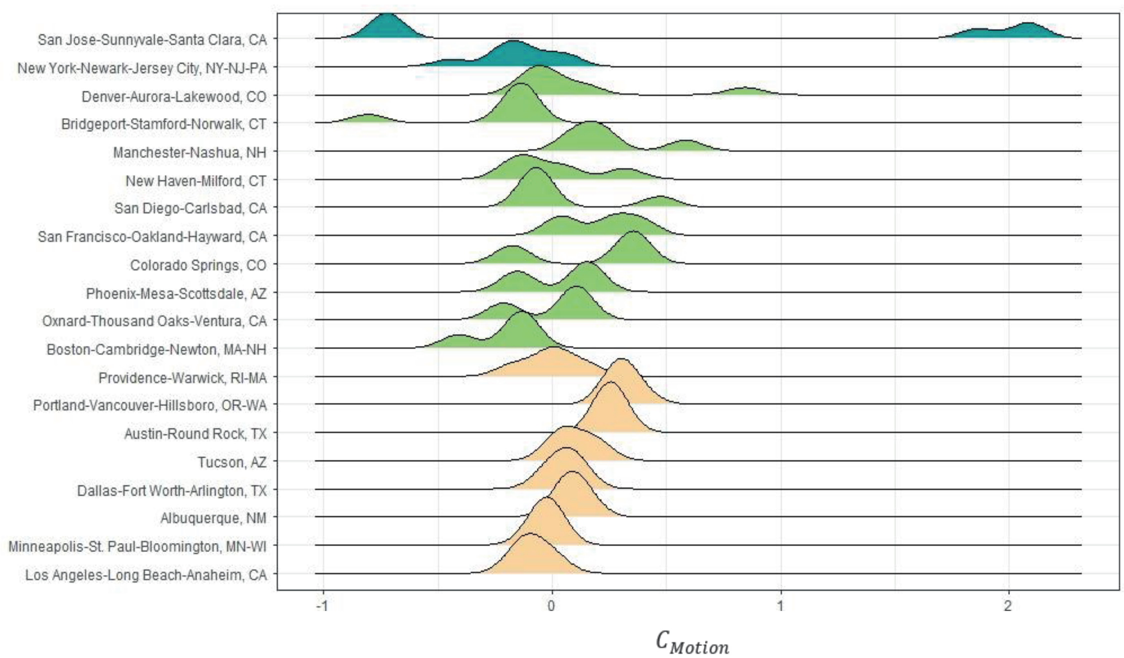


Figure 2. 4. The ridgeline plots of C_{Motion}

Table 2. 1. The results of structural break analysis

(a) The computer industry in San Diego-Carlsbad, CA

$supF_T(k)$ test	$supF_T(1)$	$supF_T(2)$	$supF_T(3)$	$supF_T(4)$	$supF_T(5)$
	95.665 [11.47]	410.146 [9.75]	321.541 [8.36]	254.824 [7.19]	237.960 [5.85]
Double maximum test	UD_{max}	WD_{max}			
	410.146 [11.7]	482.500 [12.81]			
$supF_T(\ell+1\|\ell)$ test	$supF_T(2\|1)$	$supF_T(3\|2)$	$supF_T(4\|3)$	$supF_T(5\|4)$	
	190.057 [11.47]	10.794 [12.95]	6.718 [14.03]	1.525 [14.85]	
Years of structural breaks	T_1	T_2			
	1985	1999			

Notes. The critical values at the 5% significance level are reported in squared brackets.

(b) The semiconductor industry in New York-Newark-Jersey City, NY-NJ-PA

$supF_T(k)$ test	$supF_T(1)$	$supF_T(2)$	$supF_T(3)$	$supF_T(4)$	$supF_T(5)$
	192.188 [11.47]	348.279 [9.75]	308.821 [8.36]	252.608 [7.19]	206.325 [5.85]
Double Maximum test	UD_{max}	WD_{max}			
	348.279 [11.7]	423.705 [12.81]			
$supF_T(\ell+1\|\ell)$ test	$supF_T(2\|1)$	$supF_T(3\|2)$	$supF_T(4\|3)$	$supF_T(5\|4)$	
	55.466 [11.47]	26.405 [12.95]	10.961 [14.03]	0.000 [14.85]	
Years of structural breaks	T_1	T_2	T_3		
	1990	1997	2008		

Notes. The critical values at the 5% significance level are reported in squared brackets.

Table 2. 2. The results of regression analysis for concentration trends

(a) The computer industry in San Diego-Carlsbad, CA

Concentration trend	Years	Degree	Direction	S.E.	P > |t|
Trend I	1975 – 1985	0.343	Increase	0.074	0.001
Trend II	1985 – 1999	-0.490	Decrease	0.034	0.000
Trend III	1999 – 2016	0.707	Increase	0.090	0.000
Overall trend	1975 - 2016	0.321	Increase	0.039	0.000

(b) The semiconductor industry in New York-Newark-Jersey City, NY-NJ-PA

Concentration trend	Years	Degree	Direction	S.E.	P > |t|
Trend I	1975 – 1990	-0.195	Decrease	0.021	0.000
Trend II	1990 – 1997	-0.651	Decrease	0.067	0.000
Trend III	1997 – 2008	0.085	Increase	0.026	0.009
Trend IV	2008 - 2016	-0.105	Decrease	0.050	0.072
Overall trend	1975 - 2016	-0.179	Decrease	0.016	0.000

Table 2. 3. The descriptive statistics of C_{Motion}

		All MSAs	Top 20 MSAs
Computer industry	N	16,125	860
	Mean	-0.072	0.589
	S.D.	0.396	1.381
	Min	-1.938	-1.938
	Max	5.545	5.545
Semiconductor industry	N	16,125	860
	Mean	0.000	0.063
	S.D.	0.133	0.455
	Min	-1.317	-1.317
	Max	2.463	2.463

Table 2. 4. The relative variations of C_{Motion} and C_{Mass}

	Coefficient of variation				Coefficient of quartile variation			
	All MSAs		Top 20 MSAs		All MSAs		Top 20 MSAs	
	C_{Motion}	C_{Mass}	C_{Motion}	C_{Mass}	C_{Motion}	C_{Mass}	C_{Motion}	C_{Mass}
Computer industry	5.525	3.204	2.344	1.021	0.930	0.581	0.947	0.588
Semiconductor industry	361.010	12.931	7.245	2.018	1.591	0.367	4.380	0.729

Table 2. 5. The correlations between C_{Motion} and C_{Mass}

	All MSAs	Top 20 MSAs
Computer industry	0.504 [0.492 0.515]	0.409 [0.352 0.463]
Semiconductor industry	0.116 [0.100 0.131]	0.078 [0.012 0.145]

Notes. 95% confidence intervals are reported in the squared bracket.

Chapter 3: Cluster Temporal Dynamics and Firm Technological Innovation

Strategy scholars and firm managers alike regard industry clusters as an important context for firm innovation. This is because firms in clusters, compared with firms that are geographically isolated, can access external knowledge more easily due to high levels of knowledge spillovers (Alcácer and Chung, 2007; Audretsch and Feldman, 1996; Porter and Stern, 2001). Given that external knowledge allows firms to overcome limited internal knowledge and move beyond their organizational boundaries (Henderson and Cockburn, 1994; Rosenkopf and Almeida, 2003; Song, Almeida, and Wu, 2003), accessing external knowledge is among the most critical benefits of clusters for high-technology firms.

In this vein, strategy researchers have made significant progress in understanding how geographic concentrations of industry activity influence firm innovation, but existing studies have paid little attention to considering a phenomenon that is observed to exist in many places and industries—*the temporal dynamics of industry clusters*. That is, the concentration of actors within clusters is seldom stable, and a cluster's time series (i.e., how concentration levels change over time) can be segmented into multiple distinct trends during which concentration levels move consistently in a particular direction (i.e., whether and how rapidly a cluster has been concentrating or dissipating). Moreover, clusters have their own patterns of growth distinct from other clusters. In other words, clusters may go through different sequences of these concentration trends. The processes of change are neither singular nor simple; these processes do not necessarily follow life cycle stages and may counter industry- or region-wide trends. While the implications of cluster dynamics have been relatively underexplored in academic research, firm managers are likely to care about these dynamics (e.g., the growth and decline in the levels of concentration). Moreover, how clusters change over time can inform the environmental conditions that are related to external knowledge but cannot be informed by the concentration level in and of itself.

Specifically, the sustained growth of clusters implies that resources (e.g., employees) are coming from elsewhere, which constitutes inflows of knowledge from outside cluster boundaries. In addition, a period of sustained growth reflects that relevant organizations in the local ecosystem are increasingly supportive of local firms to understand and apply such boundary-crossing knowledge. This is because relevant organizations that support knowledge activities—including suppliers, engineering consultancies, and research institutes—are also likely to cross cluster boundaries, and the repeated influx of employees and relevant organizations creates a collective knowledge base for boundary-crossing knowledge.

For example, the medical device industry (med-tech) in Minneapolis-St. Paul, Minnesota, experienced sustained growth in the 1970s. Growth generally comes from outside cluster boundaries (e.g., different geographies or industries), and the med-tech growth in Minneapolis-St. Paul was largely coming from the local computer industry, which was shrinking at that time. Accordingly, local med-tech firms had increased opportunities to hire and collaborate with local engineers who were shifting out of the computer industry. Many suppliers were also making a transition from the computer industry to med-tech. Such dynamics in the upward trend allowed local med-tech firms to access knowledge and skills from the computer industry and then apply the knowledge and skills for their innovation.

Given this context, I examine how cluster dynamics—in particular, concentration trends (i.e., the growth rates of concentration)—influence firm innovation. I argue that clusters experiencing a period of sustained growth represent environments that facilitate and support firms' disruptive innovation. Accordingly, I hypothesize that firms in clusters experiencing sustained growth will be more likely to generate innovation beyond their boundaries relative to firms in clusters of comparable size that are experiencing stable or declining periods. This is because the influx of employees and the subsequent changes in relevant organizations in the local ecosystem implied by growing clusters will help cluster firms access distant knowledge and facilitate understanding and application of this knowledge.

Furthermore, to better identify the suggested underlying mechanism of the relationship, I theorize and test a condition under which the effect of concentration trends may vary. I suggest that the effect will be significant for entrepreneurial firms, but not for large established firms if resource mobility and the subsequent changes in relevant organizations in the local ecosystem are the key mechanisms. This is because entrepreneurial firms have a greater motivation to access external resources and encounter weaker barriers to applying boundary-crossing resources than do large, established firms.

I empirically test my arguments in the context of the U.S. medical device industry over the 43-year period from 1974 to 2016. I use data on employment from the U.S. Census Bureau's County Business Pattern database and data on utility patents granted by the U.S. Patent and Trademark Office (USPTO), which was then linked with the Dun & Bradstreet (D&B) historical business register database. The latter is an inclusive register of both private and public firms operating in the U.S.

The empirical investigation consists of two parts. First, I examine relationships between concentration trends and innovation, ruling out alternative explanations and mitigating the concern for unobserved heterogeneity regarding innovation capability. Second, I highlight the mechanism—i.e., resource mobility across cluster boundaries—by developing hypotheses that specify the sources of the cited knowledge: different geographies or different industries. I also highlight the mechanism by examining the heterogeneous effects of concentration trends between large established firms and entrepreneurial firms, which tend to have stronger motivation to access external resources and be less path-dependent than large established firms.

This research contributes to the existing literature on strategy in several ways. First, this study incorporates a largely ignored phenomenon of industry clusters—their temporal dynamics—with implications that may be highly relevant for firm innovation. Second, this study transforms the current academic approach in the role of clusters in firm innovation from an emphasis on current levels of concentration to include an investigation of cluster dynamics. Third and last, this study suggests that cross-boundary resource mobility and the subsequent changes are one of the major mechanisms through which industry clusters influence firm outcomes. This complicates how researchers have long explained the mechanisms by which clusters affect firm innovation. The traditional agglomeration externalities (e.g., greater access to a pool of labor, input markets, and knowledge spillovers) are not the only major mechanisms to consider. Cross-boundary resource mobility is another important mechanism by which clusters affect firm innovation.

3.1. Literature Review and Background

3.1.1. Innovation and Industry Clusters

Innovation is often considered an output of recombining existing knowledge (Fleming, 2001; Henderson and Clark, 1990; Schumpeter, 1934). In other words, firms generate innovation by exploiting their own prior knowledge or utilizing externally-generated knowledge (i.e., existing knowledge created by other firms). Considering that a single firm can hardly possess all internal knowledge required for success in innovation (Powell, Koput, and Smith-doerr, 1996), a large body of research has emphasized the importance of acquiring external knowledge (Cohen and Levinthal, 1990; Eisenhardt and Santos, 2002; Garg and Zhao, 2018; Helfat *et al.*, 2007; Levinthal and March, 1993; Monteiro and Birkinshaw, 2017; Phene, Fladmoe-Lindquist, and Marsh, 2006; Rosenkopf and Nerkar, 2001). Moreover, external knowledge also allows recipient firms to move beyond local search and span their organizational boundaries, which is useful for new knowledge creation (Henderson and Cockburn, 1994; Rosenkopf and Almeida, 2003; Song *et al.*, 2003).

Given the important roles of external knowledge, strategy researchers regard industry clusters—i.e., regions where geographic concentrations of industry activity are high—as an important context for firm innovation. First, firms in industry clusters can access a larger pool of external knowledge than those that are geographically isolated (Marshall, 1920; Saxenian, 1994; Shaver and Flyer, 2000), because a number of firms and inventors with specialized skills and knowledge are concentrated in clusters. Second, firms in industry clusters can access external knowledge more easily due to high levels of knowledge spillovers (Alcácer and Chung, 2007; Audretsch and Feldman, 1996; Porter and Stern, 2001). Specifically, cluster firms can acquire co-located rivals' knowledge by observing their innovation activities, meeting by chance engineers at neighboring firms, or working with suppliers or buyers they share in common. In addition, clusters generally have high rates of employee mobility among neighboring firms (Cheyre *et al.*, 2015), which facilitates knowledge transfers between firms. Accordingly, knowledge search and spillovers tend to be spatially bounded (Almeida and Kogut, 1999; Jaffe, Trajtenberg, and Henderson, 1993).

Within this context, the existing literature has examined the implications of industry clusters for firm innovation. For example, Bell (2005) suggests that cluster firms can access co-located firms' knowledge effectively because they share a similar knowledge base and institutions in common and finds that cluster firms are more likely to generate innovation. Funk (2014) finds that a geographic concentration of firms operating in the same industry enables the firms to stay informed of technological frontiers and receive inspiration from their rivals, resulting in an increase in innovation. Ozer and Zhang (2015) also discover empirical evidence that cluster membership is positively related to incremental innovation that improves current product knowledge. In their studies, some researchers highlight the important role of local employee mobility between co-located rivals in facilitating knowledge spillovers and innovation in clusters (e.g., Almeida and Kogut, 1999; Fallick, Fleischman, and Rebitzer, 2006).

3.1.2. The Temporal Dynamics of Industry Clusters

Although scholars have made significant progress in understanding how geographic concentrations of industry activity influence firm innovation, existing studies have paid scant attention to an interesting phenomenon of clusters. The phenomenon is that the concentration of actors within particular industry clusters is seldom stable and often moves in ways that run counter to industry-wide or region-wide trends, thus forming the clusters' own growth trajectories. While often ignored, the consideration of the temporal dynamics of clusters is significant as they have long been prevalent in many places and industries.

The dynamic nature of industry clusters is apparent in many high-tech industries. High-tech industries have shown a wide variation in levels of concentration over time, both within and across regions. For example, the semiconductor industry in New York City and neighboring Newark and Jersey City, the original center of the U.S. semiconductor industry (cemented in the 1950s by a few leading firms, such as Bell Labs and Germanium Products Corp), experienced a steep decline during the 1980s and mid-1990s. By contrast, during the same period, the semiconductor clusters in California and Texas experienced an upward trend. These different patterns were created because many leading firms in New York, Newark, and Jersey City relocated to California and Texas, and many local firms already in these regions (e.g., Fairchild in California, Texas Instruments in Texas) grew quickly (Morris, 1990).

Minneapolis-St. Paul, another example, presents a variation in concentrations across different industries within the same geographic boundary. The large concentration of computer manufacturing firms in the area—Control Data, Univac, ERA, Cray

Research, and Honeywell—began to drop sharply in the early-1970s. Yet, the concentration of other co-located industries in Minneapolis-St. Paul, and med-tech, in particular, experienced an upward trend as many local firms and engineers in the computer industry decided to stay in the area instead of relocating with their firms to Silicon Valley or Boston's Route 128 region (Misa, 2013).

Attending to the dynamic nature of clusters—i.e., looking closely at how clusters change over time—helps reveal information on environmental conditions relevant to firm innovation that may not be available by looking at the cluster concentration level alone. Specifically, concentration trends reflect the flows of employees across cluster boundaries and the subsequent changes in relevant organizations in the local ecosystem. In particular, the sustained growth of a focal cluster implies that employees are flowing into the cluster from elsewhere and that the relevant organizations will also change following this inflow. For example, relevant organizations—e.g., suppliers, professional service firms (PSFs), and research institutes—are likely to pay more attention to a growing cluster and enter that cluster when they see a trend of sustained growth. Moreover, repeated inflows of employees and relevant organizations can create a collective knowledge base.

These environmental conditions—i.e., boundary-crossing resource mobility and the subsequent changes in relevant organizations in the local ecosystem —can hardly be inferred from the cluster's concentration level in and of itself. On the one hand, focusing on a cluster's concentration level without considering dynamics attends to the *magnitude* of resources *within* the focal cluster's boundary (i.e., its given geographic-industry boundary)—for instance, the size of a pool of specialized inventors and suppliers. On the other hand, cluster dynamics focus on the externalities created by the *flows* of employees *across* cluster boundaries and subsequent changes in the relevant organizations. These distinctions between cluster size and dynamics—regarding what they reflect—necessitate research examining the implications of cluster dynamics, which have been little investigated compared with the rich body of studies on cluster size.

3.2. Hypotheses Development

3.2.1. Cluster Temporal Dynamics, Resource Mobility, and Innovation

Given that concentration trends imply flows of employees across cluster boundaries and subsequent changes to relevant organizations in the local ecosystem, concentration trends may have implications for firm innovation—in particular, the extent to which firms create knowledge beyond their given contexts (e.g., technology streams, geographies, or industries). This is because boundary-crossing employee mobility and the subsequent changes in relevant organizations in the local ecosystem can create environmental conditions that facilitate firms' disruptive innovation.

In general, firms often tend to search narrowly for knowledge within their given boundaries (Helfat, 1994; March and Simon, 1985; Nelson and Winter, 1982; Stuart and Podolny, 1996). In other words, firms tend to identify and acquire knowledge that exists in proximity to their existing knowledge base, industry, and geography. This is because, in part, searching for knowledge across boundaries is costly (Almeida and Kogut, 1999; Jaffe *et al.*, 1993), and understanding and applying distant knowledge is more challenging than the use of knowledge from within cluster boundaries (Cohen and Levinthal, 1990; Rosenkopf and Almeida, 2003). For these reasons, firms are more likely to successfully develop innovation in areas where they already have experience (Fleming, 2001; Teece *et al.*, 1994).

However, the localization of knowledge can lead to core rigidities and myopia (Leonard, 1995; Rosenkopf and Nerkar, 2001). Moreover, although on average disruptive innovation often results in less useful inventions, it can increase the variability that leads to breakthroughs as well as failures (Fleming, 2001). In this vein, previous literature has examined what conditions help firms overcome localized innovation and generate innovation beyond their given boundaries.

Researchers suggest that for the novelty of innovation firms need, most importantly, opportunities to access external knowledge and perspectives from outside their given boundaries (e.g., Corredor, Forero, and Somaya, 2015; Frensch and Sternberg, 1989; Kogut and Zander, 1992; Merton, 1987). Exposure to external knowledge gives firms opportunities to see new components and new ways of knowledge recombination (Audia and Goncalo, 2007; Fleming, 2001), which increases the likelihood that they will create knowledge beyond their boundaries.

Yet, the opportunities to access distant knowledge do not in and of themselves necessarily result in firm innovation (Arts and Fleming, 2018). Distant knowledge is embedded in the contexts and institutions of its own boundaries, and recipient firms lack prior knowledge and expertise within those boundaries. Thus, in addition to opportunities to access distant knowledge, recipient firms need to be guided—directly or indirectly—so that they can understand what knowledge is useful and pertinent (Singh and Fleming, 2010), filter out knowledge that is unlikely to help them innovate successfully (Gieryn and Hirsh, 1983), and integrate useful acquired knowledge with their own prior knowledge (Henderson and Cockburn, 1994; Rosenkopf and Nerkar, 2001). Moreover, recipient firms need to get help from some organizations from within the distant knowledge source boundaries about how to use and apply the knowledge leading to successful innovation.

In summary, to create knowledge beyond their given boundaries, firms need certain conditions that facilitate their access to knowledge from the outside and their ability to understand and apply the acquired knowledge effectively. I suggest that these conditions can be created in clusters during a period of sustained growth. The influx of employees from outside and the subsequent changes in relevant organizations implied by the growing clusters help firms access distant knowledge and facilitate their learning and application of that knowledge.

In the next sections, I discuss how boundary-crossing employee mobility and the subsequent changes in relevant organizations, respectively, can contribute to creating the environmental conditions that facilitate disruptive innovation.

3.2.1.1. Employee mobility across cluster boundaries

The sustained growth of clusters implies that employees are increasingly coming into focal clusters from elsewhere, including different geographies or industries. These employees bring their own knowledge they have accumulated in their previous geographies or industries (Almeida and Kogut, 1999; Hoisl, 2006; Mawdsley and Somaya, 2016; Møen, 2007; Rosenkopf and Almeida, 2003; Singh and Agrawal, 2010; Song *et al.*, 2003; Tzabbar, Aharonson, and Amburgey, 2013). Local firms in a recipient cluster will then be able to receive distant knowledge from outside their own geographies or industries.

To better understand the details about the association between cluster dynamics and opportunities to access distant knowledge, I specify types of employee flows according to where the employees come from.

The first type of flow is employee mobility across *geographic* boundaries, in which employees migrate to other geographies but stay within the same industry boundaries. When knowledge producers—firms, engineers, or scientists—expect that the benefits of relocation will exceed the costs, including the opportunity costs of staying in the original geography, they are likely to relocate. For example, when leading innovating firms leave their original geographic boundaries, their employees and co-located firms that have relied heavily on those firms often also migrate, following them. Employees and co-located firms also tend to move when they observe the superior performance of firms in other geographies, expecting positive spillover effects. The example of the U.S. semiconductor industry in the 1980s and 1990s demonstrates this type of resource mobility. Many semiconductor employees in the New York City–Newark–Jersey City area moved to other areas in California and Texas while continuing to work in the industry (Morris, 1990).

Such migration of employees would allow firms in recipient clusters to access distant knowledge, which was not available to them before. This benefit is well-documented in previous literature on migration and knowledge transfers. Knowledge—especially tacit knowledge—is often embedded in a certain region (Audretsch and Feldman, 2004; Jaffe *et al.*, 1993), and regions may vary in specialties of technological areas or types of knowledge (Arora and Gambardella, 2005; Feldman, 2005; Owen-Smith and Powell, 2006). For example, the medical device firms in Minneapolis-St. Paul have focused more on the cardiovascular therapeutic area than have those in Warsaw, Indiana, which have specialized in the orthopedic area. Moreover, in the biotech industry, Boston-based firms have focused more on orphan drugs and medicines, whereas Bay Area biotech firms have concentrated on larger markets with first-to-the-world medicines (Owen-Smith and Powell, 2006). Such geographically embedded knowledge may not be transferred easily across geographic boundaries, but scholars find that migrant engineers can serve as channels to transfer such knowledge between geographies (e.g., Choudhury and Kim, 2018; Hernandez, 2014; Kerr, 2008). For example, skilled returning migrants transfer knowledge across geographic boundaries, specifically from abroad to their home countries (Choudhury, 2017; Filatotchev *et al.*, 2009; Wang, 2015). Therefore during a trend of sustained growth, cluster firms will access knowledge from different geographies because migrant employees are entering focal clusters with their own prior knowledge accumulated from their previous geographies.

The second type of flow is resource mobility across *industry* boundaries, referring to flows of resources across different industries within the same geography. When expecting the benefits of leaving a focal cluster to exceed the benefits of staying, firms or engineers tend to leave their original cluster boundaries by changing their industries while remaining in their original geographies. Employees tend to prefer this type of mobility over geographic migration if they have the ability to transfer their skills to co-located industries, or if they have issues, such as dual-career considerations or school-aged children's education, that make relocation costly (Shaver, 2018). The dynamics are shown in the computer and medical device industries in Minneapolis-St. Paul that demonstrate this type of resource mobility. The flows of local engineers from the computer to the medical device industry are illustrated in a comment made by a vice president of the Medical Alley Association whom I interviewed:

> "There is a joke long shared in Medtronic. When Control Data [a leading computer company in Minneapolis-St. Paul] was under restructuring and prepared to close their business in Minnesota, Earl [the founder and CEO of Medtronic, a leading medical device company in Minneapolis-St. Paul] knocked on the door of Control Data to hire [its] engineers."

Engineers from different industries (e.g., computers and med-tech in the case of Minneapolis-St. Paul) have different types of knowledge and disciplinary backgrounds. Thus, the inflows of engineers coming from different industries allow firms in recipient clusters to access distant knowledge, which can be a source of disruptive innovation. The following anecdote illustrates how cross-industry employee mobility during sustained growth provided a firm in a recipient cluster with opportunities to access distant knowledge, which contributed the disruptive innovation:

Manny Villafana is a founder of Cardiac Pacemakers, Inc. (CPI), one of the most successful medical device firms in the U.S. Before he founded CPI in the early 1970s in Minneapolis, he had worked at Medtronic, where he had proposed the idea of using lithium batteries to resolve the critical limitations of existing pacemakers. At that time, pacemaker batteries did not last long and required frequent surgeries to replace. Further, pacemakers had to be large enough to accommodate the batteries' size, so implanting them in the bodies of babies or children was extremely difficult. Even though his idea of using smaller, more long-lasting lithium batteries sounded good, it was turned down because the engineers in Medtronic, who were highly talented experts on medical devices, did not think the idea was feasible. Manny also proposed the idea to other medical device companies, including European companies, but they also declined. He then founded his own venture, CPI, and several years later, his company successfully invented the first lithium battery pacemaker. This invention was the outcome of interdisciplinary technologies, notably technologies from the computer sector and was one of the greatest breakthrough innovations in the medical device industry.

One of the key success factors to which Manny attributed the innovation was CPI's location in Minneapolis, where he was able to hire engineers who shifted from the computer industry to medical devices. In an interview I conducted, Manny Villafana said: "I deliberately hired engineers from the computer industry because I believed that they would be open-minded and free of preconceived notions typically held by medical engineers."

At that time in Minneapolis, the medical device sector was growing, and new hires mainly came from among the local computer industry engineers. Because of the influx of computer engineers, local medical device firms—including CPI—were able to access different knowledge and perspectives that became foundational to their disruptive innovation.

The theoretical discussion and these anecdotes illustrate that the sustained growth of a cluster implies an environmental condition in which employees are coming from outside, allowing cluster firms to access knowledge from different geographies or industries. The distant knowledge the recipient firms can access includes knowledge on how the sources of the knowledge could be used by the recipient firms.

The influx of employees—inventors, in particular—across clusters means that they continue to engage in knowledge creation activity but in new clusters. In other words, the inventors apply prior knowledge accumulated in previous geographies or industries in new contexts. Cluster firms would not be able to learn from the incoming inventors' applications in their own firms if they were merely given opportunities to access distant knowledge, but no inventors were coming in from outside (which is the case, for example, when firms co-locate with other firms in the same geography, and their inventors continue to work within the same industry).

Existing studies on disruptive innovation have emphasized the importance of the knowledge sources' use of their knowledge within recipient boundaries (e.g., Arts and Fleming, 2018; Hawkins and Rezazade M., 2012; Zhao and Anand, 2013). Recipient firms, thus, can observe and learn how the sources actually use the knowledge. Specifically, firms in recipient clusters, by hiring or collaborating with these inventors, learn directly how the inventors apply their knowledge, which helps these firms understand which technologies, components, or approaches can be relevant (Arts and Fleming, 2018; Guimera et al., 2005; Kehoe and Tzabbar, 2015; Singh and Fleming, 2010). However, firms can also learn indirectly how inventors from the outside reconfigure and apply their knowledge through the informal means of knowledge spillovers, including observation, serendipitous meetings, or commonly shared suppliers (Alcácer and Chung, 2007; Shaver and Flyer, 2000).

Opportunities to access knowledge from different geographies or industries are a prerequisite for disruptive innovation, and observations of how the sources of the distant knowledge use this knowledge in the recipient clusters may help recipient firms understand the distant knowledge to some extent. However, these conditions alone can hardly be sufficient for recipient firms to absorb and apply the knowledge from different geographies or industries and to create their own knowledge.

3.2.1.2. Subsequent changes in relevant organizations in the local ecosystem

Knowledge is embedded in the institutions of the geographies and industries where the knowledge was created. Therefore, it is more challenging for a recipient firm to learn knowledge from different locations or industries than to understand knowledge from other organizations with which it shares the same geography and industry. In this vein, Mayer, Somaya, and Williamson (2012) find evidence that firms with less industry-specific human capital are more likely to depend on outsourcing to external organizations, including suppliers.

The challenge of understanding boundary-crossing knowledge is more salient in high-tech industries. The innovation processes of firms in these industries require knowledge of diverse expertise (e.g., designing components, making prototypes, checking feasibility). Since knowledge requires high levels of interdependency and is stored collectively, accessing knowledge only from incoming inventors—either through hiring or observing—is not sufficient for acquiring and applying complete knowledge.

Considering these features, relevant organizations in the local ecosystem can help recipient firms overcome the challenges of grasping once-distant knowledge. In general, diverse organizations in the local ecosystem (e.g., suppliers, PSFs, and research institutes) have embedded knowledge with the diverse expertise necessary for innovation processes, and they can transfer this collectively-stored knowledge because they work with a number of firms. Thus, when these relevant organizations pay more attention (or shift their attention) to a new industry or geography, they work with firms in the new industry or geography, and consequently, spread and share the collectively embedded diverse knowledge.

The changes in the attention of relevant organizations can be implied from the concentration trends. Specifically, the sustained growth of a cluster suggests that relevant organizations increasingly are paying more attention or shifting their attention to the growing clusters following the continued inflows of employees into them. The changes in their attention may also lead the organizations to enter growing industries or geographies by diversifying or entirely shifting their boundaries. These organizations' flexibility across clusters comes from their characteristics. Specifically, relevant organizations in the local ecosystem tend to work with multiple firms within a particular industry or geography or across multiple industries or geographies. These organizations are freely mobile across geographies or industries, hence they may prefer to enter industries or geographies that they expect to continue to grow. Extending or shifting boundaries requires the investment of money and time to hire human capital experts, train employees, and purchase facilities. Therefore, these organizations cannot make a transition to different geographies or industries every time they see an increase in cluster concentration. Instead, they wait to see what direction and how concentration levels are moving consistently over time—such as having a sustained growth or decline—before deciding where to invest their money and time.

For example, many computer industry suppliers in Minneapolis-St. Paul who had sold products to local computer firms for decades shifted their attention to the medical device industry when they observed local computer industry employees increasingly transitioning to that industry, which had continued to grow over the years (Misa, 2013). Like computer industry employees in the Twin Cities area, the local computer suppliers then also made smooth transitions from serving the computer industry to serving the medical device industry.

The growing or shifting attention of these organizations plays an important role in recipient firms' learning boundary-crossing knowledge. They transfer knowledge that is distinct from the types of knowledge that incoming inventors are bringing to the focal cluster (Hargadon and Sutton, 1997; Wagner, Hoisl, and Thoma, 2014; Zhang and Li, 2010).

First, relevant organizations in the local ecosystem embed knowledge of diverse expertise necessary for innovation processes. For example, suppliers from another industry can help firms design new components for their innovations, using their knowledge they acquired in the industry from which they came. In the case of the medical device industry in Minneapolis-St. Paul, the suppliers that shifted from the computer industry to the medical device transferred the skills they accumulated while serving the computer industry (e.g., micro-fabrication skills for computing and high-precision machining skills) to the local firms in the growing medical device cluster (Misa, 2013). These transferred skills helped their new clients to design more innovative components.

Research institutes are another example of relevant organizations in the local ecosystem. In high-tech industries, research institutes are often closely integrated with firms' innovation processes. By joining advisory boards or collaborating with the firms, they can learn upstream knowledge and generate innovation. For example, in the med-tech industry, research institutes help firms in a variety of ways, including supporting access to cutting-edge research as well as basic scientific knowledge, evaluating the clinical development prospects for ongoing research, and connecting them to communities of practitioners and patients (Audretsh and Stephan, 1996; Powell *et al.*, 2005).

When these institutes shift their areas of research into new technologies, they can also help firms engaged in these technologies to understand and use the knowledge from their original areas of research in diverse aspects of innovation processes.

Second, relevant organizations in the local ecosystem can transfer the knowledge collectively stored in them because they tend to work with a number of firms. For example, engineering consultancies generally collaborate with multiple clients, which allows them to accumulate the knowledge of a number of firms and inventors (Wagner, Hoisl, and Thoma, 2014). This accumulated knowledge can be shared with or transferred to their client firms. Thus, working with organizations that have crossed geographic or industry boundaries can help firms access the knowledge of a number of firms and inventors. Access, in turn, enables firms to learn complete knowledge, which is interdependent with other knowledge and stored collectively.

The subsequent changes in relevant organizations suggested by a growing cluster also include the creation or expansion of a collective knowledge base, which can also help firms learn boundary-crossing knowledge. Specifically, the sustained growth of industry clusters implies that inventors and relevant organizations are increasingly entering from different geographies or industries. During this period, firms in focal clusters have repeated interactions with them. This repeated and continuous process may allow cluster firms to build a collective knowledge base that can help them grasp and apply boundary-crossing knowledge (Hawkins and Rezazade M., 2012).

In summary, sustained growth of clusters is evidence that employees are increasingly coming into focal clusters from different geographies or industries. This leads to subsequent changes in relevant organizations in the local ecosystem; as relevant organizations pay more attention to focal clusters, they become more likely to enter the clusters. The repeated influx of employees and relevant organizations further creates or expands a collective knowledge base. These dynamics are indicative of sustained growth in environments where firms can access distant knowledge and where relevant organizations in the local ecosystem are becoming supportive of firms in recipient clusters to understand the distant knowledge and apply it in their innovation. In other words, sustained growth implies environments that encourage and support firms to generate innovation beyond their given boundaries.

Therefore, I expect that firms in clusters that exhibit a period of sustained growth will tend to source and use distant knowledge, leading them to generate innovation beyond existing innovation pathways—i.e., the innovation that disrupts or breaks the existing paths of innovation.

Hypothesis 1 (H1): *Innovation by firms in clusters experiencing greater sustained growth is likely to be more disruptive relative to innovation by firms in clusters of comparable size that are experiencing stable or declining periods.*

3.2.2. Cross-Geography vs. Cross-Industry Resource Mobility

Given that disruptive innovation of firms in growing clusters is mainly driven by the inflows of employees from outside and by the subsequent changes in relevant organizations in the local ecosystem, which allow these firms to access knowledge beyond their existing contexts—i.e., knowledge from different geographies or industries, I should see that firms' innovation created during the period of sustained growth is based more on knowledge from different geographies or/and industries than the innovation of firms, not in such clusters. Within this context, I develop hypotheses that specify the sources of the cited knowledge: different geographies or different industries. Investigating these relationships also helps uncover which one—between cross-geography or cross-industry mobility—is a more contributing mechanism underlying the relationship between sustained growth and the novelty of innovation.

Hypothesis 2a (H2a): *Firms in clusters experiencing sustained growth are likely to base innovation more on knowledge from beyond their geographies relative to firms in clusters of comparable size that are experiencing stable or declining periods.*

Hypothesis 2b (H2b): *Firms in clusters experiencing sustained growth are likely to base innovation more on knowledge from beyond their industries relative to firms in clusters of comparable size that are experiencing stable or declining periods.*

3.2.3. Heterogeneous Effects on Entrepreneurial Firms vs. Large Established Firms

As another way to demonstrate the suggested mechanism underlying the effects of concentration trends on innovation—i.e., resource mobility across cluster boundaries—I consider heterogeneity. Intuitively, if such mobility is a key mechanism, I expect the effects may be stronger for firms that have a higher motivation to access and weaker barriers to applying boundary-crossing resources.

Some firms may not be as motivated or as able to apply distant knowledge as other firms. Previous literature suggests that both the incentive to access external knowledge and the ability to absorb it are apt to be especially marked among entrepreneurial venture firms as compared to large established firms. Entrepreneurial firms generally lack internal resources for innovation—including engineers, the knowledge, financial assets, and research collaborators—and so they must rely on external resources more than large established firms. In addition, large established firms are likely to have their own established knowledge or trajectories that reduce their receptivity to externally-generated knowledge. This path-dependent nature prevents large established firms from applying boundary-crossing knowledge and resources to their innovation (Song, Almeida, and Wu, 2003). By contrast, entrepreneurial firms are less likely to have their own established knowledge or trajectories. Therefore, I expect to see that the effects of sustained growth on firms' innovation are greater for entrepreneurial firms than large established firms.

Hypothesis 3a (H3a): *The effect of concentration trends on disruptive innovation is greater for entrepreneurial firms than large established firms.*

Hypothesis 3b (H3b): *The effect of concentration trends on the dependence on cross-geography knowledge is greater for entrepreneurial firms than for large established firms.*

Hypothesis 3c (H3c): *The effect of concentration trends on the dependence on cross-industry knowledge is greater for entrepreneurial firms than for large established firms.*

3.3. Methodology

3.3.1. Research Context and Data

The empirical context of this study is the U.S. medical device industry. The choice of the medical device industry is valuable for studying the relationship between industry clusters and firm innovation because it is characterized by high levels of innovation, and industry activity is highly geographically concentrated. Moreover, industry clusters play an important role in the innovation of firms in the medical device industry because these firms need to access external knowledge from diverse sources—including local industry peers, engineering consulting firms, independent experts, and suppliers—and these sources are easily accessible in clusters. The highly-interdisciplinary nature of medical device technologies is also important because this study investigates cross-industry mobility of employees and knowledge.

This study examines the relationships between variance in concentration trends of the clusters where firms create technological innovation and variance in the nature of firm innovation (i.e., the extent to which the innovation is disruptive and the extent to which it relies on knowledge from different geographies or industries). The former variance—namely, concentration trends—is assessed by utilizing year-level data from the County Business Pattern (CBP) database on the number of employees in metropolitan statistical areas (MSA). The latter variance—namely, variance in the nature of innovation—is assessed by using data on patents from the PatentsView database, which I link to data on firms from the D&B historical business register database. The specific process of generating a dataset is described below.

To assess variance in concentration trends, I use data on the number of employees in the U.S. medical device industry, which I define using SIC codes (3841, 3842, 3843, 3844, 3845, and 3851[8]) from 1974 to 2016. I collect the data from the CBP database from the U.S. Census Bureau and the National Historical Geographic Information System. The given geographic unit of the CBP data is the county,[9] so I map counties to MSAs. One of the most critical issues in studying geographic concentrations—especially when using longitudinal data—is that the boundaries of geographic units, including MSA, change over time. Considering that the degree of geographic concentration is susceptible to changes in geographic boundaries, it is crucial to deal with this issue to reduce the measurement error. For this, I look carefully at all changes made in the boundaries of counties and MSAs, which have been officially reported by the U.S. Census Bureau and compare the shapefiles of county boundaries across years using geographic information

[8] The primary industry classification code I use is the four-digit SIC. The SIC was updated five times during the sample period, resulting in six different versions (1972 SIC, 1987 SIC, 1997 NAICS, 2002 NAICS, 2007 NAICS, and 2012 NAICS). Using concordances from the NBER-CES Manufacturing Industry Database and the U.S. Census Bureau, I convert all versions of code into 1987 SIC. I use 1987 SIC as the primary version for two reasons. First, SIC codes are more aggregated and cover more years in this data than the North American Industry Classification System (NAICS). Second, there was a substantial update in the 1987 SIC, and the NAICS was created based on the 1987 SIC.
[9] MSA-level data started with 1993.

system programs to see how the boundaries actually changed and how adjacent areas were affected.[10] As a result, I convert 1,231 counties into 375 MSAs, after excluding Alaska, Hawaii, and Puerto Rico.[11]

To assess variance in the nature of firm innovation, I use the utility patents that belong to the technology sectors of medical devices, have been filed by US medical device industry firms that engage in innovation activities, and have been granted by the U.S. Patent and Trademark Office (USPTO). To define these patents, I go through three steps.

First, among the USPTO patents filed between 1974 and 2016 and granted between 1976 and 2019 (March), I select the patents for which primary sub-classes are among the medical device technology sub-classes, which have been defined by the USPTO's Patent Technology Monitoring Team (PTMT).[12] This results in 193,680 patents. I then limit the patents to those assigned to the "corporation" category rather than other categories, such as the category of government.

Second, among those patents, I select the patents that were produced in MSAs. In this study, I define the places of innovation based on the geographic information of inventors rather than that of assignees. This is because patents are often assigned to firms that have nothing to do with the creation of focal technologies. The examples include the patents that are assigned not to the actual patent-producing firms but to their headquarter

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[10] Further information about the crosswalk for the regional boundary is available in Appendix A.

[11] I excluded MSAs in Alaska, Hawaii, and Puerto Rico because of their geographic separation from the rest of the country.

[12] The PTMT periodically issues General Patent Statistics Reports, where they define five key industries, including the medical device industry, based on the major classification areas in the U.S. Patent Classification (USPC) System. Since the USPTO stopped using the USPC system in 2014 but transferred it to the CPC system, I did crosswalk between the USPC and CPC for the patents that have only CPCs.

firms. Looking at the addresses of inventors, I regard patents as MSA-born if at least one of the inventors of the focal patents are reported to reside in MSAs. This results in 178,321 patents.

Third, I limit sample patents to those generated by the US medical device industry firms that engage in innovation activities. For this, I need to exclude patents generated by non-business organizations (e.g., research institutes), which is necessary because the "corporation" category of patents includes non-business organizations as well as firms. In addition, I exclude patents generated by firms for which the medical device industry is not one of their main businesses. To exclude these patents, I link patent data to the D&B database, which has an inclusive list of firms from small firms to large established firms. Specifically, using the D&B data, I first identify a complete list of the medical device industry firms for which at least one of their six primary SIC codes is among the medical device industry SICs. This list consists of 462,996 firms, which belong to 45,185 ultimate parent firms. After matching this list of firms to the assignees of patents, 113,846 patents remained. These matched patents are assigned to 16,691 firms, which belong to 4,506 ultimate parent firms.

One of the most significant issues in using this dataset is an inconsistency between the assignees of patents and the actual producers of those patents. It is important to address this issue because this may result in systematic measurement errors in diverse aspects of analyses. For example, in my analyses, I need to exclude self-cited patents when assessing firm innovation. Yet, if a particular patent is assigned to a firm other than the actual patent-producing firm, I will fail to exclude all of the true self-citations. In addition, this study does empirical analyses at different levels, such as at a firm-level analysis. When measuring the nature of the innovation of a given firm in a firm-level analysis, it is important to include all of the firms' patents. If I omit some of the firm's patents, the calculated value for the nature of innovation (e.g., the extent of being disruptive) will be misleading. For example, if a given firm's highly disruptive patents tend to be assigned to its parent firm, while exploitative inventions (e.g., patents spun out from previous patents) tend to be assigned to the focal firm, I cannot capture the increase in the firm's innovativeness unless I identify the true patent producer. The other possible measurement error occurs when assessing job mobility. In my study, as well as previous studies using patents, job mobility is traced using the information on inventors and assignees reported in patent documents. For example, an inventor is considered to have changed his/her employer when his/her patent is assigned to a firm different from the assignee of the previous patent. Yet, it is possible that the inventor stays at the same firm over time, but his/her new patent is assigned to the headquarter of the firm where the inventor works.

The major source of this problem (i.e., inconsistency between assignees and actual patent-producing firms) is the fact that firms may have ownership-based relationships with other firms and that the focal firm's patent can be assigned to any firms that share the same family tree with the focal firm, such as its parent firm or sibling subsidiary firm. To address this issue, existing databases—such as the patent database by the NBER or that by Kogan, Papanikolaou, Seru, and Stoffman (2017)—match the assignees of patents to their ultimate parent firms. However, there are two limitations, which are critical issues in this study. First, matching has been done only for public firms. However, the majority of innovations in medical devices have been generated by entrepreneurial firms (usually private firms), meaning that a number of patents are assigned to private firms. I would be able to use the patents by private firms as well if I assume that such patents do not have the issue of inconsistency between assignees and actual patent-producing firms. However, many private firms in the medical device industry operate in more than one R&D location under different names through either their branch firms or subsidiaries. Another limitation of existing databases is that the data after 2006 or 2010 is not available in the NBER database and Kogan's database, respectively.

To address this issue, I match assignees to their ultimate parent firms for both public and private firms by identifying the firms that share the same family tree. Specifically, I first rely on the assignee disambiguation performed by the PatentsView database. Yet, this disambiguation does not identify whether the assignees are true patent-producing firms or not, and it does not identify the relationships among the assignees. Given this limitation, in my second step, I match the assignees in the PatentsView database to the firms in the D&B database based on diverse information, including their names, regions, and observation years. Since the D&B database has an inclusive list of public and private firms and identifies the ultimate parents of firms, my database is able to identify the ultimate parents of assignees if focal assignees have parent firms.

After the process of matching, each patent observation has information on its own ultimate parent firm and MSA (i.e., a place of innovation given by the addresses of inventors). Considering that each pair of the ultimate parent firm and MSA implies a location of the R&D activities of these parent firms, I consider this pair as the place where the focal patent has been actually produced. I call these distinct pairs "R&D

establishments." An ultimate parent firm may have one establishment (i.e., the ultimate parent firm itself is its sole R&D establishment) or multiple R&D establishments depending on whether the ultimate parent firm has any family relationships (e.g., parent-subsidiary) with other firms. Hereinafter R&D establishments are a concept interchangeable with "firms" but distinct from "ultimate parent firms."

3.3.2. Measures

Cluster temporal dynamics (concentration trends)

I construct a measure of cluster temporal dynamics—concentration trends (i.e., the growth rates of concentration)—drawing on the technique that other co-authors and I proposed in Kim, Shaver, and Funk (2019). Calculating the preliminary measure of concentration trends consists of three steps. First, using a z-score method with a Monte Carlo simulation, I measure the degree of a geographic concentration and then, define clusters, which will be the input data for cluster temporal dynamics. Following Alcácer and Zhao (2016), I identify clusters based on the type of economic activity (i.e., employment), geography (i.e., MSA), and the threshold of concentration to label a location as a cluster. Thus, the levels of concentration are the degree to which the number of employees in the medical device industry is concentrated within an MSA exceeds a threshold. One of the challenges in quantifying concentration trends arises from the fact that concentration levels need to be comparable across years and MSAs. To make them comparable, I normalize the concentration levels based on the logic of Ellison & Glaeser's (1997) "dartboard approach." Following the approach, the number of employees without agglomeration is determined by random throws at a dartboard. Using the random throws generated by a Monte Carlo simulation, I calculate z-scores, which are the values of concentration levels.

Second, to identify (potentially multiple) distinct trends for each cluster, I find breaks in the time series of cluster size (i.e., the z-scores) by using structural break analysis. Structural break analysis estimates a linear regression model of structural changes or unexpected shifts in a time series. As the test for the structural breaks, I use the Bai-Perron test. This test estimates the number of breaks that divide a linear regression into multiple regimes and into unknown break dates (Bai and Perron, 1998, 2003). In particular, the general logic of the test is to find a global minimizer for the sum of squared residuals. Structural break analysis methods have been used in previous studies in strategy (e.g., Rothaermel, 2001; Rothaermel and Hill, 2005).

Third, by running a regression analysis for a given clustering trend—a segment as identified in the Bai-Perron test—I quantify the direction and magnitude of change in the trend. Specifically, the regression coefficient estimates from the analysis inform the direction and magnitude of change in the clustering trend. The values of the coefficient estimates are stored as the values of the clustering trend measure.

Dependent variables

The first dependent variable is *the novelty of innovation*, referring to the extent to which firms create new knowledge beyond existing innovation pathways. To assess disruptive innovation, I employ the measure developed by Funk and Owen-Smith (2016). This measure captures the extent to which focal patents disrupt or break existing innovation pathways and has been adopted in previous studies (e.g., Azoulay, Fons-Rosen, and Zivin, 2019; Balachandran and Hernandez, 2018; Wu, Wang, and Evans, 2019). This measure is defined as

$$CD_t = \frac{1}{n_t}\sum_{i=1}^{n}\frac{-2f_{it}b_{it} + f_{it}}{w_{it}}, \qquad w_{it} > 0,$$

where $i = (i_1, i_2, \dots, i_{n-1}, i_n)$ is the vector of future patents that cite the focal patent and/or its prior art at time t, w_{it} indexes a matrix W of weights for patent i at time t, n_t is the number of forward citations to the focal patent and all of its prior art. f_{it} equals 1 if i cites the focal patent and 0 otherwise, and b_{it} equals 1 if i cites any focal patent predecessors and 0 otherwise. The CD_t values of patents range from -1 to 1 with positive values representing innovation that is more disrupting the existing technology streams and negative values highlighting innovation that is more consolidating. The values will be averaged at an MSA level or a firm level, depending on the levels of analyses.

The second dependent variable is *dependence on knowledge from outside the clusters*: specifically, dependence on knowledge from different geographies (H2a) or different industries (H2b). These variables capture the extent to which firms base their innovation on external knowledge from different geographies or industries. To measure them, I calculate the ratio of the outside-geography or outside-industry backward citations to all backward citations made by focal patents. The outside-geography backward citations refer to the cited patents that have been generated in the geographies different from those of focal patents, and the outside-industry backward citations refer to the cited patents belonging to the sub-classes different from those of medical devices defined by the USPTO PTMT.

When calculating this set of dependent variables, I exclude self-citations. I define a pair of "a focal patent and cited patent" as a self-citation if the cited patent was developed by the same R&D establishment as the focal patents. Even if they do not share the same R&D establishments, I define cited-patents as self-citations when their assignees are the same. This is because an R&D establishment's ultimate parent firm may change because of acquisitions or divestitures while the establishment remains as the same organization.

Entrepreneurial firms

I identify entrepreneurial firms in two different ways. First, I define entrepreneurial firms using the information on firms' ages and family trees. Specifically, I filter out firms that are older than ten years. I also filter out firms belonging to large established family trees because those firms—even if they are younger than ten years—would have innovation capability spillovers from their established family trees. Considering that the average number of firms per family tree in the sample dataset is four, I define large established family trees like those that have four or more firms. Given this information, I define firms as entrepreneurial firms if they are 10-years-old or younger and belong to family trees that have four or fewer firms. The rest of the firms in the sample—those that are older than ten years and belong to family trees that have more than five firms—are considered as established firms. I construct a binary variable—1 if they are entrepreneurial, 0 otherwise. Second, for a more strictly defined condition, I also define entrepreneurial firms based on the SBIR/STTR funding information reported in patent documents. These funds are given only to entrepreneurial firms by the United States government. I construct a binary variable, which is 1 if they are entrepreneurial, 0 otherwise.

Control variables

I control for possible covariates at the MSA level, including the current levels of industry concentration, which is measured by a z-score (I call *cluster size* as a distinctive concept from cluster dynamics). I also control for *population size*, the *number of inventors,* and the *number of large firms* (i.e., firms hiring more than 1,000 employees). At the firm (i.e., R&D establishment) level, I control for the number of inventors, the number of patent stock, and the number of establishments that belong to the family tree of a given establishment. At the patent level, I control for technological classes. I also control for a trend-specific characteristic, the *length of a given trend*, which counts the years within a given trend.

3.3.3. Estimation Strategies

While the unit of observation of this dataset is a patent, inventor, ultimate parent firm, MSA, and year level (i.e., a patent-inventor-R&D establishment-year level), I use different units of analysis. First, the main unit of analysis is an MSA-trend level. A trend refers to a distinct segment of the time series of concentration for a given MSA. For example, the time series of an MSA's concentration can be segmented into two distinct trends—a period of decline and then that of growth. I use an MSA-trend level as a main unit of analysis because the explanatory variable in this study (i.e., the concentration trends) varies at the MSA-trend level. Second, I also use an R&D establishment-trend level (i.e., ultimate parent firm-MSA-trend) because I am interested in how concentration trends influence the outcomes of "firms" (in this study, R&D establishments). In this sense, R&D establishment-level analysis is important because I can control for R&D establishment-level confounders, such as heterogeneity of sample establishments.

The analysis begins by examining the correlations between concentration trends and innovation and then runs the simple pooled OLS, which controls for time-varying control variables. I expect positive correlations and positive regression coefficients.

However, for two reasons, it is unlikely that a "naïve" OLS regression will identify the causal relationship between concentration trends and firm innovation. First, one potential source of endogeneity is simultaneous causality. In other words, local firms' innovation is also likely to influence the concentration levels of focal clusters. Specifically, if disruptive innovation represents good innovation performance, and cluster firms' innovation becomes more disruptive, firms of different geographies or industries will pay more attention to focal clusters and then come into the clusters. This is because these firms expect positive spillover effects from local firms. The inflows of these firms will lead to a period of sustained growth of clusters. This could be a reason why I see a positive association between sustained growth in concentrations and firms' disruptive innovation.

Second, another source of endogeneity is unobserved heterogeneity among clusters. Some cluster-specific characteristics affect both concentration trends and disruptive innovation. For example, regional variance in local firms' innovation capabilities might influence concentration trends because cluster firms with higher innovation capabilities can attract outsiders to the focal clusters, leading to an increased concentration. In addition, higher innovation capabilities can encourage focal firms to engage in distant search, which allows for disruptive innovation. Similarly, regional variance in local research institutes' performance might also affect both concentration trends and firm innovation. If the research institutes do well, outsider firms are likely to come into focal clusters in order to have opportunities for research collaboration with the institutes or to hire graduates from the institutes. Also, since the research institutes can be a bridge through which local firms can obtain knowledge across different fields of technologies, the greater performance of local research institutes can lead to an increase in firms' disruptive innovation.

To mitigate the issues inherent in a "naïve" research design, I take two steps to evaluate whether it is appropriate to reject the null hypothesis that the periods of sustained growth do not play a role in influencing firms' innovation.

First, in order to mitigate the concern that local firms' innovation is also likely to influence concentration trends, I measure dependent variables at year t+3 and t+5, and I report the results of t+3 as the main analysis results. I report the results of t+5 in Appendix B as robustness checks. Also, as another way to show that simultaneity bias would not be a serious issue, I address the source of the simultaneity bias concern. The concern comes from the assumption that disruptive innovation can represent good innovation performance and that good innovation performance can lead concentration levels to grow. Conceptually, as shown in the existing literature, the disruptive nature of innovation does not necessarily represent firms' innovation performance or the values of innovation (e.g., Arts and Fleming, 2018; Kaplan and Vakili, 2015; Simon, 1983). Yet, to empirically address the concern, I demonstrate that disruptive innovation does not have positive correlations with innovation volume, which is a conventional measure of innovation performance. Moreover, I show that innovation volume is not correlated with concentration trends.

Second, to mitigate the concerns about unobserved heterogeneity of clusters that affect both concentration trends and innovation, I employ an estimation approach that controls for cluster-specific and firm-specific attributes. Based on the panel structure of the data and the continuous dependent variables, I adopt a linear fixed-effect specification.

The empirical analysis of this study does not take into account the year fixed effects. This is because concentration trends are measured using the concentration levels that are normalized across years, so any year effect that influences the relationship between concentration trends and innovation is already pulled out.

To test heterogeneous effects between entrepreneurial firms and large established firms (H3a, H3b, and H3c), following Shaver (2019), I run fixed-effect models by sub-groups—entrepreneurial firms vs. the established firms (or their establishments)—rather than including an interaction term in the models. This is because fixed-effect regression models with interaction terms confound within- and between-variation in identifying interaction coefficient estimates.

3.4. Results

Table 3.1 presents the descriptive statistics and correlations of the main variables for the top five percent of clusters[13] (i.e., 20 MSAs) with the largest mean of z-scores from 1974 to 2016 in the medical device industry. The variables in Table 3.1 are measured at an MSA-trend level, which is the main level of analysis in this study. Specifically, the concentration trend is measured by calculating the growth rates of concentration, and the length of trends is measured by and counting the years of a given trend. The other variables, such as disruptive innovation, are measured by calculating the average of annual data for given trends. There are 68 MSA-trend observations, which, on average,

[13] Specifically, for all 375 MSAs in each industry, I calculated the mean of z-scores over the years when their z-scores are positive (i.e., during the periods of time when the focal region is identified as a cluster). I then selected the top 20 MSAs with the largest mean of z-scores.

means that each MSA has about three distinct trends between 1974 and 2016. Specifically, as shown in the table, trends on average span about 13 years, ranging from 4 to 38 years.

---Insert Table 3.1 here---

The concentration trends of the sample clusters range from -10.51 to 45.39. As shown in the correlation (0.0049), concentration trends are not highly correlated with cluster size. This implies that the concentration trend measure is a distinct construct from cluster size.

The correlations between concentration trends and other variables foreshadow the main results in this study. The main relationship that I examine in this study is the association between concentration trends and disruptive innovation (H1). I hypothesize that innovation by firms in growing clusters is likely to be more disruptive relative to innovation by firms in stable or declining clusters. The null hypothesis is that there is no difference in the extent of innovation disruptiveness between firms in growing and non-growing clusters. The assumption behind the null hypothesis is that the employees moved from outside cluster boundaries—which growing clusters imply—have similar knowledge to the focal growing cluster employees rather than having distant knowledge. This is because employees might cross geographic or industry boundaries only when they have similar types of knowledge to focal clusters. In addition, if those moving had different knowledge, the 'local' approach or knowledge is imposed on them. Given the assumption, there might not be variance in disruptiveness between firms in growing and non-growing clusters.

As I theorize in hypothesis 1, concentration trends have a positive association with disruptive innovation. This means that firms in growing clusters are more likely to generate innovation beyond existing paths of innovation. Another relationship that I investigate is the association between concentration trends and the extent to which cluster firms depend on knowledge from different geographies and industries (H2a and H2b). While concentration trends' correlation with different industry dependence is positive and significant, which is consistent with my argument, their correlation with different geography dependence is insignificant. Moreover, the absolute value of the correlation is very small. This low correlation is not consistent with my prediction that cross-geography resource mobility is a key mechanism underlying the relationship between concentration trends and firm innovation. To further investigate the relationship while controlling for confounders, I run regressions.

In Table 3.2, Columns (1), (2), and (3) present the results of the pooled OLS regression models with robust standard errors clustered at the MSA level. Throughout the models, the estimated coefficients of concentration trends are consistently positive and statistically significant at the 1% level. In Column (2), I control for cluster size, so the result implies that firms in growing clusters are likely to generate more disruptive innovation relative to firms in clusters of comparable size that are experiencing stable or declining periods. In Column (3), I show that the correlation is similar when I control for population, the total number of medical device inventors, the length of given trends, as well as cluster size. While these correlations are consistent with the theory of this study, the result may be due to unobserved MSA heterogeneity that is correlated with concentration trends and disruptive innovation. To address these concerns, in Column (4), I run an MSA fixed-effect model, clustering standard errors at the MSA level. Column (4) shows that the coefficient estimate of concentration trends is consistently positive and statistically significant at the 1%. This result suggests that as a cluster is moving into a more increasing concentration trend than before, innovation by firms in the cluster will be more likely to be disruptive than the cluster's previous trend. This within-variance model result supports a positive relationship between concentration trends and innovation disruptiveness as the results from between-variance models—i.e., Columns (1), (2), and (3)—do. Yet, the implications suggested by within- and between-variance models slightly differ; the results from between-variance models suggest that the extent of firms' innovation disruptiveness is larger in clusters that are experiencing more increasing concentration trends than clusters that are experiencing less increasing or decreasing concentration trends. The results shown in Columns (1) – (4) are largely consistent with those of the models using the dependent variable measured at time t+5 instead of t+3 and using the 30 largest MSAs (Appendix B1).

---Insert Table 3.2 here---

The previous analysis demonstrates the positive and robust effect of the sustained growth of clusters on disruptive innovation. My theoretical framework indicates that the main channel through which concentration trends affect disruptive innovation is boundary-crossing resource mobility—the influx of employees and their knowledge from different geographies and/or industries. To assess the importance of this mechanism, I investigate the relationship between concentration trends and dependence on knowledge from different geographies or industries. In Table 3.3, Columns (1) – (3) present the results of the pooled OLS, and Column (4) shows the result of an MSA fixed-effect model. All models have robust standard errors clustered by MSAs. As shown in Table 3.1, the coefficients of concentration trends on different geography dependence are positive but generally statistically insignificant throughout the models. Thus, this does not support my prediction (H2a) that cross-geography resource mobility is a mechanism underlying the relationship between concentration trends and disruptive innovation.

---Insert Table 3.3 here---

By contrast, Columns (5) – (8) in Table 3.3 show that the relationships between sustained growth and dependence on knowledge from different industries are found to be largely consistent with my argument. The estimated coefficients of concentration trends on different industry dependence are positive and statistically significant throughout the models at the 1% level (the pooled OLS models) and the 5% level (the fixed-effect model). These results imply that firms in clusters experiencing a sustained growth period are likely to base their innovation more on knowledge from beyond their industries than firms in clusters of comparable size that are experiencing stable or declining periods. This further confirms that cross-industry resource mobility is an underlying mechanism of the relationship between concentration trends and disruptive innovation, which supports H2b. I also confirm that the results are largely consistent with those of the models using the dependent variable measured at time t+5 and using the 30 largest MSAs (Appendix B2 and B3).

I find that different industry dependence is a mechanism, whereas different geography dependence is not. This might be because the frequency of employee inflows from different regions is too small to see a large variation. In other words, the sustained growth periods of sample clusters in the US medical device industry might have been fueled by cross-industry resource mobility (inflows from different industries within the same MSA), not chiefly by cross-geography mobility (i.e., inflows from different MSAs while in the med-tech industry). To further investigate this alternative, I compare the frequency of employee inflows between these two types—cross-geography mobility and cross-industry mobility—by calculating the proportion of cross-geography mobility to a whole (i.e., a sum of cross-geography and cross-industry mobility). The stacked bars in Figure 3.1 show the annual frequency of cross-geography mobility, demonstrating that sample clusters have been fueled largely by cross-industry resource mobility rather than by cross-geography mobility.

---Insert Figure 3.1 here---

As another way to demonstrate the suggested underlying mechanism, I consider heterogeneity in the effects of concentration trends on innovation between large established firms and entrepreneurial firms (H3a, H3b, and H3c). I expect that the effects are greater for entrepreneurial firms because they have a higher motivation to access and weaker barriers to applying boundary-crossing resources than do large established firms. To test this, I first divide the firm-year-level data table into two subsamples using the cut-off point[14] that defines firms as entrepreneurial firms or established firms. I then aggregate the data, respectively, at the MSA-trend level and run regressions. Table 3.4 shows that, for entrepreneurial firms, the coefficients of concentration trends on disruptive innovation are positive and statistically significant. By contrast, for established firms, the coefficients are not statistically significant, which does not support H3a.

[14] The cut-off point used in Tables 4, 5, and 6 is that firms are 10-years-old or younger and belong to family trees that have four or fewer firms.

---Insert Table 3.4 here---

Tables 3.5 and 3.6 present the relationships between concentration trends and firms' dependence on knowledge from different geographies and industries, respectively, for entrepreneurial and established firms. In Table 3.5, the coefficients for established firms are consistently negative (Columns 5-8), whereas those for entrepreneurial firms are consistently positive (Columns 1-4). However, the statistical significance shown in Columns (1) and (2) disappears when controlling for confounders, as shown in Columns (3) and (4). These results do not support hypothesis H3b that the effects of concentration trends on firms' dependence on knowledge from different geographies are significant for entrepreneurial firms. In Table 3.6, the coefficients for entrepreneurial firms are consistently positive and statistically significant at the 1% level. Yet, the coefficients for established firms are not statistically significant, which does not support H3c. I also confirm that the results are largely consistent with those of the models using the dependent variable measured at time t+5 and using the 30 largest MSAs (Appendix B4, B5, and B6). Even though these test results fail to demonstrate greater effect size for entrepreneurial firms than established firms, it would be worth in future studies discovering conditions under which the coefficients for both types of firms are statistically significant, which allows for the comparison of effect size.

---Insert Tables 3.5 and 3.6 here---

One of the most interesting findings throughout all models in Tables 2 and 3 is that cluster size and total medical device inventors, which are traditional measures for cluster size, show different coefficient estimates from those of the concentration trends variable, particularly in terms of the direction of effects. Whereas the coefficients of concentration trends are positive, those of cluster size and total inventors are generally negative. This means that cluster firms in bigger clusters consolidate—rather than disrupt—the existing pathways of innovation as they tend to base their knowledge creation more on their existing contexts (e.g., industry) than those in isolated regions do. This is consistent with previous studies suggesting that knowledge spillovers are bounded within current contexts (Almeida and Kogut, 1999; Jaffe *et al.*, 1993) and fostered by the geographic concentration of industrial activity (Marshall, 1920; Saxenian, 1994). However, my findings suggest that after controlling for cluster size, firms are likely to be exploratory when focal clusters present a period of sustained growth in concentration levels.

Another interesting finding is that the associations between concentration trends and innovation are found to be strong throughout the models even though the number of observations is small in the MSA-trend-level analysis (i.e., 63 pairs of MSA-trend[15]). Moreover, even MSA fixed-effect models also show statistically significant coefficient estimates on concentration trends, although each MSA has only three distinct trends, on average. These facts make the evidence more convincing that concentration trends have sufficient variance and that the variance in trends explains variance in firm innovation.

Table 3.7 shows the results of examining the relationship between concentration trends and innovation volume (i.e., the number of patents), which is an analysis I design to reduce concern about simultaneity causality between concentration trends and disruptive innovation. As shown in the table, the coefficient estimates of concentration

[15] Even though there are 63 observations in the MSA-trend-level analysis, these observations consist of 113,846 patents of 16,651 firms.

trends are statistically insignificant. These results imply that concentration trends do not correlate with innovation volume, which may reduce the concern about simultaneity bias. I also confirm that the results are largely consistent with those of the models using the dependent variable measured at time t+5 instead of t+3 and using the 30 largest MSAs (Appendix B7).

---Insert Table 3.7 here---

Alternative Explanation: Competition Effects

One alternative explanation for the positive correlation between sustained growth of concentration and innovation is that the measure of concentration trends is simply capturing variation in regional industry rivalry that can be correlated with disruptive innovation. In other words, the presence of effects of sustained growth on disruptive innovation might be due to growing competition rather than increased rates of boundary-crossing resource mobility. Specifically, if sustained growth correlates with increased competition and if competition forces firms to differentiate themselves from their competitors, competition might be the reason why I see higher levels of disruptive innovation in clusters presenting sustained growth.

Whether the geographic concentration of high tech industry activity indicates greater competition among firms is still debated in the literature (Gambardella and Giarratana, 2010). Yet, concentration representing competition is possible, considering that there may be mutual learning and imitation (Barnett and Sorenson, 2002; Barney, 1991) as well as greater congestion of firms in a few similar markets (Gimeno and Woo, 1996).

In order to rule out this alternative explanation, I run the regression models by including the "competition" variable, which is measured based on the Herfindahl-Hirschman Index. Table 3.8 shows that the results are robust to introducing an additional measure of local competition. The coefficient estimates of cluster dynamics are relatively consistent over the models after including the competition variable. I also confirm that the results are largely consistent with those of the models using the dependent variable measured at time t+5 and using the 30 largest MSAs (Appendix B8).

---Insert Table 3.8 here---

3.5. Conclusions

The geographic concentration of industry activity is fundamental to understanding firms' innovation. Although existing literature has focused on how cluster size in and of itself affects firms' technological innovation, the temporal dynamics of clusters may have strategic implications that are not accounted for by the existing approaches but that may influence the relationship between clusters and firm innovation.

This study examines how concentration trends influence the nature of innovation. I suggest that firms in clusters experiencing a period of sustained growth will be more likely to generate more disruptive innovation—i.e., the innovation that disrupts or breaks the existing paths of innovation—relative to firms in clusters of comparable size that are experiencing stable or declining periods. This is because sustained growth implies that employees are increasingly coming in from elsewhere, and this influx constitutes inflows of knowledge from different geographies or industries. In addition, this cross-cluster employee mobility also leads to changes in relevant organizations in the local ecosystem in that they are increasingly supportive of local firms to understand such boundary-crossing knowledge.

Through empirical analyses, I find that firms in clusters experiencing a period of sustained growth are likely to produce more disruptive innovation. I further investigate the mechanism underlying the relationship between cluster trends and disruptive innovation by examining the sources of knowledge on which firms base innovation. I find that firms in growing clusters base their knowledge creation more on knowledge from different industries, which reinforces that cross-cluster resource mobility is a key mechanism, than firms in clusters of comparable size experiencing a stable or declining period. Furthermore, this finding is also interesting as I find that cross-industry resource mobility is a more dominant mechanism than cross-geography mobility.

One of the most interesting findings is that cluster size shows different coefficient estimates from those of the concentration trends variable. The findings suggest that firms in bigger clusters tend to be less exploratory, meaning that they consolidate the existing pathways of innovation, which is consistent with findings in previous studies. This is because they tend to base their innovation more on their existing contexts (e.g., industry) than those in isolated regions. However, my findings suggest that after controlling for cluster size, firms are likely to be more exploratory when focal clusters experience a period of sustained growth.

This study contributes to the existing literature on industry clusters in several ways. First, this study enriches the understanding of the relationships between industry clusters and firm outcomes by considering the temporal dynamics of clusters. This enlightens a mechanism through which clusters affect firm outcomes. Second, the results of this study confirm previous studies' arguments about cluster size, and at the same time, the results demonstrate that cluster dynamics have strategic implications for innovation that are distinct from the implications of cluster size. Last, the implications of cluster motion may help resolve conflicting findings within longstanding debates—e.g., whether higher industry concentration improves or deters innovation (e.g., Bell, 2005; Ozer and Zhang, 2015). Considering cluster motion in addition to cluster mass may provide clear evidence of the role of clusters in innovation.

I acknowledge the limitations of this study. Specifically, although the empirical analysis is designed to mitigate the sources of endogeneity—simultaneous causality and unobserved heterogeneity—this study does not perfectly identify the causal relationship. Future research could investigate the relationship by using exogenous shocks that affect concentration trends so that researchers can infer causal relationships. Also, this study uses a predetermined geographic unit, MSA. Yet, actual economic activity does not necessarily follow the predetermined administrative boundary. Thus, future research could identify cluster boundaries organically, using a density-based cluster identification method, for example (Alcácer and Zhao, 2016; Wang and Zhao, 2018). In addition, this study utilizes only U.S. data while ignoring clusters in other countries. Considering that inventors are migrating across countries, the use of the multinational data as well as the U.S. data could help understand the relationship between cluster dynamics and innovation.

Although not without its limitations, I believe that this study builds a framework for understanding cluster dynamics and their effects on firm innovation. I also believe that this research can be expanded to studies that examine how diverse firm outcomes—e.g., new venture creation, resource acquisition—are affected by cluster dynamics, which helps improve our understanding of the relationships between industry clusters and firm outcomes.

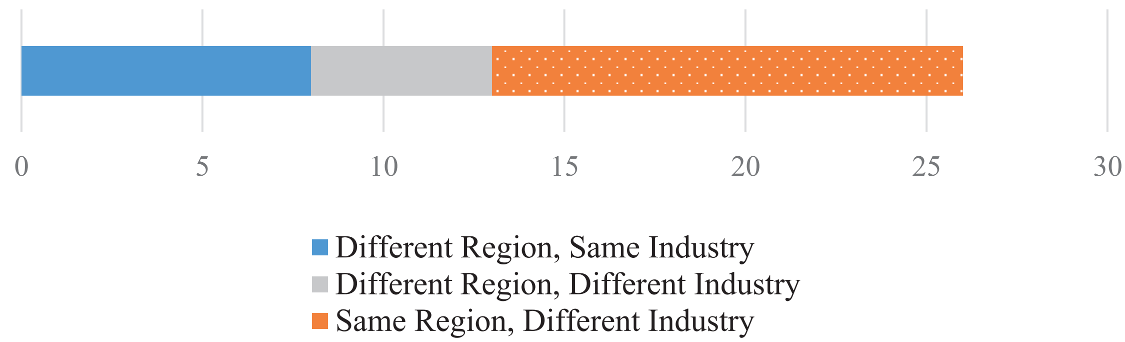

Figure 3. 1. Types of employee mobility

Table 3. 1. Descriptive statistics and correlations (Top 20 MSAs)

	Variable	Mean	Min	Max	SD	N	1	2	3	4	5	6	7	8	9
1	Concentration trend	0.97	-10.51	45.39	7.23	68	1								
2	Cluster size	62.05	-18.15	259.16	56.15	68	0.0049	1							
3	Different geography dependence	95.13	82.33	100.00	4.02	68	0.1399	-0.4620*	1						
4	Different industry dependence	39.82	12.70	90.83	21.23	68	0.3225*	-0.2834*	0.4452*	1					
5	Disruptive innovation	0.07	-0.02	0.54	0.11	68	0.3962*	-0.2377	0.4374*	0.8554*	1				
6	Population	182	18	1245	220	68	0.0298	0.1123	-0.4051*	-0.0472	-0.0553	1			
7	Total med-tech inventors	86.62	0.70	875.00	148.18	68	0.0039	0.5865*	-0.7292*	-0.3963*	-0.2908*	0.4324*	1		
8	Competition	0.78	0.25	0.97	0.17	68	0.0434	0.3320*	-0.3962*	-0.3194*	-0.3455*	0.4536*	0.4155*	1	
9	Length of trends	12.65	4.00	38.00	6.60	68	-0.0664	0.0586	-0.2332	-0.2761*	-0.3091*	0.131	0.2175	0.1259	1

Table 3. 2. The OLS regression models of disruptive innovation (H1)

	DV: *Disruptive innovation*			
Variables	(1)	(2)	(3)	(4)
Concentration trend	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.005*** (0.001)
Cluster size		-0.000*** (0.000)	-0.000 (0.000)	-0.001 (0.000)
Population			0.000 (0.000)	-0.001* (0.000)
Total med device inventors			-0.000 (0.000)	0.000 (0.000)
Length of trend			-0.004*** (0.001)	-0.005*** (0.001)
MSA-FE				*Included*
Constant	0.067*** (0.009)	0.096*** (0.015)	0.139*** (0.027)	
Observations	68	68	68	68
R-squared	0.157	0.214	0.307	0.385

Robust standard errors in parentheses; clustered by MSAs
*** p<0.01, ** p<0.05, * p<0.10

Table 3. 3. The OLS regression models of dependence on external knowledge from different geographies (H2a) and different industries (H2b)

	DV: *Different geography dependence*				DV: *Different industry dependence*			
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Concentration trend	0.078 (0.054)	0.079* (0.045)	0.079 (0.059)	0.094 (0.081)	0.947*** (0.209)	0.951*** (0.206)	0.903*** (0.245)	0.637** (0.255)
Cluster size		-0.033** (0.013)	-0.006 (0.004)	0.006 (0.013)		-0.108** (0.040)	-0.026 (0.058)	-0.102 (0.111)
Population			-0.002 (0.002)	-0.003 (0.008)			0.013* (0.007)	-0.145 (0.093)
Total med device inventors			-0.017*** (0.004)	-0.018*** (0.005)			-0.054** (0.023)	-0.028 (0.045)
Length of trend			-0.042 (0.034)	-0.022 (0.053)			-0.604** (0.263)	-0.664** (0.244)
MSA-FE				*Included*				*Included*
Constant	95.055*** (0.665)	97.110*** (0.714)	97.832*** (0.946)		95.055*** (0.665)	97.110*** (0.714)	97.832*** (0.946)	
Observations	68	68	68	68	68	68	68	68
R-squared	0.020	0.234	0.572	0.507	0.104	0.185	0.313	0.463

Robust standard errors in parentheses; clustered by MSAs
*** p<0.01, ** p<0.05, * p<0.10

Table 3. 4. The OLS regression models of disruptive innovation for entrepreneurial firms vs. established firms (H3a)

	DV: *Disruptive innovation*							
	Entrepreneurial firms				Established firms			
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Concentration trend	0.004*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.003* (0.001)	0.004 (0.003)	0.005 (0.003)	0.004 (0.003)	0.003 (0.003)
Cluster size		-0.001*** (0.000)	-0.001 (0.000)	-0.000 (0.000)		-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Population			0.000 (0.000)	0.000** (0.000)			0.000 (0.000)	-0.000 (0.001)
Total med device inventors			-0.000 (0.000)	0.000 (0.000)			-0.000 (0.000)	-0.000 (0.000)
Length of trend			-0.005*** (0.002)	-0.008*** (0.002)			-0.004*** (0.001)	-0.004*** (0.001)
MSA-FE				*Included*				*Included*
Constant	0.065*** (0.012)	0.108*** (0.022)	0.178*** (0.050)		0.052*** (0.013)	0.076*** (0.025)	0.134*** (0.049)	
Observations	59	59	59	59	59	59	59	59
R-squared	0.060	0.134	0.238	0.318	0.073	0.098	0.198	0.385

Robust standard errors in parentheses; clustered by MSAs
*** p<0.01, ** p<0.05, * p<0.10

Table 3. 5. The OLS regression models of dependence on external knowledge from different geographies for entrepreneurial firms vs. established firms (H3b)

	DV: *Different geography dependence*							
	Entrepreneurial firms				Established firms			
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Concentration trend	0.063* (0.036)	0.075* (0.042)	0.063 (0.039)	0.085 (0.053)	-0.119 (0.104)	-0.095 (0.087)	-0.102 (0.117)	-0.136 (0.111)
Cluster size		-0.037** (0.015)	-0.007 (0.006)	-0.001 (0.009)		-0.040*** (0.011)	-0.023** (0.008)	-0.012 (0.013)
Population			-0.002 (0.001)	-0.001 (0.010)			-0.006*** (0.002)	-0.004 (0.011)
Total med device inventors			-0.017*** (0.000)	-0.013** (0.000)			-0.009* (0.005)	-0.009 (0.006)
Length of trend			0.022 (0.042)	-0.020 (0.054)			0.038 (0.052)	-0.011 (0.071)
MSA-FE				*Included*				*Included*
Constant	95.659*** (0.744)	98.266*** (0.787)	97.894*** (0.969)		95.284*** (0.810)	98.127*** (0.820)	98.362*** (1.196)	
Observations	60	60	60	60	59	59	59	59
R-squared	0.013	0.260	0.630	0.435	0.044	0.311	0.566	0.368

Robust standard errors in parentheses; clustered by MSAs
*** p<0.01, ** p<0.05, * p<0.10

Table 3. 6. The OLS regression models of dependence on external knowledge from different industries for entrepreneurial firms vs. established firms (H3c)

Variables	DV: *Different industry dependence*							
	Entrepreneurial firms				Established firms			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Concentration trend	0.846*** (0.170)	0.887*** (0.194)	0.748*** (0.160)	0.810*** (0.222)	0.377 (0.395)	0.450 (0.331)	0.340 (0.341)	0.102 (0.285)
Cluster size		-0.134*** (0.039)	-0.085 (0.062)	-0.086 (0.141)		-0.120*** (0.029)	-0.102* (0.050)	-0.092 (0.118)
Population			0.006 (0.007)	-0.098 (0.078)			0.007 (0.007)	-0.082 (0.087)
Total med device inventors			-0.033 (0.021)	-0.015 (0.046)			-0.014 (0.018)	-0.014 (0.042)
Length of trend			-0.775*** (0.187)	-0.931*** (0.254)			-0.616*** (0.193)	-0.827** (0.338)
MSA-FE				*Included*				*Included*
Constant	40.752*** (2.184)	50.082*** (3.399)	59.879*** (5.938)		38.446*** (1.492)	47.033*** (2.849)	54.695*** (5.902)	
Observations	60	60	60	60	59	59	59	59
R-squared	0.107	0.254	0.414	0.525	0.026	0.171	0.269	0.372

Robust standard errors in parentheses; clustered by MSAs
*** p<0.01, ** p<0.05, * p<0.10

Table3. 7. The OLS regression models of the innovation volume

Variables	DV: *Innovation volume*			
	(1)	(2)	(3)	(4)
Concentration trend	-0.195 (1.258)	-0.244 (1.522)	-0.293 (0.302)	-0.028 (0.459)
Cluster size		1.304** (0.580)	-0.006 (0.068)	-0.003 (0.115)
Population			0.013 (0.020)	0.176* (0.098)
Total med device inventors			0.844*** (0.063)	0.764*** (0.059)
Length of trend			-0.312 (0.341)	0.018 (0.315)
MSA-FE				*Included*
Constant	84.169*** (20.528)	3.331 (25.464)	13.168 (8.240)	
Observations	68	68	68	68
R-squared	0.000	0.327	0.962	0.957

Robust standard errors in parentheses; clustered by MSAs
*** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 3. 8. The OLS regression models of the nature of innovation, having the competition effects controlled

Variables	DV: Disruptive innovation (H1)		DV: Different geography dependence (H2a)		DV: Different industry dependence (H2b)	
	(1)	(2)	(3)	(4)	(5)	(6)
Concentration trend	0.006***	0.004***	0.080	0.091	0.930***	0.577**
	(0.001)	(0.001)	(0.061)	(0.085)	(0.289)	(0.265)
Cluster size	-0.000	-0.001	-0.005	0.007	-0.003	-0.091
	(0.000)	(0.001)	(0.005)	(0.013)	(0.056)	(0.118)
Population	0.000***	-0.001*	-0.002	-0.002	0.023**	-0.121
	(0.000)	(0.000)	(0.002)	(0.008)	(0.010)	(0.073)
Total med device inventors	-0.000	0.000	-0.016***	-0.018***	-0.049**	-0.028
	(0.000)	(0.000)	(0.004)	(0.005)	(0.021)	(0.043)
Length of trend	-0.004***	-0.003***	-0.040	-0.013	-0.568*	-0.512**
	(0.001)	(0.001)	(0.033)	(0.052)	(0.285)	(0.244)
Competition	-0.223*	-0.457***	-1.847	-3.662	-34.817	-65.999**
	(0.113)	(0.156)	(2.799)	(3.425)	(25.351)	(28.666)
MSA-FE		*Included*		*Included*		*Included*
Constant	0.286**		99.049***		73.391***	
	(0.100)		(2.342)		(20.517)	
Observations	68	68	68	68	68	68
R-squared	0.389	0.583	0.576	0.522	0.366	0.580

Robust standard errors in parentheses; clustered by MSAs
*** p<0.01, ** p<0.05, * p<0.10

Table 3. 8. (continued)

Variables	DV: *Disruptive innovation* (H3a)				DV: *Different geography dependence* (H2a)				DV: *Different industry dependence* (H2b)			
	Entrepreneurial		Established		Entrepreneurial		Established		Entrepreneurial		Established	
	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Concentration trend	0.004** (0.001)	0.003* (0.002)	0.004 (0.003)	0.003 (0.003)	0.062 (0.040)	0.082 (0.058)	-0.105 (0.120)	-0.130 (0.103)	0.747*** (0.185)	0.788*** (0.249)	0.319 (0.384)	-0.012 (0.365)
Cluster size	-0.000 (0.000)	0.000 (0.001)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.006)	0.001 (0.009)	-0.020** (0.007)	-0.015 (0.014)	-0.033 (0.063)	-0.040 (0.138)	-0.081 (0.052)	-0.043 (0.102)
Population	0.000** (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.001)	-0.000 (0.001)	0.001 (0.010)	-0.005** (0.002)	-0.005 (0.013)	0.016*** (0.005)	-0.072 (0.068)	0.013 (0.010)	-0.053 (0.069)
Total med device inventors	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.017*** (0.004)	-0.013*** (0.004)	-0.009* (0.005)	-0.008 (0.006)	-0.035* (0.020)	-0.025 (0.043)	-0.013 (0.017)	-0.024 (0.037)
Length of trend	-0.005** (0.002)	-0.006*** (0.002)	-0.004*** (0.001)	-0.008** (0.003)	0.023 (0.039)	-0.011 (0.056)	0.037 (0.051)	-0.016 (0.069)	-0.784*** (0.188)	-0.801*** (0.209)	-0.623*** (0.189)	-0.728* (0.355)
Competition	-0.312* (0.150)	-0.603** (0.283)	-0.038 (0.079)	-0.118 (0.169)	-4.592 (2.830)	-3.551 (5.982)	-2.529 (2.918)	3.631 (5.820)	-25.033 (15.375)	-55.297** (26.079)	-19.063 (15.912)	-68.537 (44.557)
MSA-FE		*Included*		*Included*		*Included*		*Included*		*Included*		*Included*
Constant	0.367*** (0.118)		0.158** (0.061)		100.639*** (1.838)		99.976*** (1.983)		73.438*** (11.703)		66.858*** (11.055)	
Observations	58	58	59	59	59	59	59	59	59	59	59	59
R-squared	0.349	0.490	0.199	0.392	0.649	0.445	0.572	0.377	0.457	0.591	0.289	0.457

Chapter 4: Mini Case - The Medical Device and Computer Industries in Minneapolis-St. Paul, MN

In this chapter, I conduct an in-depth qualitative study on cluster temporal dynamics in the Minneapolis-St. Paul region. The purpose of this study is to unpack the phenomenon of cluster motion, based on interviews and historical case studies. Specifically, I describe what was happening during a period of sustained growth of the local medical device industry. I focus on demonstrating whether and how resources were flowing from outside of the local medical device industry during its growth, from sources such as the local computer industry.

4.1. The Medical Device Industry in Minneapolis-St. Paul, MN

Minnesota, particularly the Minneapolis-St. Paul region, is the state with the second most medical technology patents granted, earning the nickname "Medical Alley." Minneapolis-St. Paul also has the highest concentration of medical technology workers in the nation and shows the highest talent retention rates among the US top 25 markets. Nearly 700 medical device companies have their headquarters or major operations in Minneapolis-St. Paul and adjacent areas–from promising startup companies to industry leaders such as Medtronic, Boston Scientific, 3M, and St. Jude Medical. Minnesota's depth of medical know-how and infrastructure give it an advantage in speeding medical innovations to market. For example, in Minnesota, FDA 510K clearances are 26% faster than the national average—i.e., a 30-day advantage—and FDA pre-market approvals are 6.5 months faster[16].

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[16] A nonprofit trade association in Minneapolis, Medical Alley

While Medtronic triggered the emergence of a medical device cluster in Minnesota, the emergence was possible because of a strong basis in the medical field. The basis was created by two medical institutions in Minnesota, the University of Minnesota and Mayo Clinic. Minnesota was the first state in the US to require a board exam to receive a medical license, which led to the establishment of the College of Medicine and Surgery at the University of Minnesota, and the University's Variety Club Heart Hospital was the first hospital in the US to focus solely on cardiac patients. The University of Minnesota hospitals and the Mayo Clinic, through competition and collaboration, created surgical innovation and laid the strong foundations for the medical field.

Supported by such a strong foundation, Earl Bakken established an anchoring company of the local medical device industry, Medtronic, in 1949. The emergence and growth of Medtronic go back to the company's first technological innovation, "the Medtronic 5800 cardiac pacemaker." This is the first portable cardiac pacemaker, requested by Dr. C. Walton Lillehei at the Variety Club Heart Hospital. In addition, Medtronic later got a license for another great innovation, the first implantable pacemaker. Based on these innovations, Medtronic grew exponentially during the 1960s and 1970s.

Along with Medtronic's growth, Minnesota's supportive medical institutions and environments attracted more companies and employees from the other industries and regions, resulting in the formation and growth of a medical device cluster.

4.2. Dynamics During the Sustained Growth of the Medical Device Industry in MN

One of the most obvious dynamics that I observe during a period of sustained growth of the medical device industry in the Minneapolis-St. Paul region is the influx of the local computer industry resources and activities into the local medical industry. A quick example that demonstrates such dynamics is the transformation of physical spaces from the computer to the medical device and relevant industries. 4201 Lexington Avenue in Arden Hills is home to the cardiac rhythm management business of Boston Scientific, but it had previously housed manufacturing plant by Control Data. In addition, a building at the intersection of Old Shakopee Road and 33rd Avenue in Bloomington served as the Control Data headquarters, but now it is occupied by HealthPartners, a large health care provider.

In the following sections, I describe a brief background of the local computer industry and the inflows of specific resources from the computer to the medical device industry.

4.2.1. The computer industry in Minneapolis-St. Paul

Minneapolis-St. Paul was one of the largest computer industry clusters in the US, preceding the better-known computer industrial districts of Route 128 around Boston and Silicon Valley. After World War II ended, Minnesota attracted engineers, especially those from the computer industry, and became a center of computer technology.

The region's reputation as a computer industry cluster began in the late 1940s with an entrepreneur William Norris and the company he co-founded, Engineering Research Associates. In 1957, Norris created a new startup, Control Data Corporation. With the company's early success in developing superfast scientific computers, Control Data became a billion-dollar venture in a little over a decade and one of the largest mainframe computer companies in the world. Control Data had a number of innovative engineers, including Seymour Cray, who is called "the father of supercomputing." Further growth as a computer industry cluster was fueled by Cray Research, which is a company founded by Seymour Cray with business headquarters in Minneapolis. Another mainframe computer giant, Honeywell, had its headquarters in Minnesota, too.

However, after the anchor companies had been acquired and relocated into other states such as California, Minnesota lost its reputation as a computer industry cluster. Moreover, local computer industry activities and resources shift their attention to the local medical device industry.

4.2.2. Resource flows

4.2.2.1. Financial resources

In late 1959, Medtronic prepared an offering of 5 percent debentures, which investors could convert into common stock at $1.50 per share by 1960. Selling these debentures was critical for Medtronic because the company needed high levels of financial investment. Even though it had been two years since the company made its first success in product innovation (i.e., the first portable cardio pacemaker), company size was still small in terms of sales as well as assets. Typically, low levels of sales and assets rarely attract many investors. However, Medtronic sold all debentures the company wanted to sell to local inventors, and the following conversion led to the IPO of the company.

According to Hall (2014), former Medtronic president Thomas Holloran attributed Medtronic's success of selling the offering to positive spillover effects from the local computer industry, especially, Control Data:

> "Today, Holloran says Medtronic could not have succeeded in its offering without the unusually receptive market created by the early success of Control Data. It took a leap of faith to believe the company could eventually become a financial success."

In other words, local inventors looked Medtronic favorably as they regarded Medtronic as another Control Data, which had brought lots of fortune to the inventors. Because of the local inventors' favorable attitude, Medtronic was able to achieve the goal.

In addition, local medical device companies during the 1970s and 1980s also benefited from the local computer industry. Until the 1960s, the majority of venture capital firms and angel investors in the Minneapolis-St. Paul region invested mainly in the local computer industry. However, during the 1970s and 1980s (i.e., a period of sustained growth of the local medical device industry), they shifted their attention to medical devices, resulting in a huge influx of financial resources into the local medical device industry (Smith, 2015).

4.2.2.2. Employees

During a period of sustained growth in the local medical device industry, many employees of local computer companies also moved to the local medical device companies. The occupations of those employees include general managerial jobs as well as engineers.

For example, Ron Stuedemann, who is a chair at the Medtronic VSP Retiree Group Minnesota, worked in the finance department at Medtronic, creating an accounting system for efficient R&D investment. Before joining Medtronic, he worked at the finance department of Honeywell (also in Minnesota). The reason for his leaving Honeywell to

Medtronic, which Ron shared during my interview with him, was learning about an opportunity by chance and seeing the growth of the medical device industry. When he was purchasing a house, Ron learned about an opportunity to work at Medtronic from the previous owner of the house, who was a Medtronic employee. Although Medtronic was much smaller and less established than Honeywell, Ron valued the growth of the medical device industry as well as Medtronic, leading him to change industries and employers.

The anecdotes discussed in Chapter 3 also demonstrates the flows of employees—in particular, engineers—from the computer to medical device industry: Medtronic founder Earl Bakken's knocking on the door of Control Data to hire local computer engineers, and CPI founder Manny Villafana's hiring local computer engineers to seek open-minded engineers.

4.2.2.3. Relevant organizations

Along with the emergence of a computer industry hub in Minnesota, there were many small and medium-sized organizations that supported the local computer firms, such as high precision machining shops, design firms, and engineering firms. During a period of sustained growth of the local medical device industry, many of them made a transition to serving the local medical industry.

For example, Metalcraft Machine and Engineering was a small local machining shop established in 1978. The company was equipped with the precision machining of aluminum heat sinks and heat exchangers and previously served the local computer companies. However, during the sustained growth of the medical device industry, it became a specialist manufacturer of medical devices. Specifically, their facilities for gun drilling, wire-cut electrical discharge machining, and computer numerical-controlled grinding and machining met the ISO and FDA standards of medical devices, so the company was able to make a smooth transition to medical devices (Misa, 2013).

4.3. The Effects of the Resource Inflows on the Local Medical Device Companies

The influx of local computer industry resources—especially, employees and suppliers—brought knowledge and skills that they had previously accumulated in the computer industry, which were likely to be new or unfamiliar to the medical device companies. Such an influx of new knowledge and skills contributed to the local medical device companies' technological innovation.

For example, as discussed in Chapter 3, CPI's success in inventing the first lithium battery pacemaker was possible because of Manny Villafana's hiring of computer engineers. Specifically, those engineers had perception and knowledge that were different from the medical device engineers, who turned down the idea of using lithium batteries as they did not believe the feasibility of the idea. The former computer engineers' different perception and knowledge contributed to the breakthrough innovation.

Relevant organizations, including suppliers, also facilitated innovation by the medical device companies. Their skills they transferred from computers to medical devices helped the medical device companies develop new and improved components. Thomas Misa, who was a Professor at the History of Science, Technology, and Medicine at the University of Minnesota and studied the history of the high technology industries—mainly, the computer industry, said:

> "…there were skills these companies had developed doing micro-fabrication for computing, or high-precision machining, or advanced prototyping that were useful in the rising medical-device industry. Some

of this might be patented, or otherwise formally disclosed. But, I'd bet that much of the important transfer would, instead of patents, fall into the realm of informal connections, tacit knowledge, workforce competence/experience."

These examples and anecdotes demonstrate that during a period of growth in the medical device industry in the Minneapolis-St. Paul region, a variety of resources were flowing from outside the local medical device industry boundary, mainly the local computer device industry. Moreover, these inflows of resources brought new knowledge and skills, which led to innovation in medical devices.

Chapter 5: Discussion

The purpose of this dissertation is to understand the temporal dynamics of industry clusters and the effects of these dynamics on firm innovation. For this purpose, I propose an empirical technique that systematically measures cluster dynamics, which allows for the documentation of cluster dynamics phenomenon and empirical analysis. Applying the measure to the U.S. medical device industry data, I examine the relationships between cluster dynamics and firm innovation. The focus of the hypotheses and empirical tests is to show that firms in clusters experiencing a period of sustained growth are likely to generate disruptive innovation and that the mechanism behind the relationship is the inflows of employees from outside clusters. The results consistently support this theory. In addition, to provide further evidence, I qualitatively unpack the phenomenon of the temporal dynamics using a case study of the medical device industry in the Minneapolis-St. Paul region.

In this chapter, I draw out implications for literature and practitioners beyond the immediate conclusions that I report in the previous chapters.

Implications for the Literature on Clusters and Firm Outcomes

The findings of this dissertation raise an important implication for the literature on the relationships between clusters (or agglomeration economies) and firm outcomes. Specifically, the documentation of the fact that clusters are best viewed as dynamic entities implies that an inherent assumption about the temporal dynamics typically made in the literature might lead to an incomplete understanding of the cluster-firm relationships. Specifically, I document that many clusters experience more than one concentration trend and that patterns of cluster change vary not only across regions but also across industries within the same region. Although researchers are generally aware of the fact that clusters change over time, they underestimate the extent of these dynamics.

For example, existing studies using a single industry context rarely considers the temporal trend of each region while accounting for cross-sectional variance across regions. This suggests that researchers inherently assume that the extent of dynamics is not large enough to be accounted for, or each region's pattern of changes is consistent with the industry-wide trend. Similarly, studies using a single region context also rarely account for the temporal trend of each local industry while accounting for cross-sectional variance across the industries. This also shows the inherent assumption that the degree of dynamics is not large, or each local industry's temporal trend is consistent with the region-wide trend. However, considering this dissertation's finding that clusters are largely dynamic, this assumption about the temporal dynamics overlooks the important variance that exists in the real world.

Implications for the Literature on Clusters and Firm Innovation

The findings of this dissertation also have a significant implication for the literature on the relationships between industry clusters and innovation (or knowledge spillovers). I suggest and find that the underlying mechanism behind the relationship between cluster dynamics and firm innovation is employee mobility across cluster boundaries (i.e., different geographies or industries). Yet, the literature emphasizes employee mobility within a cluster boundary while paying little attention to employee mobility across cluster boundaries. Researchers suggest that employees in large-sized clusters are likely to change their employers more frequently as large clusters provide more opportunities compared to those in regions with a small number of firms. Additionally, researchers highlight that such high levels of within-cluster mobility result in high levels of knowledge spillovers and facilitates innovation. Yet, the knowledge and ideas shared via within-cluster mobility are more homogeneous, compared to those shared through the influx of employees from different industries or regions. This means that knowledge from cross-cluster mobility might contribute to innovation more than knowledge from within-cluster mobility. Therefore, existing studies' explanation about the role of clusters in facilitating innovation without consideration of cross-cluster employee mobility might omit an important factor that actually contributed to innovation. This may be a reason why existing literature finds conflicting evidence on whether a larger cluster presents higher levels of firm innovativeness.

Implications for the Broader Strategy Literature

In this dissertation, I propose an empirical technique that systematically identifies and quantifies cluster temporal dynamics. This measure allows researchers to check the dynamics of their own research contexts and apply the concept of cluster dynamics to empirical models, which can be a benefit to studies that control for regional effects or local industry effects as well as studies examining clusters as a main explanatory variable. Moreover, this measure can also be applied to a variety of concepts other than industry clusters, such as firm performance or network centrality. This allows for an understanding of the temporal dynamics of many important concepts in strategy research.

Implications for Practice

As the environment changes more rapidly and frequently than before, industries also become more dynamic. Additionally, climate changes lead to changes in regions, which may lead some clusters to fall apart or become more concentrated. For example, Smith et al. (2016) find that global warming could make many cities around the world too hot to host the Summer Olympic Games in the coming decades. Business establishments in such cities could be affected in that firms in those cities might be forced to relocate into other cities, resulting in a trend of shrinking concentration, and remaining firms will lose the sources of external knowledge. Given that firms will be more likely to experience such changes in their clusters than before, firm managers need to understand the temporal dynamics of industry clusters—in particular, how cluster dynamics affect firm outcomes. Within this context, this dissertation can be groundwork that facilitates more studies on cluster dynamics, and this will allow firm managers to understand cluster dynamics and help them build strategies for how to react to changes in clusters.

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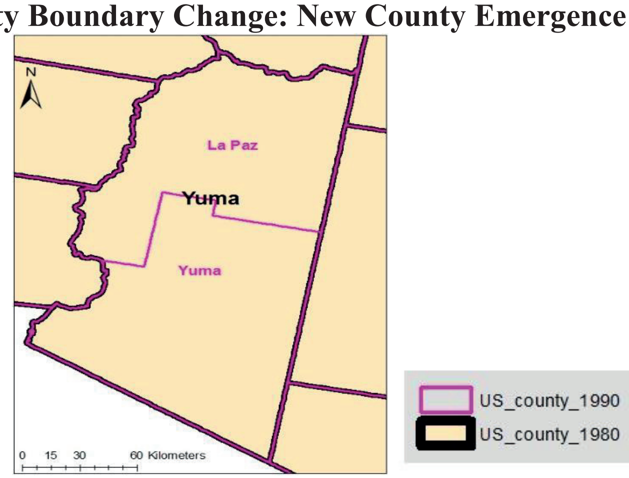
Appendix A. Changes in the Boundaries of Geographic Units

The issue of county boundary changes needs to be addressed before the crosswalk because there have been changes in county boundaries, and each MSA is an aggregate of multiple counties. The U.S. Census Bureau provides a list of substantial boundary changes by decade. According to the U.S. Census Bureau, substantial county changes refer to *"all county boundary changes affecting an estimated population of 200 or more people, changes of at least one square mile where no estimated population was provided, and research indicated that the affected population might have been 200 people or more, or 'large' annexations of unpopulated territory (10 square miles or more)*"[17]. I looked carefully at each change by comparing county boundary maps across time. There are four types of changes. The first type is where a new county was created out of one or more counties and the second type is where a county was merged with another county. The third type is where a county boundary changed, and the fourth type is where a county had a name and code change. For the first three types of changes, I merged all influenced neighboring counties into a single county.

Figure A1 shows an example of the first type. In 1983, part of Yuma county (FIPS code: 04-027) in Arizona was taken to create a new county, La Paz (FIPS code: 04-012). I merged two counties into one county by coding both counties as 04-027. Because around half of the county was detached, Yuma county's economic activity size including the number of establishments dropped in 1983. Even though the decrease is not driven by firms' leaving or closing, it is possible to identify the decrease as de-agglomeration if Yuma county is a part of the cluster. Also, Yuma county is in an MSA (CBSA code: 49749) while La Paz is not part of any MSA. Thus, the same problem may also occur when utilizing MSA level data. Through the merges, I have made changes for 41 counties, resulting in changes in 20 MSAs.

FIGURE A1. **County Boundary Change: New County Emergence**



After dealing with county boundary changes, I mapped counties to the MSAs defined in 2013. Which counties constitute a particular MSA may vary across years, so I use the MSA definition of the specific year (i.e., 2013).

[17] For more information, see https://www.census.gov/geo/reference/county-changes.html

Appendix B. Robustness Checks

B1. DV: Disruptive innovation (H1)

	Top 20 MSAs				Top 30 MSAs							
	DV at t+5				DV at t+3				DV at t+5			
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Concentration trends	0.004***	0.004***	0.004***	0.002*	0.005***	0.005**	0.005***	0.004***	0.003***	0.003***	0.003***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Cluster size		-0.000***	-0.000*	-0.001*		-0.000**	-0.000	-0.001		-0.000**	-0.000	-0.001*
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Population			0.000	-0.001**			0.000*	-0.001**			0.000*	-0.001**
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Total med device inventors			-0.000	0.000			-0.000**	-0.000			-0.000*	0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Length of trend			-0.003***	-0.004***			-0.004***	-0.005***			-0.003***	-0.004***
			(0.001)	(0.001)			(0.001)	(0.001)			(0.001)	(0.001)
MSA-FE				*Included*				*Included*				*Included*
Constant	0.048***	0.071***	0.105***		0.065***	0.079***	0.121***		0.046***	0.058***	0.090***	
	(0.007)	(0.009)	(0.017)		(0.008)	(0.012)	(0.024)		(0.006)	(0.008)	(0.016)	
Observations	65	65	65	65	93	93	93	93	89	89	89	89
R-squared	0.125	0.197	0.277	0.365	0.087	0.113	0.262	0.377	0.079	0.111	0.246	0.355

Robust standard errors in parentheses; clustered by MSAs
*** $p<0.01$, ** $p<0.05$, * $p<0.10$

B2. DV: Different geography dependence (H2a)

	Top 20 MSAs				Top 30 MSAs							
	DV at t+5				DV at t+3				DV at t+5			
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Concentration trends	0.048	0.050	0.049	0.050	0.069	0.080*	0.080*	0.063	0.080	0.045	0.057	0.038
	(0.060)	(0.051)	(0.062)	(0.087)	(0.049)	(0.040)	(0.040)	(0.049)	(0.069)	(0.055)	(0.046)	(0.052)
Cluster size		-0.034**	-0.008	0.002		-0.033***	-0.033***	-0.013**	0.002		-0.034***	-0.014**
		(0.013)	(0.005)	(0.013)		(0.011)	(0.011)	(0.005)	(0.011)		(0.012)	(0.006)
Population			-0.003	-0.004				-0.003*	-0.009			-0.003*
			(0.002)	(0.007)				(0.001)	(0.006)			(0.002)
Total med device inventors			-0.016***	-0.016***				-0.015***	-0.016***			-0.015***
			(0.004)	(0.005)				(0.003)	(0.004)			(0.003)
Length of trend			-0.054	-0.043				-0.007	-0.010			-0.009
			(0.034)	(0.056)				(0.031)	(0.044)			(0.031)
MSA-FE				*Included*				*Included*				*Included*
Constant	94.797***	96.897***	97.851***		95.650***	97.246***	97.246***		95.399***	97.021***	98.004***	
	(0.698)	(0.742)	(0.916)		(0.518)	(0.479)	(0.479)		(0.548)	(0.508)	(0.751)	
Observations	68	68	68	68	93	93	93	93	93	93	93	93
R-squared	0.007	0.218	0.545	0.448	0.014	0.252	0.252	0.563	0.500	0.006	0.237	0.542

Robust standard errors in parentheses; clustered by MSAs
*** p<0.01, ** p<0.05, * p<0.10

B3. DV: Different industry dependence (H2b)

	Top 20 MSAs				Top 30 MSAs							
	DV at t+5				DV at t+3				DV at t+5			
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Concentration trends	0.800***	0.804***	0.766***	0.576**	0.646**	0.677**	0.687***	0.449*	0.541*	0.567*	0.576***	0.430**
	(0.168)	(0.176)	(0.188)	(0.210)	(0.290)	(0.304)	(0.208)	(0.224)	(0.270)	(0.286)	(0.188)	(0.206)
Cluster size		-0.092**	-0.021	-0.080		-0.090***	-0.024	-0.106		-0.077**	-0.019	-0.081
		(0.038)	(0.055)	(0.099)		(0.030)	(0.038)	(0.092)		(0.028)	(0.035)	(0.081)
Population			0.010	-0.115			0.023**	-0.183**			0.020*	-0.144*
			(0.007)	(0.075)			(0.010)	(0.088)			(0.010)	(0.071)
Total med device inventors			-0.047**	-0.025			-0.062***	-0.032			-0.054***	-0.029
			(0.020)	(0.039)			(0.020)	(0.041)			(0.018)	(0.036)
Length of trend			-0.486*	-0.554**			-0.602***	-0.577**			-0.504**	-0.501**
			(0.235)	(0.211)			(0.211)	(0.226)			(0.184)	(0.193)
MSA-FE				*Included*				*Included*				*Included*
Constant	94.797***	96.897***	97.851***		38.901***	45.583***	50.441***		35.834***	41.548***	45.522***	
	(0.698)	(0.742)	(0.916)		(2.246)	(4.020)	(6.972)		(2.198)	(3.915)	(6.584)	
Observations	68	68	68	68	93	93	93	93	93	93	93	93
R-squared	0.099	0.178	0.299	0.452	0.041	0.098	0.262	0.458	0.038	0.093	0.253	0.447

Robust standard errors in parentheses; clustered by MSAs
*** p<0.01, ** p<0.05, * p<0.10

B4. DV: Disruptive innovation (H3a)

	Top 20 MSAs				Top 30 MSAs							
	DV at t+5				DV at t+3				DV at t+5			
	Entrepreneurial		Established		Entrepreneurial		Established		Entrepreneurial		Established	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Concentration trends	0.004***	0.003*	0.004	0.003	0.004***	0.003*	0.004	0.002	0.004***	0.003*	0.004	0.002
	(0.001)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)
Cluster size	-0.001	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Population	0.000	-0.000	0.000	-0.000	0.000	-0.001**	0.000	-0.001	0.000	-0.001**	0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total med device inventors	-0.000	0.000	-0.000	-0.000	-0.000	0.000	-0.000*	0.000	-0.000	0.000	-0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Length of trend	-0.005***	-0.008***	-0.004***	-0.008**	-0.004***	-0.006***	-0.003**	-0.006**	-0.004***	-0.006***	-0.003**	-0.006**
	(0.002)	(0.002)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)
MSA-FE		*Included*		*Included*		*Included*		*Included*		*Included*		*Included*
Constant	0.178***		0.134**		0.126***		0.105***		0.126***		0.105***	
	(0.050)		(0.049)		(0.035)		(0.033)		(0.035)		(0.033)	
Observations	59	59	59	59	89	89	87	87	89	89	87	87
R-squared	0.238	0.318	0.198	0.385	0.177	0.303	0.162	0.317	0.177	0.303	0.162	0.317

Robust standard errors in parentheses; clustered by MSAs
*** p<0.01, ** p<0.05, * p<0.10

B5. DV: Different geography dependence (H3b)

	Top 20 MSAs				Top 30 MSAs							
	DV at t+5				DV at t+3				DV at t+5			
	Entrepreneurial		Established		Entrepreneurial		Established		Entrepreneurial		Established	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Concentration trends	0.063 (0.039)	0.085 (0.053)	-0.102 (0.117)	-0.136 (0.111)	0.055 (0.036)	0.082 (0.050)	-0.107 (0.104)	-0.129 (0.106)	0.055 (0.036)	0.082 (0.050)	-0.107 (0.104)	-0.129 (0.106)
Cluster size	-0.007 (0.006)	-0.001 (0.009)	-0.023** (0.008)	-0.012 (0.013)	-0.008* (0.004)	-0.000 (0.008)	-0.024*** (0.008)	-0.011 (0.008)	-0.008* (0.004)	-0.000 (0.008)	-0.024*** (0.008)	-0.011 (0.008)
Population	-0.002 (0.001)	-0.001 (0.010)	-0.006*** (0.002)	-0.004 (0.011)	-0.002* (0.001)	-0.008 (0.009)	-0.005*** (0.001)	-0.004 (0.007)	-0.002* (0.001)	-0.008 (0.009)	-0.005*** (0.001)	-0.004 (0.007)
Total med device inventors	-0.017*** (0.005)	-0.013** (0.005)	-0.009* (0.005)	-0.009 (0.006)	-0.018*** (0.005)	-0.013** (0.005)	-0.009* (0.005)	-0.009* (0.005)	-0.018*** (0.005)	-0.013** (0.005)	-0.009* (0.005)	-0.009* (0.005)
Length of trend	0.022 (0.042)	-0.020 (0.054)	0.038 (0.052)	-0.011 (0.071)	-0.005 (0.031)	-0.033 (0.040)	0.014 (0.037)	-0.021 (0.047)	-0.005 (0.031)	-0.033 (0.040)	0.014 (0.037)	-0.021 (0.047)
MSA-FE		*Included*		*Included*		*Included*		*Included*		*Included*		*Included*
Constant	97.894*** (0.969)		98.362*** (1.196)		98.488*** (0.589)		98.766*** (0.762)		98.488*** (0.589)		98.766*** (0.762)	
Observations	60	60	59	59	91	91	88	88	91	91	88	88
R-squared	0.630	0.435	0.566	0.368	0.636	0.403	0.626	0.358	0.636	0.403	0.626	0.358

Robust standard errors in parentheses; clustered by MSAs
*** p<0.01, ** p<0.05, * p<0.10

B6. DV: Different industry dependence (H3c)

	Top 20 MSAs				Top 30 MSAs							
	DV at t+5				DV at t+3				DV at t+5			
	Entrepreneurial		Established		Entrepreneurial		Established		Entrepreneurial		Established	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Concentration trends	0.748*** (0.160)	0.810*** (0.222)	0.340 (0.341)	0.102 (0.285)	0.762*** (0.162)	0.545** (0.265)	0.397 (0.349)	-0.057 (0.194)	0.762*** (0.162)	0.545** (0.265)	0.397 (0.349)	-0.057 (0.194)
Cluster size	-0.085 (0.062)	-0.086 (0.141)	-0.102* (0.050)	-0.092 (0.118)	-0.025 (0.047)	-0.127 (0.096)	-0.061 (0.054)	-0.132 (0.094)	-0.025 (0.047)	-0.127 (0.096)	-0.061 (0.054)	-0.132 (0.094)
Population	0.006 (0.007)	-0.098 (0.078)	0.007 (0.007)	-0.082 (0.087)	0.006 (0.005)	-0.205*** (0.059)	0.002 (0.007)	-0.148** (0.064)	0.006 (0.005)	-0.205*** (0.059)	0.002 (0.007)	-0.148** (0.064)
Total med device inventors	-0.033 (0.021)	-0.015 (0.046)	-0.014 (0.018)	-0.014 (0.042)	-0.043** (0.019)	0.005 (0.033)	-0.019 (0.017)	-0.003 (0.034)	-0.043** (0.019)	0.005 (0.033)	-0.019 (0.017)	-0.003 (0.034)
Length of trend	-0.775*** (0.187)	-0.931*** (0.254)	-0.616*** (0.193)	-0.827** (0.338)	-0.657*** (0.191)	-0.888*** (0.235)	-0.356 (0.258)	-0.595** (0.277)	-0.657*** (0.191)	-0.888*** (0.235)	-0.356 (0.258)	-0.595** (0.277)
MSA-FE		*Included*		*Included*		*Included*		*Included*		*Included*		*Included*
Constant	59.879*** (5.938)		54.695*** (5.902)		51.711*** (4.783)		47.050*** (8.071)		51.711*** (4.783)		47.050*** (8.071)	
Observations	60	60	59	59	91	91	88	88	91	91	88	88
R-squared	0.414	0.525	0.269	0.372	0.239	0.443	0.114	0.305	0.239	0.443	0.114	0.305

Robust standard errors in parentheses; clustered by MSAs
*** p<0.01, ** p<0.05, * p<0.10

B7. DV: Innovation volume

Variables	Top 20 MSAs DV at t+5 (1)	(2)	(3)	(4)	Top 30 MSAs DV at t+3 (5)	(6)	(7)	(8)	Top 30 MSAs DV at t+5 (9)	(10)	(11)	(12)
Concentration trends	0.077	0.027	-0.022	0.318	-0.249	-0.632	-0.162	-0.052	0.004	-0.385	0.117	0.129
	(1.547)	(1.782)	(0.588)	(0.657)	(1.150)	(1.202)	(0.311)	(0.451)	(1.424)	(1.419)	(0.575)	(0.558)
Cluster size		1.328**	0.075	0.173		1.118**	0.074	0.038		1.137**	0.121	0.153
		(0.594)	(0.108)	(0.176)		(0.504)	(0.069)	(0.103)		(0.518)	(0.087)	(0.136)
Population			0.036*	0.245**			0.004	0.094			0.019	0.123
			(0.019)	(0.110)			(0.020)	(0.112)			(0.025)	(0.139)
Total med device inventors			0.799***	0.653***			0.825***	0.766***			0.800***	0.681***
			(0.063)	(0.060)			(0.055)	(0.051)			(0.051)	(0.048)
Length of trend			0.015	0.855			-0.246	-0.079			-0.161	0.583
			(0.734)	(0.783)			(0.299)	(0.353)			(0.456)	(0.679)
MSA-FE				*Included*				*Included*				*Included*
Constant	88.783***	6.409	8.207		74.396***	21.054	8.434		78.691***	24.433	8.463	
	(21.405)	(26.142)	(12.633)		(15.575)	(18.252)	(7.671)		(16.356)	(19.011)	(9.088)	
Observations	68	68	68	68	93	93	93	93	93	93	93	93
R-squared	0.000	0.331	0.924	0.901	0.000	0.287	0.958	0.948	0.000	0.288	0.924	0.896

Robust standard errors in parentheses; clustered by MSAs
*** p<0.01, ** p<0.05, * p<0.10

B8. The OLS regression models of the nature of innovation, having the competition effects controlled

(a) Top 20 MSAs

	DV: *Different geography citation*				DV: *Different industry citation*				DV: *Disruptive innovation*			
	t+3		t+5		t+3		t+5		t+3		t+5	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Concentration trends	0.080	0.091	0.050	0.047	0.930***	0.577**	0.788***	0.528**	0.006***	0.004***	0.004***	0.002**
	(0.061)	(0.085)	(0.063)	(0.090)	(0.289)	(0.265)	(0.213)	(0.207)	(0.001)	(0.001)	(0.001)	(0.001)
Cluster mass	-0.005	0.007	-0.007	0.003	-0.003	-0.091	-0.003	-0.072	-0.000	-0.001	-0.000	-0.001
	(0.005)	(0.013)	(0.006)	(0.012)	(0.056)	(0.118)	(0.052)	(0.104)	(0.000)	(0.001)	(0.000)	(0.000)
Population	-0.002	-0.002	-0.003	-0.003	0.023**	-0.121	0.018**	-0.097	0.000***	-0.001*	0.000**	-0.000**
	(0.002)	(0.008)	(0.002)	(0.006)	(0.010)	(0.073)	(0.008)	(0.062)	(0.000)	(0.000)	(0.000)	(0.000)
Total med-tech inventors	-0.016***	-0.018***	-0.016***	-0.016***	-0.049**	-0.028	-0.043**	-0.025	-0.000	0.000	-0.000	0.000
	(0.004)	(0.005)	(0.004)	(0.005)	(0.021)	(0.043)	(0.019)	(0.038)	(0.000)	(0.000)	(0.000)	(0.000)
Length of trend	-0.040	-0.013	-0.053	-0.035	-0.568*	-0.512**	-0.456*	-0.432*	-0.004***	-0.003***	-0.003***	-0.003**
	(0.033)	(0.052)	(0.033)	(0.055)	(0.285)	(0.244)	(0.251)	(0.211)	(0.001)	(0.001)	(0.001)	(0.001)
Competition	-1.847	-3.662	-1.130	-3.675	-34.817	-65.999**	-28.680	-53.003**	-0.223*	-0.457***	-0.161**	-0.336***
	(2.799)	(3.425)	(3.092)	(3.711)	(25.351)	(28.666)	(22.510)	(24.133)	(0.113)	(0.156)	(0.077)	(0.108)
MSA-FE		*Included*		*Included*		*Included*		*Included*		*Included*		*Included*
Constant	99.049***		98.596***		73.391***		64.426***		0.286**		0.211***	
	(2.342)		(2.511)		(20.517)		(18.633)		(0.100)		(0.066)	
Observations	68	68	68	68	68	68	68	68	68	68	65	65
R-squared	0.576	0.522	0.547	0.464	0.366	0.580	0.347	0.557	0.389	0.583	0.362	0.567
Number of MSAs		20		20		20		20		20		20

Robust standard errors in parentheses; clustered by MSAs
*** p<0.01, ** p<0.05, * p<0.10

(b) Top 30 MSAs

Variables	DV: *Different geography citation*				DV: *Different industry citation*				DV: *Disruptive innovation*			
	t+3		t+5		t+3		t+5		t+3		t+5	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Concentration trends	0.064	0.076	0.039	0.044	0.701***	0.379	0.587***	0.374*	0.374*	0.005***	0.003**	0.003***
	(0.050)	(0.072)	(0.054)	(0.079)	(0.224)	(0.231)	(0.191)	(0.203)	(0.203)	(0.001)	(0.001)	(0.001)
Cluster mass	-0.012**	0.002	-0.014**	-0.001	-0.009	-0.101	-0.006	-0.077	-0.077	0.000	-0.001	-0.000
	(0.006)	(0.010)	(0.006)	(0.010)	(0.038)	(0.095)	(0.035)	(0.084)	(0.084)	(0.000)	(0.000)	(0.000)
Population	-0.002	-0.007	-0.003	-0.005	0.032**	-0.158**	0.027**	-0.124**	-0.124**	0.000**	-0.001**	0.000**
	(0.002)	(0.006)	(0.002)	(0.006)	(0.013)	(0.072)	(0.012)	(0.060)	(0.060)	(0.000)	(0.000)	(0.000)
Total med-tech inventors	-0.015***	-0.016***	-0.015***	-0.015***	-0.055***	-0.031	-0.048***	-0.028	-0.028	-0.000**	0.000	-0.000*
	(0.003)	(0.004)	(0.003)	(0.004)	(0.019)	(0.039)	(0.017)	(0.034)	(0.034)	(0.000)	(0.000)	(0.000)
Length of trend	-0.005	-0.001	-0.008	-0.019	-0.586**	-0.431*	-0.490**	-0.383*	-0.383*	-0.004***	-0.004***	-0.003***
	(0.031)	(0.042)	(0.031)	(0.045)	(0.223)	(0.227)	(0.192)	(0.194)	(0.194)	(0.001)	(0.001)	(0.001)
Competition	-2.090	-3.610	-1.636	-3.566	-30.104	-62.275**	-26.329	-50.108**	-50.108**	-0.201**	-0.449***	-0.152**
	(2.317)	(3.096)	(2.521)	(3.422)	(20.295)	(26.330)	(18.044)	(22.194)	(22.194)	(0.091)	(0.144)	(0.059)
MSA-FE		*Included*		*Included*		*Included*		*Included*		*Included*		*Included*
Constant	99.488***		99.094***		69.357***		62.169***		109.891***		0.593***	
	(1.857)		(1.996)		(16.330)		(14.743)		(17.799)		(0.119)	
Observations	93	93	93	93	93	93	93	93	93	93	93	89
R-squared	0.569	0.515	0.545	0.459	0.301	0.546	0.292	0.526	0.526	0.333	0.554	0.330
Number of MSAs		30		30		30		30	30		30	

Robust standard errors in parentheses; clustered by MSAs
*** p<0.01, ** p<0.05, * p<0.10