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An Evolutionary Theory of Regional Economic Growth and Change

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An Evolutionary Theory of Regional Economic Growth and Change

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by

Christopher Ross Esposito

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ABSTRACT OF THE THESIS

An Evolutionary Theory of Regional Economic Growth and Change

by

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Masters of Arts in Geography
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Professor David L. Rigby, Chair

This article develops a theoretical model of regional economic growth and change. It does so by first identifying how the spatial economy creates, selects, and retains knowledge variety through an examination of patent records and relevant literatures. The article then synthesizes these findings to create a theoretical model and formalizes the theoretical model into a computer simulation. The resulting simulation model is highly predictive and adaptable, as we demonstrate by applying the model to test a core hypothesis from the economic geography literature. Since Saxenian's (1994) comparison of the circumscribed technology firms of Boston to the relatively open and porous technology firms of Silicon Valley, the innovativeness of regional economies is broadly understood to be rooted in their propensity to create knowledge spillovers. The simulation model isolates the mechanism of knowledge spillovers to explore its relationship with regional dynamism. The results show that knowledge variety and innovation are maximized in regions with firms that allow most, but not all, of their knowledge to spill over to neighboring firms. The results give scientific clarity to how localized knowledge spillovers can both enhance and diminish regional innovative growth, and underscore the practical utility of formalized evolutionary modeling.

The thesis of Christopher Ross Esposito is approved.

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1. Introduction

Why do regional economies grow and change? Scholars from a broad range of disciplines have sought to unpack the causes. Despite differences in their assumptions, theory, and methods, a growing consensus now argues that that the leading way for regions to upgrade their economies is by upgrading the technologies that their firms use in production (Nelson and Winter 1982, Romer 1987, Martin and Sunley 2006).

It is precisely for this reason that economic geographers have sought to understand how regions change their technological structures. These efforts have given rise to the sub-discipline of Evolutionary Economic Geography (EEG), which loosely adopts the Darwinian concepts of variation, selection, and retention to explain regional dynamics (Boschma and Frenken 2006, Boschma and Frenken 2011, Essletzbichler and Rigby 2007, Martin and Sunley 2006, Martin and Sunley 2014).

Although promising, EEG does not yet have the tools it needs to explain regional economic growth. This is because EEG is theoretically incomplete. While recent empirical studies have gone a long way toward showing how regional economies retain their existing technological capabilities through cognitively-proximate search, we know much less about how regional economies create and select various technologies (Martin and Sunley 2006, Hidalgo et al. 2007, Essletzbichler and Rigby 2010, Rigby 2014, Heimericks and Boschma 2014, Boschma et al. 2014, Boschma et al 2015, Frenken and Mas Tur 2016). In evolutionary economics, the creation of variety is necessary for organisms to mutate and seed the opportunities for change. Likewise, the selection of variety is then needed to realize these mutations and changes (Nelson and Winter 1982, Rigby and Essletzbichler 1997, Jonard and Yidizoglu 1998). EEG therefore needs to explain how regions create and select variety in order to show how their economies are able to evolve and grow over time.

This article forms a cohesive evolutionary theory of regional economic growth and change by: 1) showing how regional economies create and select variety, and 2) exploring how selection, variety, and retention cause regional economies to grow. The article addresses the first objective by reviewing relevant literatures in geography and management science and by systematically analyzing patent records from the United States and France. A computer simulation model is developed to address the second objective.

The simulation model captures the mechanisms that create, select, and retain knowledge variety in firms and regions and shines light on many of the core questions in the economic geography literatures. We demonstrate the model's utility by applying it to the classic but unresolved hypothesis in the regional development literature of whether the growth of regional economies is linked to their propensity to connect workers and ideas across the boundaries of firms (Saxenian 1994). Our findings add nuance to this theory, as we find that that firm openness has an inverted U-shaped relationship with the innovativeness of regions. Increased firm openness only increases regional innovativeness up to a certain point.

This paper is organized in reverse-order, with empirics near the beginning and theoretical discussion and the development of the simulation model toward the end. Section 2 discusses the current strengths and limitations of EEG theory. Sections 3-5 review related literatures, investigate patent data, and synthesize the findings in order to develop an understanding of how regions create and select technologies. Section 7 discusses how innovation occurs in the economy and how innovation affects market prices. Section 8 adds additional notes on the role that geography plays in innovation. Sections 9-13 outline the simulation model, and sections 13-15 discuss the model's results. Section 16 concludes.

2. Evolutionary Economic Geography and Regional Path Dependence

The effect of distance in clustering certain economic activities while spreading out others serves as the cornerstone of economic geography theory. While some economic activities can be done across distance, especially the transportation of finished goods and services, many intermediate and input goods experience much greater friction from space. Knowledge, particularly its subsets that are complex and tacit, has extraordinary difficulty in flowing between geographic regions (Polanyi 1966, Jaffe et al. 1993, Storper and Venables 2002, Sorenson et al. 2006). Because complex and tacit knowledge are the instruction manuals that economic actors need to perform economic activities (Nelson and Winter 1982, Maskell and Malmberg 1999, Gertler 2002, Balland and Rigby 2016), the communication costs associated with sharing these instructions across distance effectively puts regional economies on metaphorical islands (Essletzbichler and Rigby 2007). With the exception of the occasional but costly knowledge pipeline (Bathelt et al. 2004), economic inputs are heavily localized while their outputs are heavily globalized. Therefore, regional economies are both independent and interdependent (Storper 1997). They are islands, separated by distance, but connected through the trade of their outputs.

Scale economies cause the relative cognitive isolation of regional economies to create dynamic outcomes. Indeed, few ideas have helped push economic geography theory further than the lock-in theories of economists Paul David and Brian Arthur. David (1985) and Arthur's (1989) theories of scale economies and the associated technological lock-in explain how and why old and sometimes inefficient technologies continue to be used long after they are invented. The aspect of these theories that geographers find so appealing is the notion of cumulative causation, in which small differences in an initial time period are reinforced and strengthened by increasing returns and network effects.

Across two leading sub-disciplines of economic geography, increasing returns and network effects are used to explain how and why regional economies retain their existing economic structures. In New Economic Geography, these scale economies take the form of increasing returns in the manufacturing sector; as once one region gains an advantage in manufacturing relative to other regions, scale effects cause a greater share of the manufacturing industry to agglomerate there (Krugman 1991). For Evolutionary Economic Geographers, increasing returns exist in the cognitive dimension through learning-by-doing (Arrow 1962). Inventors and firms invent or adopt new ideas that are similar to the ones they already know because local search is less costly and more certain than distant search (Martin and Sunley 2006, Boschma et al. 2005, Frenken and Mas Turk 2016). Therefore, regional capabilities in certain types of technologies are retained and strengthened over time and their evolution becomes path dependent.

While the path dependence understanding of regional economic change has taught us much about how regional economies retain their existing technological capabilities, progress has not moved very far in terms of explaining how regions generate new varieties of capabilities and how they select their most advantageous ones. To be sure, it is difficult to identify how regions create technological variety. Though an expansive regional branching literature has shown that regions create variety by developing new technological capabilities that are similar to the ones they already have (Hidalgo et al. 2007, Essletzbichler and Rigby 2010, Rigby 2014, Heimericks and Boschma 2014, Boschma et al. 2014, Boschma et al 2015, Frenken and Mas Tur 2016), it is doubtful that proximate technological entry creates enough variety to change the trajectory of regional economies. Moreover, the recent history of regional economic growth and decline in the United States is characterized by large ruptures, such as the falling apart of the rust belt and the rapid climb of the San Francisco Bay Area.

These transformations are hard to explain through the limited variety creation of proximate technological search.

EEG then needs to be able to explain not only how regions create proximate variety, but how they create the degree of variety necessary to shift their economies to new development paths. Unfortunately, regional path creation has proven to be a thorny issue to resolve. The processes that lead to the creation of new development paths are often thought to be random, fleeting, trivial, or aspatial (Massey 1992, Feldman 2005, Martin and Sunley 2006). Accordingly, economic geographic analysis usually relegates path creation to mere random events (Krugman 1991, Martin and Sunley 2006). Even management science, the discipline that pioneered the concept of path dependence in the social sciences, has difficulty in advancing a succinct theory of how path creation. As Arthur (1989, p. 118) wrote, the creation of new paths must lie somewhere in the bounded rationality, or discerning power, of inventors:

> Were we to have infinitely detailed prior knowledge of events and circumstances that might affect technology choices – political interests, the prior experience of developers, timing of contracts, and decisions at key meetings – the outcome or adoption market-share gained by each technology would presumably be determinable in advance. We can conclude that our limited discerning power, or more precisely the limited discerning power of an implicit observer [inventor], may cause indeterminacy of outcome. I therefore define 'historical small events' to be those events or conditions that are outside the ex-ante knowledge of the observer – beyond the resolving power of his 'model' or abstraction of the situation.

The ability to change the trajectory of a technology, industry, or regional economy by creating the sufficient variety for a new evolutionary path therefore rests deep in the bounded agency of inventors and entrepreneurs. While it has proven difficult enough to pinpoint this capability within inventors (Garud and Karnoe 2001, Garud et al. 2010, Frenken et al. 2012), it is another problem altogether to locate the differential access to this agency and its accompanying patterns of path creation within regions.

We acknowledge the difficulty of identifying how regions create the variety for new evolutionary paths. Perhaps the best direct explanation that geographers can give is that regions are always creating some degree of variety through the regular churning of their economies (Martin and Sunley 2006). Despite these difficulties in identification, EEG can generate a deeply informative understanding of how regions initiate new development paths by emphasizing the role of path selection. In order to initiate a given evolutionary path, a region must both create and select variety. Path creation may constantly occur in regions through forces that are trivial, random, aspatial, and hard to predict and study, but the selection and pursuit of particular paths follows clearly defined market and geographical forces. Moreover, path selection holds the key to understanding how regions realize new paths and variety.

Economic theory generates a persuasive hypothesis as to which development paths regions will select and pursue. When regions have many paths that they can choose to pursue but limited resources constrain the number of paths that they can pursue, regions will select paths largely on basis of the paths' immediate or near-term profitability. The primary agents behind innovations, including inventors and firms and their supporting financers and universities, face an incentive structure that is tied, directly or indirectly, to the market and profits. Therefore, microeconomic incentives and temporal myopia allocate resources toward the development path opportunities that offer sufficient economic returns. The predictability of path selection can then be leveraged to explore how regions begin to pursue particular development paths, thereby informing us on how regional economies are able to grow.

3. Exploration and Exploitation

As we hypothesize, path selection should follow clearly delimitated market forces. We believe that the management science literature on exploration and exploitation provides clues into how these market forces operate through myopic choice. The exploration and exploitation literature was initiated by March and Simon (1958) and exploded in activity following March's (1991) stylized models of explorative and exploitative firms with the intention to create a framework for understanding the creation and selection of variety in firms. To the extent that regional economies are collections of co-located firms, the exploration and exploitation literature creates a framework for us to understand regional growth and change.

March's (1991) mean-distribution model was fundamental in establishing the orientation of the exploration and exploitation literature and is illustrative of the literature's strengths and weaknesses toward our purposes. Generally, the exploration and exploitation literature is descriptively rich but lacking on mechanisms and dynamics. In his model, March imagines a world with two firms, Firm A and Firm B, where each firm performs several activities of varying profitability. Firm A's activities have a lower average profitability but a lot of variance; some of Firm A's activities are highly profitable, but most of its activities are not. Firm B's activities have a higher average profitability and less variance. Over time, both firms chose to perform the most profitable activities that they know how to do and discard their least-profitable ones. After several time periods, Firm B will have hardly increased its mean profitability. However, Firm A will have drastically increased its mean profitability and might even surpass Firm B because its large variance in profitable gives it great potential for growth. In essence, Firm A grew by selecting its most profitable activity and pursuing this activity's development trajectory. Exploration, as demonstrated by Firm A, is associated with greater variety, higher costs, higher risks, and higher potential rewards, while exploitation, as demonstrated by Firm B, is associated with less variety (or even a convergence to a best-practice), lower costs, few risks, and minimal potential rewards.

Stylistically, March's model describes two important components of exploration and exploitation. First, it describes the nature of these activities and their associated organizational forms. Secondly, it describes a likely outcome of these activities, as the exploiting firm has higher mean profitability but falls behind the exploring firm in the long-run. While these descriptions give us a clear account of how exploration and exploitation operate, they do not tell us why firms pursue these actions. March's model begs the follow-up question: why do firms sometimes choose to explore, and why do they sometimes choose to exploit? If the decision of a firm to exploit simultaneously causes it to embark along a development path, and if regional economies are composed of interacting firms, the answer to this firm-level question will also shine light on how regional economies select paths.

Unfortunately, the voluminous literature on exploration and exploitation that followed March (1991) has left this issue mostly unresolved, though we do owe to this literature a crystalized understanding of the nature of exploring and exploiting. These descriptive findings are relevant in that they help us think of regions and their selection of development paths in a static framework; the duty is left to us to connect this static firm-based framework to a dynamic, regionally-based application. Importantly though, the management science literature has shown that exploring firms have more variety: they are more decentralized, less hierarchical, and have higher rates of employee turnover. Firms with less process variety and a greater degree of cohesion are more exploitative (see Gupta et al. 2006 and Li et al. 2006 for reviews). Likewise, the *outputs* of exploration and exploitation are defined using the same taxonomy. Explorative outputs are generally identified by the degree of novelty that they introduce by shifting the trajectory of a technology, while exploitation creates outputs that are "improvements in existing components and architectures and build on the existing technological trajectory" (Benner and Tushman 2002, Jansen 2005).

These descriptive accounts of exploring and exploiting firms also appear, perhaps in more cogent form, in theoretical exercises. To explore how firm innovation is influenced by their pursuit of explorative and exploitative strategies, Rivkin and Siggelkow (2006) build on Kaufmann's NK model (Kaufmann 1993, Levinthal 1997) to develop a computer simulation in which firms navigate across a rugged fitness landscape by changing their organization, one component at a time. Siggelkow and Rivkin alter the traditional NK model by introducing randomly-placed "sticky points" on the fitness surface. When a firm stumbles onto one of these sticky points, the firm ceases to evolve and stays on the sticky point. Explorative and exploitative firms differ in the number of sticky points that they have in their fitness landscapes; exploitative firms have more sticky points and are therefore more likely to become stationary. Explorative firms, on the other hand, move across the surface tirelessly.

In our view, the tirelessly exploring firm resembles the region that experiments with many varieties of production strategies; the more static and exploitative firm resembles the region that has selected and is pursuing a development path. Although this model provides a clear descriptive understanding of the organization of explorative and exploitative firms and their resulting evolutionary outcomes, it does not answer the central question of why firms pursue strategies that give them more or fewer "sticky points" on their fitness landscapes. Moreover, it does not explain why firms choose to explore for more variety or exploit by selecting existing variety.

Management science proposed the concept of organizational ambidexterity to resolve some of these issues, but once again these additions will take us closer but not all the way toward understanding how regions select development paths. Observing that firms must both explore and exploit in order to remain dynamic in the long-run, the ambidexterity literature seeks to understand how firms can sustain both seemingly mutually-exclusive activities at the same time. Hypothesized mechanisms of ambidexterity include the creation of subdivisions within organizations (Benner and Tushman 2003), the formation of teams with varying objectives and incentive structures (Adler et al. 1999), the assignment of different roles and duties to individuals (Jansen et al. 2008), the balancing of the strategic input from the more risk-taking lower-level managers and the more conservative executives in a firm (Smith and Tushman 2005, c.f. Siggelkow and Rivkin 2006), and to great extent, the aptitude of the organization's influential players and executives in balancing the priorities of a large and complex firm (Teece 2007). While these strategies may seem divergent, they are connected by a common thread in that they advise firms to decentralize decision-making and incentives by spreading them across the groups, teams, employees, and priorities, thereby allowing the firm to generate and select variety simultaneously.

The ambidexterity literature takes the important step toward linking exploitation and exploration to the long-run success of firms by observing that long-run success is a balancing act of the two activities. It therefore develops a framework for thinking about explorative and explorative firms that relates to regional path selection; we know that exploitation causes firms to become more centralized, shed variety, and pursue development paths. We also know that the two activities largely compete for the scarce resources of the firm, so firms must choose how to allocate their resources between the two. Now we must show how firms choose to do this allocation; how, for example, an exploring firm chooses to switch the bulk of its resources from exploring to exploiting. Evidence toward this end is fragmented but can be coherently assembled from across a small handful of literatures.

Generally in empirical studies, firms are shown to engage in explorative search when their existing variety is not worth exploiting, such as when their profit margins are slim. On the other hand, firms engage in exploitative search when their existing variety is proftible. Exploration is more frequent in industries that are more competitive, and firms tend to explore more when the distance between their profit level and aspiration level increases (Peters 1992, Hamel 2000). From Lerner's analysis in the patent race literature, we know that increases in the storage density of disk drives were disproportionally created by less-profitable and less-advanced firms in the industry (Lerner 1993). Therefore, the exploitative firms were the ones that already had highly profitable technologies. This finding was confirmed more recently by Igami (2015). Indeed, Schumpeter's emphasis on the downturn of the business cycles as the primary stimulus to innovation, and its resulting Kondratieff Wave, are based on the notion that narrowing profit margins reduces the opportunity cost of exploration, causing firms to shift their resources in this direction. Song et al. (2003) summarized these views succinctly when they observed that when "firms perform well, they may be satisfied with their current programs of innovation and may thus be less motivated to [explore by] accessing other firms' expertise to improve their own performance. As organizations experience success, their routines and products become more standardized."

Connecting these literatures creates a dynamic image of firm exploration and exploitation. Firms explore to generate variety and find new technologies, but finding an initial valuable technology narrows their search. Because one valuable technology is likely surrounded by similar valuable technologies, the firm begins to search for new technologies proximately, and continues to produce new but similar high-value technologies without incurring high search costs through proximate exploitation. This argument, however, still lacks an explanation of how firm-level exploitation can map into regional-level exploitation. Therefore, in the following two sections we first theorize how this micro to macro causational force operates and then present supporting patent-based evidence toward our claims.

4. Exploration and Exploitation at the Regional Level

While exploration and exploitation are generally thought to occur at the micro-level, these behaviors can occur on a regional basis through two potential mechanisms. In the first scenario, inventors and firms in a region observe that other regions have developed the capability to produce high value knowledge. The inventors and firms in regions without valuable knowledge will try to imitate the others' success by exploiting their discovery, pulling the regional knowledge core in the direction of valuable technology classes.

Although inter-regional imitation has high potential returns, it has three barriers that prevent it from frequently occurring. For one, economic incentives dissuade inventors from sharing their highly-valued inventions (Zucker et al. 2002). Two, the tacit dimension of valuable knowledge makes it difficult-to-codify and difficult to share (Polanyi 1966). Third, the high complexity of valuable knowledge requires the coordination of research teams (Powell, et al. 1996), entire regions (Saxenain 1994), and even cultures for its production (Storper 1997, Gertler 2002, Storper 2015). In sum, inter-regional technological imitation faces uncooperative economic incentives, high to untenable communication costs, and the exorbitant fixed costs involved in replicating the key functions of regional economic ecosystems.

A less costly alternative to inter-regional imitation is local technological exploitation. When a sector of a regional economy "gets hot" and repeatedly develops high-value patents, the inventors in other sectors of the same region take notice. A strong economic incentive emerges to imitate their success as inventors in the region can generate the high revenues associated with the valuable technologies without facing high cognitive and geographic search costs.

Local technological exploitation is more likely than inter-regional imitation. Most importantly, inventors imitating local inventors share regional hard and soft infrastructure. Resources relating to absorptive capacity (Cohen and Levinthal 1990) used in initially inventing valuable technologies, such as universities, local politics, research institutions, and a skilled labor force, are already in place for local imitators. Further, geographic proximity makes it easier for the imitating inventors to gain access to and retain the high-value knowledge by allowing frequent face-to-face communication and by providing local and fluid labor markets (Storper and Venables 2002, Sorenson and Fleming 2004, Breschi and Lissoni 2005). Although the inventors already endowed with the high-value knowledge are incentivized to keep it secret, the cheaper communication costs and mobility of inventors increases the probability that others will either learn it or develop competitive alternative technologies. Geographic proximity makes excludable knowledge less exclusive and enables inter-firm copying and exploitation.

These arguments lead us to believe that local technological exploitation causes regions to reorient their productive resources away from their less valuable activities and toward their more valuable ones. We hypothesize that when a sector in a region “gets hot” to the extent that it increases the regions’ average value of its technologies, micro-decisions to imitate this success will cause the region to refocus its technological production away from its less valuable technologies and toward its more valuable ones. Moreover, rent seeking and imitation will shape the region’s evolutionary trajectory, with large repercussions for the degree of economic growth that it can later realize.

5. Empirical framework

Our primary objective in the empirical section of this paper is to show how an increase in the value of patents that a region produces causes the region reduce its variety and select a development path. Ideally, this hypothesis would be tested using micro-level data that would reveal how and why firms and inventors cause the consolidation of a region's technological structure. Unfortunately, we do not have access to such data and must utilize data that is aggregated to the regional (CBSA and NUTS3) level. In particular, we use patent data from the U.S. and France between 1976 and 2005.

While our dataset prohibits us from identifying the particular micro-mechanism that causes regions to reduce their technological variety, we are not overly concerned with this limitation because we seek to explain regional-level outcomes. Our findings show that regions do two things when the average profitability of their patents increases. First, regions reduce the number of technology classes that they are engaged in. Second, regions increase their aggregate patent output, presumably in its remaining high-value technology classes by coordinating their agents through knowledge spillovers. Regions, moreover, exploit profitable knowledge.

We adopt two specifications of our independent variable to show that our results are robust to our definition of patent value. The first specification is the average weighted ubiquity of the patents a region produces, or *AVGWU*. *AVGWU* has a straightforward economic interpretation. In a market economy, the technologies that are valuable are those that are hard-to-produce and scarce. These technologies can command quasi-monopoly rents by virtue of their restricted supply (Maskell and Malmberg 1999), making the technological classes with the lowest ubiquity the most valuable and the regions that produce low-ubiquity technologies realize high rents.

To calculate the ubiquity of each technology class, we first sum the number of regions that demonstrate revealed comparative advantage (RCA) in a given technology class (Hidalgo et al. 2007). An RCA value of a region for a given technology of greater than 1 indicates that the region's specialization of that technology is greater than the country's average specialization in that technology. We then scale RCA such that RCA values greater than or equal to 1 are assigned a value of 1 and RCA values less than 1 are assigned a value of 0. The ubiquity of a technology class is calculated by summing these binary RCA values across regions. Finally, we compute the average weighted ubiquity (*AVGWU*) of each region by taking the mean weighted ubiquity value of the technologies it has RCA in.

Our second measurement of patent value, the Knowledge Complexity Indicator (*KCI*), is the eigenvector centrality of regions from the bimodal network that links regions to technologies (Hidalgo and Hausmann 2009, Balland and Rigby 2016). The technical definition of *KCI* is a mouthful, but again it has a simple economic interpretation of monopolistic rents. A high *KCI* scores indicate that a city's patent basket is similar to the patent baskets of cities with a large degree of knowledge variety. A city does not need to have a high degree of knowledge variety to receive a high *KCI* value. When the *KCI* score of a city climbs, the city is entering the technologies that are usually only produced by highly-diverse cities.

KCI recognizes that the most valuable types of technologies can only be produced in cities with a lot of variety. In general, major economies of scale are required to produce sophisticated, highly valued technologies. While some smaller and specialized cities may be able to produce a few sophisticated technologies, these are generally the norm. Likewise, while diverse cities also produce low-value technologies, small and specialized cities also produce these low-value technologies.

One must understand eigenvector properties to fully appreciate *KCI*. Consider Google's eigenvector method for identifying which webpages are important, PageRank. PageRank assess the importance a given webpage *W* by counting the number of other webpages that link to *W*. However, observing that not all webpages that link to W are of equal importance, PageRank also weights the strength that a linking page, *LP*, that links to W has based on the number of webpages that link to *LP*. This weighting process continues until the centrality value of *W* converges. By performing this multi-step weighting process, PageRank is able to remove noise from the data; so long as receiving a link is an indication of authority, PageRank will find the webpages with the greatest authority. The reasoning behind *KCI* runs parallel. So long as diversified cities generally produce highly valued patents and cities that are able to attain RCA in a few classes are not, KCI will produce a set of scores for regions of the difficulty involved in producing their patent basket. In practice *KCI* is highly correlated with *AVGWU*, but we believe that the eigenvector property of *KCI* makes it more precise.

We test the role of a region's knowledge value (*AWGWU* and *KCI*) on its propensity to engage in fewer technology classes but with greater intensity, and find consistent results using both US and French patent data. The structure of our data for each country varies slightly, which causes our dependent and control variables to be different across the two countries. Our French data is disaggregated to the technology class level while our US data is aggregated at the regional level. Therefore, the meaningful indicator of a reduction in the number of technologies that regions are producing in France is the binary indicator *exit*, in which *exit* takes a value of 1 if a French region loses RCA in a technology that it used to have RCA in. In turn, we expect average ubiquity to be negatively associated with *exit* and *KCI* to be positively associated with *exit*.

In the US, we use *variety* to calculate the technological variety of regions. *Variety* counts the number of different technologies that a region has RCA in at the regional level. We therefore anticipate that *AVGWU* will be positively associated with *variety*, and for *KCI* to be negatively associated with *variety*. For both countries, *patents* captures the increased aggregate patent output of regions.

We introduce a series of control variables in order to test for causal effect. In the French model, the entry/exit decomposition of the data allows us to control for the relatedness between the class being exited and the knowledge core of the region. In effect, this control variable allows us to ensure that regions are not only shedding classes that are distant from the regional core and irrelevant to its evolutionary trajectory (Frenken et al. 2007). Relatedness also allows us to compare the strength of rent-seeking behavior on regional technological change relative to the strength of cost-reducing behavior through cognitively proximate search. We include 3-way fixed effects (technology, region, and time period) in this model, and control for the national number of patents that are produced in a given technology class. In the US model, we include a comprehensive list of socioeconomic and technical controls and 2-way region and time period fixed effects.[1] Results for the contemporary US are shown in Table 1 and contemporary France in Table 2 in the appendix.[2]

We interpret the persistent significance and direction of average ubiquity and KCI as resounding evidence that regions select their profitable variety, which sorts them onto development paths. When regions move into more valuable technologies, exploitation causes the region to select these valuable technologies. Consolidation, however, comes at the expense of reduced variety that could have opened up new development paths. For these

[1] The control variables in this model are regional population, number of inventors, number of employees, the number of firms, average firm size, manufacturing share of the workforce, average earnings per worker, percent of the workforce that is college-educated, and the dollar value of NSF grants awarded to the region.

[2] Unreported historical results for the US confirm the results of tables 1 and 2.

reasons, in the next section we hone the concept of rent exploitation within regions and insert exploitative behavior within regional path dependence theory.

6. Theorizing the Schumpeterian Market

The purpose of the following two sections is to synthesize the results found in the earlier empirical models and to hypothesize their implications for uneven regional development. The outcome of this synthesis is a simulation model in which the selection of profitable technologies and recombinant search produce spatially uneven levels of economic development. Finally, we use this model to test the key geographical hypothesis of how increased localized knowledge spillovers boost regional innovativeness.

We begin with a Schumpeterian understanding of the creative forces behind economic growth and change. In a globalized economy with a surplus supply of workers, firms, and regions capable of producing generic products and technologies, competitive advantage hinges on the ability to produce products and technologies that are difficult for others to make. As many workers and firms bid for and compete to perform economic activities with a low degree of sophistication and a high degree of codifiable knowledge, economic rents and profits gravitate toward the workers and firms that perform sophisticated and difficult-to-codify activities. These select firms and workers hold monopolistic control over scarce skillsets and knowledge, which they leverage to command superprofits and rents (Maskell and Malmberg 1999).

Over time, scarce knowledge has an adverse effect. Its immediate high rents incentivize others to try to learn and use it as well. The knowledge diffuses and its ubiquity rises, which drives its associated rents downward. Inventors try to protect the valuable knowledge they hold, but no knowledge is perfectly protected, and the reverse engineering of products, technologies, and organizational structures, along with the organic catch-up of laggards to the technological frontier, ubiquifies scarce knowledge. Even when scarce knowledge cannot be perfectly replicated, similar and competing knowledge is often created. For example, only one company can produce the iPhone, but many companies produce competing Android-based smartphones. If the search costs to reproduce valuable knowledge are sufficiently low, the successive selection of scarce knowledge causes it to multiply in quantity.

So long as time raises the ubiquity and flattens the rents of existing knowledge, recently invented knowledge that is not yet old enough to widely disseminate will be scarce and command high rents. Recently invented knowledge is scarce for two reasons. First, its newness necessarily implies that it has not yet had time to broadly disseminate. Second, because the ubiquity of knowledge is relative, the introduction of new, scarce knowledge makes existing knowledge relatively more ubiquitous.

To illustrate this second point, consider a simple world in which there are two types of knowledge, A and B. Two people have access to knowledge A and two people have access to knowledge B. Therefore, the ubiquity (number of people with this knowledge) of A is 2, and of B is 2. Because each type of knowledge has a ubiquity value of 2, we know that the average world ubiquity of all types of knowledge is equal to 2 and that A and B command average rents. Now, in a later time period, imagine that an inventor pioneers a new type of knowledge, C. In this next time period, 2 people have A, 2 people have B, and 1 person has C. Knowledge C is less ubiquitous than knowledge A and B in *absolute* terms because 1 is less than 2. But knowledge C is also less ubiquitous than knowledge B and C in *relative* terms because the introduction of C has decreased the average ubiquity of all knowledge types from 2 to [(2 + 2 + 1) / 3] = 1.666. Therefore, while the ubiquity of A and B has not actually increased in absolute terms, their ubiquity has appreciated relative to the world mean. Their respective rents therefore must decline in real terms.

As we have shown, new knowledge is not only scarce because it is new. Its introduction also makes existing knowledge relatively more ubiquitous. Competitive advantage then hinges on the invention of new and scarce knowledge, and in the following section we set out to theorize how new inventions are invented.

7. Developing a theory of invention

In a world without innovation, scarce knowledge to be selected until it is no more profitable than the existing, ubiquitous sets of knowledge. The ubiquity and rents across all knowledge sets would converge to a mean value. Complete convergence of the returns to the knowledge-based factors of production would eliminate all economic incentives. Stasis would ensue as the economy enters a perverse general equilibrium.

The continued vitality of the capitalist economy, then, is contingent on its ability to maintain disequilibrium through creative destruction. In our model, as well as in our broader understanding of the global economy, innovation is the creative destruction that keeps the capitalist economy churning. Through dynamically altering the world average ubiquity, the creation of new knowledge variety incentivizes the forgetting of old, ubiquitous and low-value knowledge and the experimentation for new, high value knowledge.

Inventions are invented in one of three ways. Each form of innovation has unique implications for the uneven development of regional economies. In the first, innovation occurs randomly in time, across people, and across space. This form of innovation diminishes the strength of regional path dependence, because it influences the knowledge stock of regions without regard to their prior conditions. Random innovation, including historical accidents, will in turn always remain variance that cannot be explained because it has no explanation. The second source of innovation, in which new ideas emerge as an externality from regular economic activity, is foundational to theories of innovation in evolutionary economics (Nelson and Winters 1982). In this format, innovation naturally emerges from repeated business routines. Because invention occurs through normal economic practices, it is spatially concentrated in the most economically active regions. These large regions naturally produce new but related technologies over time. If these new technologies get selected, they will exert a gravitational pull on the region's developmental trajectory. The third source of innovation is strategic action (Lerner 1997). Firms that operate with less profitable technologies have a greater incentive to invest in research and development than firms that already have access to more profitable technologies. Therefore, firms that have narrower profit margins innovate more. The model that we develop captures all three forms of innovation that we discuss in this section.

8. The Role of Geography in Innovation

The highest rents are awarded to the people and firms that develop new and scarce skills, products, technologies, and knowledge. Rarely, though, are these inventions produced by lone inventors or isolated firms. The world economy is highly complex and layered, and knowledge that is scarce and valuable is too sophisticated for one inventor or firm to invent independently (Powell et al. 1996, Hidalgo 2015). The sophistication of this knowledge requires the support of entire networks or milieus of actors in order to produce them, including a collection of inventors working directly on particular innovations, source of capital, decades of prior research experience, effective demand for invention's outputs, federal governments that support property rights including intellectual property, local politics that at the very least do not impede research efforts, and so on (Teece 2010, Storper 1997). The specific inventors that embody tacit knowledge rely on extensive support structures. As innovations have become more complex, they have also become more collective in order to overcome this complexity.

Since Jaffe et al. (1993)'s seminal work, a multitude of studies have argued that geographic proximity is the primary determinant of the structure of collaborative and knowledge-transfer networks (c.f. Storper and Venables 2004, Boschma 2005, Balland et al. 2015). By no means is the role of geography in forming networks fully agreed upon, as some continue to argue that space does not play a substantial role in connecting people (Peri 2005, Breschi and Lissoni 2009). However, we find the assertion that face-to-face communication is a necessary condition for the sharing of the complex, innovative knowledge between team members to be deeply persuasive.

Nonetheless, while the increasing geographic concentration of innovative activity suggests the need to co-locate in order to innovate (Sonn and Storper 2006), the proposed economic model of innovation and path dependence is agnostic to these issues. In its current form, the model embeds inventive networks and milieus into regions, but these networks can be easily disembedded from regions without altering the model's core mechanisms. The key drivers of path dependence, including the exploitation of rents, the ubiquification of existing knowledge, and the invention of new technologies would continue to propel an aspatial model along development paths. However, disembedding the networks from regions would cause the model's outcome to shift from an explanation of the emergence of regional evolution to an explanation of network evolution. These interpretations of the model are orthogonal to one-another, but nonetheless advance different policy recommendations. In the former, a geographical interpretation lends itself to place-based innovation policies while the latter advances either policy developed without regard to space or altogether disputes the role of public policy in innovation, as inventors unaffiliated by the friction of space may already sort into spatially-disembedded networks as if they maximize profit (Friedman 1953). The impact of the embeddedness debate this model, however, is restricted to the interpretation of the model's outcome and policy recommendations.

9. Outlining the Simulation: Technologies and Firm Incentives

In this section, we describe the initial steps that we take to move from the appreciative verbal model to our computer simulation. We finish by using the simulation to inform our understanding of the drivers behind uneven regional development.

We begin with firms that use a heterogeneous set of technologies in production. Each production technology translates directly into an output. For example, a firm that uses the technology A in production produces an output of type A. Therefore, the production capabilities of firms are directly subject to the selection forces of the market.

The market price of technologies is determined on basis of their inverse ubiquity. Technologies that are scarce and have a high value of inverse ubiquity command monopolistic rents. Ubiquitous technologies, on the other hand, are highly competitive and generate minimal rents. Moreover, by assuming uniform and price-inelastic demand for the outputs associated with each technology of production, we can write the price commanded by technology a in terms of its ubiquity value:

$$Price_a = \frac{1}{\text{ubiquity}_{a,t-1}}$$

The use of a particular technology generates revenue, R. We assume that all revenue generated using a particular technology is reinvested in that same technology; the switching costs between using technologies are infinitely high. Therefore, we know that a firm using a quantity *X* of *a* will generate a revenue devoted to technology *a*:

$$R_a = \frac{1}{\text{ubiquity}_{a,t-1}} * X_a$$

Firms reinvest their revenue *R* in the same technology with regard to the cost of using a technology. We assume that the cost of using a single technology is the world average weighted inverse ubiquity across all technologies, or WIUBIQ. WIBUIQ can be written as

$$WIUBIQ = \frac{\frac{1}{\sum_a^n W_a * \ ubiquity_{a,t-1}/_{\text{n}}}}{\sum_a^n W_a}$$

and is theoretically motivated because WIUBIQ calculates the average level of rents across all technologies in the world. Moreover, we assume that the cost of using technologies is invariant across all technology types and that the world average rate of rents establishes this cost level. This assumption implies that the outputs of all world technologies from the previous time period are used as inputs to create the new technologies. Firms are insensitive to changes in prices in the input market. They are perfectly price-inelastic.

The change in use of a given technology can then be written as the quotient of the revenue generated by that technology and the cost of using a technology:

$$\Delta \text{X}_a = {}^{R_a}/_{WIUBIQ}$$

Without friction in the marketplace, this economy would cause the inverse ubiquity values of all technologies to converge to the world average after one time period. Firms would perfectly increase or decrease their use of technology *a* in order to maximize profits. We therefore dampen the entry and exit of firm's use of technologies by making ΔX_a a function of the quantity of *a* used by the firm in the earlier time period:

$$\Delta X_a = \frac{{}^{R_a}/_{WIUBIQ}}{2} + \frac{X_{a,t-1}}{2}$$

10: Firm-Level Agency: Exploitation and Exploration

The model endows firms with a very simple degree of agency: firms chose to exploit existing technologies or explore for new variety based on the expected value of these two activities. Because technologies are valued based on their inverse ubiquities, the expected value of exploiting a technology (EXVPLT) is its inverse ubiquity from the previous time period.

The expected value of exploring (EXVPLR) with a technology is less certain. Because exploration is characterized by risk, information asymmetries, and indeterminacy, we assume that the expected value of exploring with a technology is the world average weighted inverse ubiquity across all technologies. Moreover, firms expect to realize the world average rate of returns, WIUBIQ, when they chose to explore with a technology, because they are unaware of how valuable the resulting variety will be.

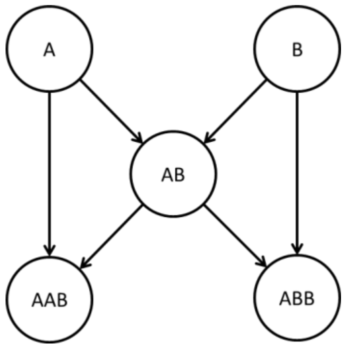
Firms therefore chose to exploit technologies for which the expected value of exploitation is greater than that of exploration:

$$Exploit_a = \frac{1}{\mathrm{ubiquity}_{a,t-1}} \geq \frac{\frac{1}{\sum_a^n W_a * \ ubiquity_{a,t-1}/_{\mathrm{n}}}}{\sum_a^n W_a}$$

Firms explore with technologies that they do not exploit, when the expected value of exploration is greater than or equal to the expected value of exploitation. In order to reduce the number of technologies that firms choose to explore with, we introduce a tuning parameter into the model. Moreover, we assume that each technology that a firm choses to explore with has a ρ (rho) probability of actually being exploited. While ρ can be interpreted as an exogenous, uniform degree of risk aversion, ρ's primary purpose is to curtail the amount of exploration that occurs in the model. In unreported simulation runs, we show that augmenting the value of ρ does not substantively change the results' qualitative interpretation.

The decision-making of firms to explore and exploit with their technologies are illustrated by the flowchart in Table 3. Technologies that end up in the exploitation pool are exploited, and no additional actions are performed on these exploited technologies for the remainder of the time period. The firm then sets out to innovate with its exploring technologies through recombination.

Firms recombine by piecing together existing technologies into new technologies. For example, a firm might explore with a technology A and a technology B to create a new technology, AB. That firm might later recombine A again with AB to create another novel technology, AAB. Technologies are then created according to a family tree that continues indefinitely:



More specifically, firms recombine by generating all possible pairs of their exploring technologies. For example, a firm exploring with the technologies A and B, will generate the resulting pairs A-B, B-A, A-A, and B-B. This firm therefore has 4 possible technology pairs. The order of recombination does not matter, so B-A becomes a second A-B. Applying this rule to all possible pairs the firm can generate, the firm is now expected to generate 2 A-B's, 1 A-A, and 1 B-B through exploration. We write these expected pairs as a vector of length 3:

Possible Pairs = 2AB; 1AA; 1BB

Because exploration does not produce any growth independent of ΔX_a, we normalize the possible pairs vector such that it sums to the total number of exploring technologies. Therefore, in this example the possible pairs vector must sum to 2. Normalization is performed by dividing the possible pairs vector by the number of exploring technologies, which gives us the realized pairs vector:

Realized Pairs = 1AB; 0.5AA; 0.5BB

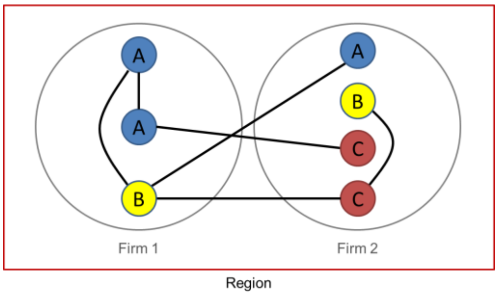
Recombination can produce the seemingly bizarre outcome in which identical types of knowledge recombine. In the above example, technology A recombines with itself to produce the technology AA. This outcome is a common property of Markov chains, but in our context it can be interpreted as the event in which two workers with identical skillsets converse and share their knowledge. Despite their similarities, they can mantain a conversation. However, because their skillsets are identical, the conversation creates no variety and no new knowledge is generated. Therefore, AA is structurally identical to the base technology A. We therefore write technology AA as simply A, and rewrite the realize pairs vector as follows:

$$\text{Realized Pairs} = 1AB;\ 0.5A;\ 0.5B$$

The above scenario applies to the boundary case in which a firm tries to explore with just one type of technology. In this case, the firm has no variety with which it can produce new technologies. It therefore cannot recombine, so it will hold onto the same technology when it tries to explore with it.

11. The Region

Economic regions are groupings of co-located firms. Technologies are able to spill-over between firms within the same region but not to firms in other regions. Specifically, when a firm explores with a technology, it is able to recombine its exploring technology with the exploring technologies in the same firm and with the exploring technologies held by other firms in the same region. In our base version of the model, half of the technologies that a firm explores with recombine locally (meaning within the same firm), and half recombine externally (meaning any firm in the same region). Below, we illustrate how two co-located firms explore to generate new technologies through internal and external recombination.



While our base variant of the model assumes that every firm explores externally with half of its technologies, we develop a second variant in which the propensity for firms to explore externally varies across regions. We call this model variant the "Saxenian Model", because it is designed to test the mechanism popularized by AnnaLee Saxenian's 1994 book *Regional Advantage*.[3] In our Saxenian Model, the first region's firms explore externally with 10% of their technologies and locally with 90%; the second region's firms explore externally with 20% of their technologies and locally with 80%; and so on. Endowing regions with a varying propensity for their firms to explore locally or externally allows us to test the mechanism behind institutional arguments of how localized knowledge spillovers relates to regional economic growth.

12: Simulation Parameters and Initial Conditions

We run the base model and the Saxenian Model variants each 25 times and collect the output trace. The base model shows us the inherent behavior of the model while the Saxenain variant allows us to test how differing propensities for localized knowledge transfer influence regional competitive advantage. Our additional model specifications and initial conditions are described in Table 4. In general, the results do not qualitatively change under different initial

[3] This line of reasoning is a mainstay in the economic geography and economic sociology literatures and features most recently in Storper's (2015) analysis of the biotech industries of Los Angeles and San Francisco

conditions, though setting very high initial conditions (such as a model with 100 firms per region or a much longer time horizon) makes the model too cumbersome to run.

13. Single-Run Simulation Results

We provide three sets of simulation results. The first set of results is a walkthrough of a single run of the simulation with a time-horizon set to 25. This walkthrough conveys an image of how the model unfolds over time to produce regional-level outcomes, and is shown in Table 5.

This walkthrough is expressed through bipartite networks that connect region nodes (at the bottom) to the technologies that their firms use (at the top). An edge is drawn between regions and technologies if at least one firm in the region is using at least one of a given type of technology. The size of the city nodes are scaled relative to their size, measured by the number of technologies they produce. The size of the technology nodes are scaled relative to their profitability, with more profitable and less ubiquitous technologies shown in larger size. Therefore, an edge that connects a region to a large technology node suggests that the region can realize high gains through exploiting that technology.

The first time period begins with the initial model conditions and each city produces some of each type of technology: A, B, AB, AAB, and ABB. However, small differences begin to emerge over time, when stochastic behavior allows certain regions to develop new technologies by chance. These stochastic differences create a snowballing effect as they lead some cities to continuously invent new and valuable technologies. Regions such as Region 5 are able to continually grow over time through the interaction of its stochastically-generated early advantages and their reinforcing path dependency. Region 5's early invention of a novel technology (technology AABAB) creates a large opportunity to generate rents. The region's firms are able to exploit these rents and grow, thereby increasing the number of AABAB they use in production. Exploitation creates resources that are later used to explore, and through the subsequent iterations of the model, the region enters into new and profitable technologies, extending its regional advantage. By the end of the model run (time period 25) we see that the cities that invented new technologies early on tend to do well.

Early advantages in the model are influential but not deterministic. Region 2, for instance, did not develop a significant early advantage, but is able to outperform Region 5 by the conclusion of the model runs. Region 2 does this by exploring near time period 15. The region's firms must have concluded that a pair of technologies was better explored with than exploited, which creates a novel recombination for the region by time period 15. The resulting technology is highly valuable, so the region's firms select this technology and exploit it heavily, creating more resources to further explore with and deepen the newly developed evolutionary path. This path proves to be the seeds of the most profitable development path in the simulated world, and the region is able to ride this path through the end of the run.

14. Batch Simulation Results

The qualitative results, although suggestive, only show the output of two model runs. To illustrate more regular results, we run the base model simulation 25 times and collect the results. We present the results from these runs in Table 6, wherein the cell values indicate the region size at the conclusion of the time horizon. Region size is calculated by summing the total number of technologies that the cities' firms produce. This table shows the consistency of the results and the degree of regional inequality that emerges from the base model.

Importantly, no patterns emerge from the base model. Regions always diverge in terms of size, but there are no forces that induce some regions to grow more than others. These results confirm that our base model is neutral as to which city ends up as the most innovative.

In the final model, we endow each region with a different degree of firm porosity. Region 1 has almost entirely open firm boundaries; when the firms in Region 1 look to explore, only 10% of their knowledge recombines within the same firm, and 90% of their knowledge recombines with other firms in the same region. Likewise, in Region 2, 20% of the knowledge recombines within the same firms and 80% recombines in the region. This pattern continues until we reach Region 10, where 100% of the knowledge recombines within the same firm. Each firm in Region 10 acts as an island.

The dynamism of regions varies widely in the Saxenian Model, as shown in Tables 7 and 8. The regions with more open firm borders, toward the left-hand side of the charts, grow more than the ones with more closed borders, on the right side. This general result supports the Saxenian Hypothesis as we find that cities with a greater degree of inter-firm knowledge sharing and transfer are able to invent new and valuable technologies and are more innovative in the long run. However, our model generates an additional key finding: innovativeness is not a constantly increasing function of firm openness, but peaks at the optimal value. Regional economies maximize their dynamism when 20% of their knowledge circulates within firms and 80% circulates across the region. Beyond this threshold, increased knowledge transfer hurts the region and its firms. We believe that this finding is novel to understandings of regional and cluster growth and development, and we devote the remainder of this paper to analyzing this result and interpreting its policy implications.

15. Innovation in Insular Regions

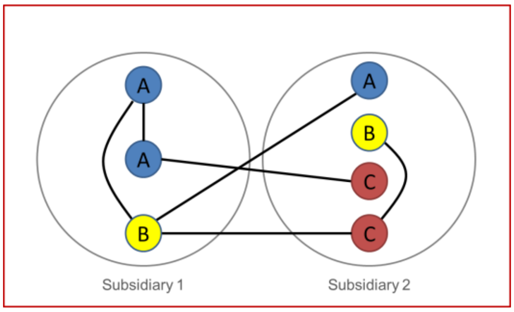
A key finding from our model is that regional long-run dynamism declines when firms share nearly all of their knowledge with the region's other firms. While more work needs to be done to definitively confirm this pattern's cause, we believe that we are witnessing the dynamic outcome a network property that traces back to Granovetter's canonical work on the strength of weak ties. Strong network ties do not always create as much knowledge variety as weak ones do (Granovetter 1974), and occasional frictions in sharing knowledge can produce greater knowledge variety in the larger environment (Jonard and Yildizoglu 1998).

Overly porous firm borders act as overly strong ties. When firms' borders are too porous, the overall variety of knowledge in the region decreases. The firms' knowledge stocks converge through excessive knowledge transfer so that, over time, each firm's portfolio of technologies begin to look more alike those of their neighboring firms. When these technologically-similar firms try to collaborate and create new technologies, the results are not particularly novel. Knowledge in these regions becomes redundant.

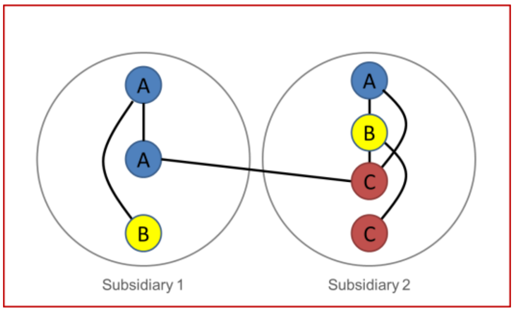
This finding makes key contributions to network theory and economic geography. Within network theory, reducing the difficulty for nodes to interact is generally associated with an increase knowledge variety (see, for example, the small worlds network structure, beginning with Watts 1998). As we show, a particular network structure in a dynamic setting, in which a network interacts within a community of other networks, does not follow this general pattern. Our results should apply to any network arranged in this nested structure.

The nested network structure is widely prevalent across disciplines, and we predict that our result has cross-disciplinary appeal. One immediate application is to the exploration and exploitation literature. As we have discussed in earlier sections, the exploration and exploitation literature seeks to understand how firms can maintain ambidexterity simultaneously both generate and select variety. Explanations toward these ends usually emphasize the degree of decentralization of a firm and how it helps the firm pursue exploration, exploitation, or both. Firms and their subdivisions can be modeled using the nested network structure we use to model regional economies. In a network model of the firm, technologies are contained in the firm's subdivisions, which are able to collaborate or share knowledge with one-another. More decentralized firms have greater subsidiary autonomy and therefore share less knowledge with the other subsidiaries; more centralized firms, by contrast, have greater inter-subsidiary knowledge flow. Because this network model of the firm is the same network as the one we use to describe regional economies, the results from our simulation will apply to it. Therefore, our model identifies the optimal degree of decentralization that maximizes firm ambidexterity and long-run profit.

The application of our results to firm decentralization is illustrated by the example of Google's recent creation of the conglomerate Alphabet, as we illustrate in the following chart. In creating Alphabet, the Google has increased the independence of its subsidiaries. We expect that increased independence will increase the variety of knowledge that Google is able to produce. In the new Alphabet, the occasional cross-subsidiary flow of knowledge within Alphabet keeps each of its subsidiaries dynamic through knowledge sharing, but these flows are sufficiently infrequent to eschew knowledge redundancy. Certainly, the quantity of knowledge variety that Alphabet will produce will be strongly augmented by other components of the firm; however, its recent decentralization should move it one step in a more innovative direction.



Old Google: Cross-Division Knowledge Sharing



New Alphabet: More Closure

Within Economic Geography, the Saxenian argument that increased inter-firm interaction makes regions innovate more has long been accepted as the rule-of-thumb. While close ties may have been beneficial for some regions at certain points of time, there are dozens of examples we can think of in which too-close ties seem to have worked against regional economies in the long run. Grabher's (1993) classic study of the German Ruhr immediately comes to mind, where too-close ties between firms were shown to reduce the variety of knowledge in the region and created technological lock-in.

The German Ruhr is not an exceptional case. Some of the largest and most innovative cities in North America during the early-to-mid 20th century, now constituting the Rust Belt, have experienced similar outcomes. It seems well plausible that the mechanism we have identified here – that the links between their firms became too close – was at play. Qualitative and quantitative-driven studies are now needed to see if these cities developed close intra-firm linkages, and the extent to which these linkages can explain their economic decline.

16. Conclusion

While EEG's explosion of interest in in the past twenty-some years has generated an empirically-rich literature, the sub-discipline has made much less progress in its development of theory. Trouble arises when advancements in empirics and theory are not in sync. More often than not, literatures in which empirics outrace theory develop fuzzy concepts, encounter difficulty in showing how these concepts interact with one-another, and lose sight their long-term goals and aims.

In this article, we merged together existing concepts from the EEG literature. The outcome of this combinatorial effort is a cohesive evolutionary model of regional growth and change. The model clarifies how the key evolutionary mechanisms of variety creation, selection, and retention create measurable regional outcomes. Additionally, the model gives us a clearer understanding of how regions move through the knowledge space by recombining technologies and how monopolistic rents create differential levels of economic development.

The most important contribution of the model, however, is that it reconnects EEG with EEG's original goal. The purpose of EEG is to explain the growth and change of regional economies, but its recent literature on regional diversification through branching is very indirectly related to regional growth. Our model connects regional branching to regional economic growth directly.

We nonetheless sense that the model is the result of a long-running collective effort. The ideas behind the model are not new, as they have existed for years in the communities of economic geographers, management scientists, network scientists, economic sociologists, evolutionary economists, among others. The value that the model adds is to bring these ideas into interaction with one-another and to explore the outcome of the resulting conversation through an iterative process.

Applying the model to the Saxenian Hypothesis indicates the pragmatic utility of creating such a conversation. As we find, regions can achieve an optimal degree of knowledge transfer. While more work needs to be done to see how real-world regions can go about realizing this optimal degree, policy makers now have a concrete goal to work toward.

The Saxenian Hypothesis is just one of many instances in which the model can make regional policy smarter. EEG's rich and expansive count of qualitative studies have asked many important policy-related questions that have yet to be subjected to rigorous, systematic examination. We believe that our simulation model can be adapted to examine many of these questions, especially those for which data is hard to come by. If we are not misguided in the model's capabilities, the policy recommendation that the model generates for how regions can achieve an optimal degree of knowledge transfer will be just the first of its many such contributions.

Appendix: List of Tables

Table 1: Effects of Increased Patent Value in United States, 1975-2005

Variable	Dependent Variable					
	Variety	Variety	Patents	Variety	Variety	Patents
Average Scarcity	-97.9*** (16.7)	-57.0*** (18.4)	1.12*** (0.219)			
Average $Scarcity_{t-1}$	-44.1*** (12.0)	-68.0*** (15.0)	0.873*** (0.291)			
KCI				-525*** (93.5)	-482*** (77.1)	4.16*** (0.751)
KCI_{t-1}				-392*** (67.1)	-331*** (60.6)	4.76*** (0.745)
Socioeconomic Controls	Yes	Yes	Yes	Yes	Yes	Yes
2-Way Fixed Effects	No	Yes	Yes	No	Yes	Yes
R-Squared	0.80	0.89	0.95	0.90	0.92	0.95

Each model contains 1915 observations. Observations with fewer than 5 patents dropped. Standard errors clustered at the regional level. Socioeconomic controls include log number of patents, log adult population, log number of inventors, log total employment, log number of firms, log earnings per worker, log NSF grants value, manufacturing share of labor force, and percent college educated.

Table 2: Effects on Exit in France

Variable	Dependent Variable					
	Exit	Exit	Patents	Exit	Exit	Patents
Average Scarcity	0.00255*** (0.000234)	0.000865** (0.000369)	-21.5*** (6.49)			
KCI				0.906*** (0.169)	0.332** (0.168)	-6.90*** (0.558)
Relatedness Density	-0.00150*** (0.000549)	-0.000962** (0.00048)		-0.00147*** (0.000526)	-0.000971** (0.000479)	
Number of Patents in Region	6.01e-6*** (5.59e-6)	-5.47e-6 (1.11e-5)		1.12e-5* (6.66e-6)	-1.19e-5 (1.23e-5)	
3-Way Fixed Effects	No	Yes	Yes	No	Yes	Yes
R-Squared	0.012	0.096	0.0861	0.0085	0.0960	0.087

Each model contains 28676 observations. Standard errors clustered at the regional level. Relatedness density calculates the cognitive distance between the city and the technology class being exited using the co-occurrence of technologies in cities following the methodology of Balland et al (2015). 3-way fixed effects include time period, regional, and technology class fixed effects.

Table 3: Flowchart of Firm Actions

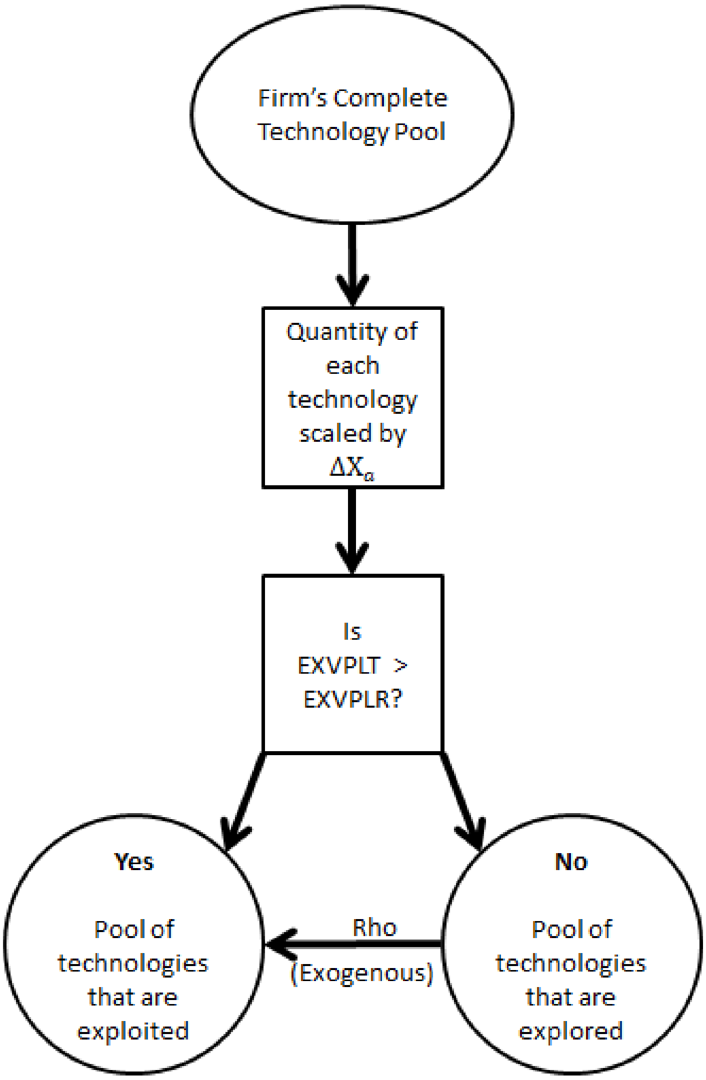
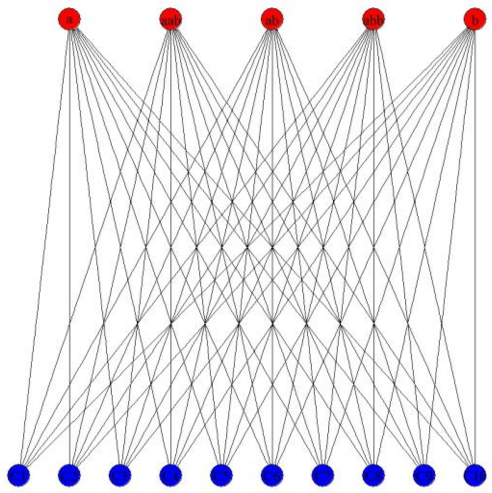


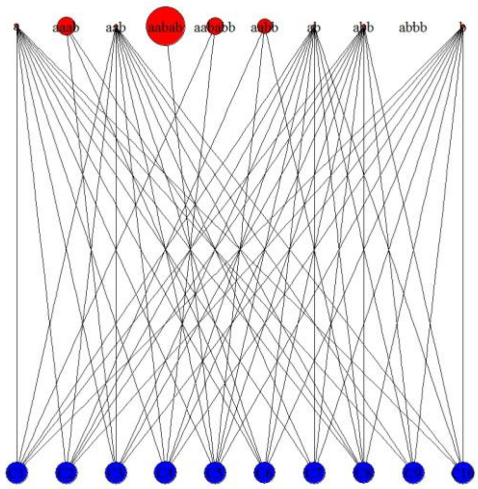
Table 4: Model Parameters and Initial Conditions

Simulation Specifications	
Number of Regions	10
Number of Firms per Region	4
Initial Technologies of Firms	A, B, AB, AAB, ABB
Initial Quantity of each Technology per Firm	10
ρ (Risk Aversion)	95%
Time Horizon	25
Number of Model Runs	25

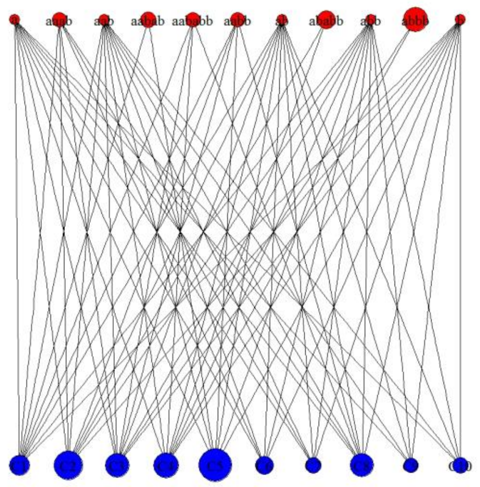
Table 5: Simulation Walk-Through



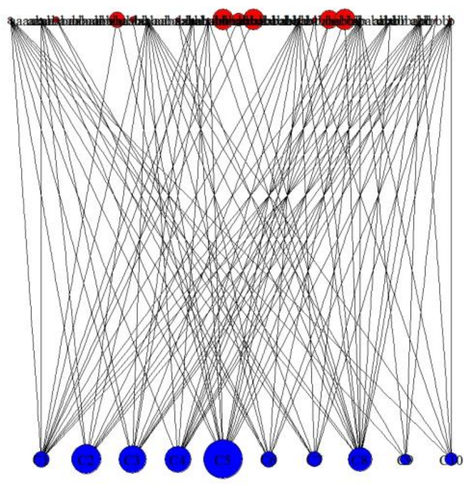
Time Period 1



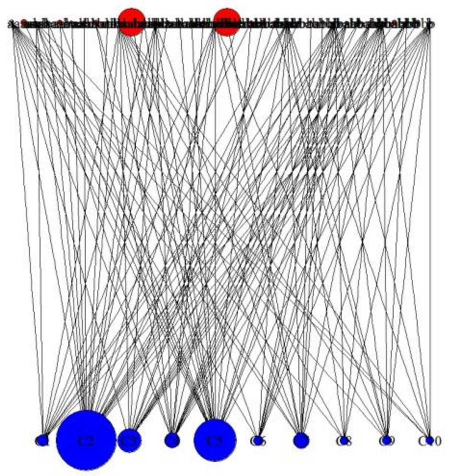
Time Period 2



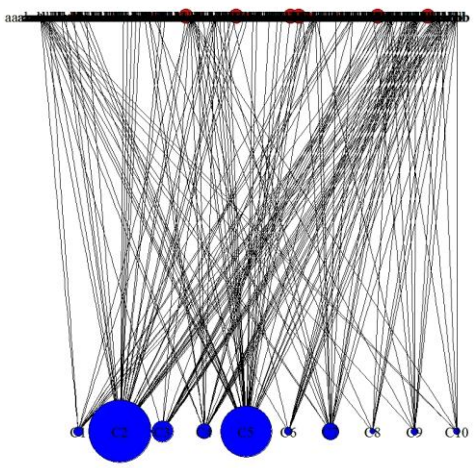
Time Period 5



Time Period 15



Time Period 20



Time Period 25

Table 6: Batch Results from Base Model

Model Run Number	Region Number 1	2	3	4	5	6	7	8	9	10	Mean
1	49	54	268	440	614	54	57	383	49	358	232.6
2	70	105	301	549	796	122	187	162	63	117	247.2
3	295	252	231	70	282	79	427	76	758	76	254.6
4	53	657	75	433	212	550	177	50	60	208	247.5
5	396	47	438	201	760	389	45	173	59	49	255.7
6	85	248	91	404	393	84	97	233	88	655	237.8
7	174	431	171	266	565	161	62	230	172	70	230.2
8	143	281	227	142	61	138	409	909	149	132	259.1
9	129	53	47	485	54	1337	106	56	356	40	266.3
10	659	55	614	337	569	55	51	110	120	118	268.8
11	256	419	133	70	411	67	131	75	82	643	228.7
12	484	249	62	273	129	480	226	73	127	444	254.7
13	159	264	65	172	165	797	690	63	60	64	249.9
14	235	235	410	148	59	611	490	60	69	97	241.4
15	104	38	38	41	69	566	43	37	844	777	255.7
16	336	227	73	67	498	142	154	335	528	65	242.5
17	58	95	56	527	56	170	184	46	271	1050	251.3
18	61	418	152	57	65	695	156	262	59	151	207.6
19	44	1149	145	41	92	37	86	792	34	91	251.1
20	113	102	209	166	102	566	439	103	405	113	231.8
21	326	431	49	520	48	53	447	297	419	58	264.8
22	54	450	224	59	50	521	730	296	43	46	247.3
23	196	348	214	59	306	137	54	667	269	134	238.4
24	56	55	937	231	233	224	231	239	60	211	247.7
25	321	434	254	265	265	103	273	226	103	255	249.9
Mean	194.2	283.8	219.3	240.9	274.1	325.5	238.0	238.1	209.8	240.8	

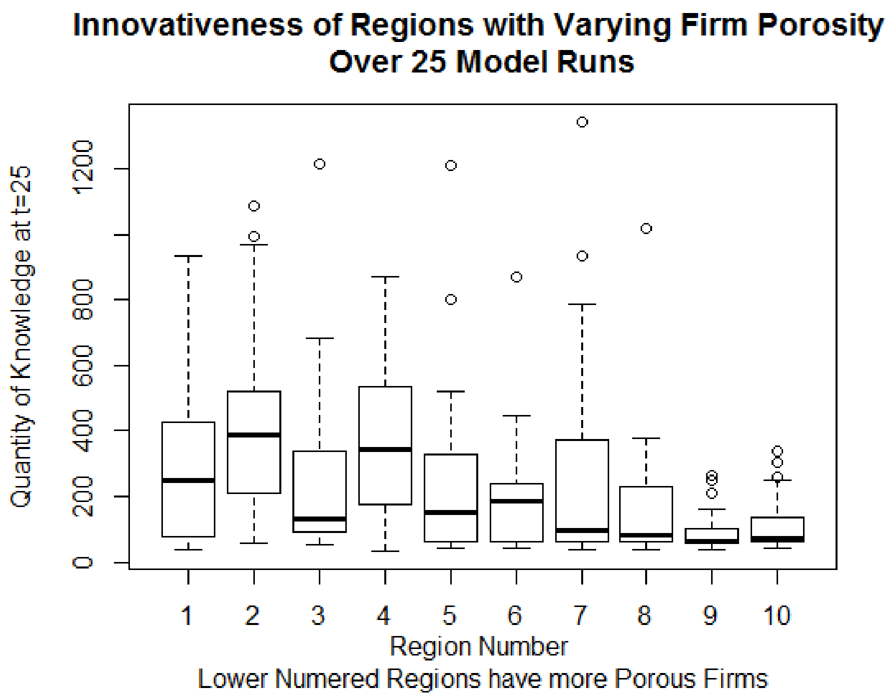
Cell values indicate total number of technologies in a region a time period 25

Table 7: Batch Results from Saxenian Model

	Region Number										
Model Run Number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Mean**
1	90	406	90	367	1210	42	39	39	39	48	237
2	49	1088	682	136	61	52	183	51	89	61	245.2
3	496	700	112	351	68	150	62	380	63	74	245.6
4	95	185	429	177	802	313	156	99	44	41	234.1
5	270	522	67	633	449	141	63	271	59	63	253.8
6	38	994	101	849	150	41	47	48	52	144	246.4
7	39	690	340	869	195	43	46	136	50	50	245.8
8	525	184	58	819	62	242	160	251	154	74	252.9
9	124	322	1217	53	301	56	149	63	62	304	265.1
10	251	82	91	537	94	400	532	88	83	97	225.5
11	353	406	681	343	47	384	49	229	59	56	260.7
12	129	57	62	809	417	202	373	126	63	137	237.5
13	38	412	337	33	42	136	1344	40	100	43	252.5
14	50	466	633	205	521	326	54	53	161	64	253.3
15	76	209	188	336	145	185	787	84	211	337	255.8
16	408	902	71	321	192	62	77	63	71	79	224.6
17	429	337	52	152	124	871	371	62	264	66	272.8
18	435	255	95	281	272	96	264	84	249	251	228.2
19	57	257	333	372	56	226	60	1017	56	57	249.1
20	572	247	103	247	258	242	97	90	86	257	219.9
21	300	404	561	475	52	50	438	52	54	61	244.7
22	635	385	131	428	328	184	59	245	61	147	260.3
23	313	969	256	71	418	68	75	64	249	70	255.3
24	935	71	251	69	143	449	82	252	65	70	238.7
25	158	73	68	607	61	238	935	67	57	97	236.1
Mean	274.6	424.9	280.3	381.6	258.7	207.9	260.0	158.1	100.0	109.9	
SD	229.9	297.8	279.1	254.9	267.0	180.7	321.8	197.3	69.15	83.54	

Cell values indicate total number of technologies in a region a time period 25

Table 8: Batch Results from Saxenian Model, Means and Deviations



Bibliography

Adler, P.S., et al. (1999). Flexibility Versus Efficiency: A Case Study of Model Changeovers in the Toyota Production System. *Organization Science* 10(1).

Arrow, K. (1962). The Economic Implications of Learning by Doing. *Review of Economic Studies* 29.

Arthur, B. (1989). Competing Technologies, Increasing Returns, and Lock-In by Historical Events. *Economic Journal* 99.

Balland, P.A. (2012). Proximity and the Evolution of Collaboration Networks: Evidence from Research and Development Projects within the Global Navigation Satellite System (GNSS) Industry. *Regional Studies*, 46(6).

Balland, P.A., and Rigby, D. (2016). The Geography and Evolution of Complex Knowledge. *Economic Geography*, forthcoming.

Bathelt, H., et al. (2004). Clusters and Knowledge: Local Buzz, Global Pipelines, and the Process of Knowledge Creation. *Progress in Human Geography* 28(1).

Benner, M.J., and Tushman, M.L. (2003). Exploitation, Exploration, and Process Management: The Productivity Dilemma Revisited. *Academy of Management Review* 28(2).

Boschma, R.(2005). Proximity and Innovation: A Critical Assessment. *Regional Studies* 39(1).

Boschma, R., and Frenken, K. (2006) Why is Economic Geography not an Evolutionary Science? Towards an Evolutionary Economic Geography. *Journal of Economic Geography* 6(3).

Boschma, R., and Frenken, K. (2011). Emerging Empirics of Evolutionary Economic Geography. *Journal of Economic Geography* 11.

Boschma, R., et al. (2014). Scientific Knowledge Dynamics and Relatedness in Biotech Cities. *Research Policy* 43(1).

Boschma, R., et al. (2015). Relatedness and Technological Change in Cities: The Rise and Fall of Technological Knowledge in U.S. Metropolitan Areas from 1981-2010. *Industrial and Corporate Change* 24(1).

Cohen, W., and Levinthal, D. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly* 35(1).

David, P.A. (1985). The Economics of QWERTY. *American Economic Review* 75.

Essletzbichler, J., and Rigby, D. (1997). Exploring Evolutionary Economic Geography. *Journal of Economic Geography* 7(5).

Essletzbichler, J., and Rigby, D. (2010). Generalized Darwinism and evolutionary economic geography. In Boschma, R., and Martin, R. (eds), *The Handbook of Evolutionary Economic Geography*. Cheltenham: Edward Elgar.

Feldman, M.P. (2005). The Entrepreneurial Event Revisited: Firm Formation in a Regional Context. In Breschi, S., and Malerba, F. (eds), *Clusters, Networks and Innovation*. Oxford: Oxford University Press, 136–168.

Fleming, L., and Sorenson, O. (2001). Technology as a Complex Adaptive System: Evidence from Patent Data, *Research Policy* 30.

Frenken, K., et al. (2007). Related Variety, Unrelated Variety, and Regional Economic Growth. *Regional Studies* 41(5).

Frenken, K., et al. (2012). Branching Innovation, Recombinant Innovation, and Endogenous Technological Transitions. *Environmental Innovation and Societal Transitions* 4.

Frenken, K., and Mas Tur, E. (2016). Innovation as a Percolation Process. Paper presented at the 2016 Geography of Innovation Conference. Toulouse, France.

Friedman, M. (1953). *Essays in Positive Economics*. Chicago: University of Chicago Press.

Garud, R., and Karnoe, P. (2001). Path Creation as a Process of Mindful Deviation. In: Garud, R., and Karnoe, P. (eds), *Path Dependence and Path Creation*. Lawrence Earlbaum, Malwah, NJ, 1-38.

Garud, R., et al. (2010). Path Dependence or Path Creation. *Journal of Management Studies* 47.

Gaspar, J., and Glaeser, E. (1998). Information Technology and the Future of Cities. *Journal of Urban Economics* 43(1).

Gertler, M. (2002). Tacit Knowledge and the Economic Geography of Context, or the Undefinable Tacitness of Being There. *Journal of Economic Geography* 3(1).

Glaeser, E., et al. (1992). Growth in Cities. *Journal of Political Economy* 100(6), 1126-1152.

Gupta, A.K. et al. (2006). The Interplay Between Exploitation and Exploration. *Academy of Management Journal* 4.

Grabher, G. (1993). The Weakness of Strong Ties: The Lock-in of Regional Development in the Ruhr Area. In: Grabher, G. (ed), *The Embedded Firm*. New York: Routledge, 255-277.

Granovetter, M. (1973). The Strength of Weak Ties. *American Journal of Sociology* 78(6).

Hamel, G. (2002). *Leading the Revolution*. Boston: Harvard Business School Press.

Heimeriks, G., and Boschma, R. (2014). The Path- and Place-Dependent Nature of Scientific Knowledge Production in Biotech 1986-2008. *Journal of Economic Geography* 14.

Hidalgo, C., et al. (2007). The Product Space Conditions the Development of Nations. *Science* 317(5837).

Hidalgo, C., and Hausmann, R. (2009). The Building Blocks of Economic Complexity. *Proceedings of the National Academy of Sciences* 106(26).

Igami, M. (2015). Estimating the Innovator's Dilemma: Structural Analysis of Creative Destruction in the Hard Disk Drive Industry, 1981-1998. *Journal of Political Economy*, forthcoming.

Jacobs, J. (1969). *The Economy of Cities*. New York: Random House.

Jaffe, A., et al. (1993). Geographical Localization of Knowledge Spillovers as Evidenced by Patent Citations. *Quarterly Journal of Economics* 108.

Jansen, J.J.P., (2005). Exploration and Exploitation in Technology Marketing: Building the Ambidextrous Organization. *International Journal of Technology Marketing* 1.

Jansen, J.J.P., et al. (2007). Senior Team Attributes and Organizational Ambidexterity: The Moderating Role of Transformational Leadership. *Journal of Management Studies* 45(5).

Jonard, N., and Yildizoglu, M. (1998). Technological Diversity in an Evolutionary Industry Model with Localized Learning and Network Externalities. *Structural Change and Economic Dynamics* 9.

Lerner, J. (1997). An Emperical Exploration of a Patent Race. *RAND Journal of Economics* 28(2).

Levinthal, D. (1997). Adaptation on Rugged Landscapes. *Management Science* 43.

Kauffman, S.A. (1993). *The Origins of Order: Self-Organization and Selection in Evolution*. Oxford: Oxford University Press.

Krugman, P. (1991). Increasing Returns and Economic Geography. *Journal of Political Economy* 99(31).

Li, Y., et al. (2008). Exploration and Exploitation in Innovation: Reframing the Interpretation. *Creativity and Innovation Management* 17(2).

March, J. (1991). Exploitation and Exploration in Organizational Learning. *Organization Science* 2(1).

March, J., and Simon, H. (1958). *Organizations*. New York: Wiley-Blackwell.

Martin, R., and Sunley, P. (2006). Path Dependence and Regional Economic Evolution. *Journal of Economic Geography* 6(4).

Martin, R., and Sunley, P. (2014). Toward a Developmental Turn in Evolutionary Economic Geography? *Regional Studies* 49(5).

Maskell, P., and Malamberg, A. (1999). The Competitiveness of Firms and Regions: 'Ubiquitification' and the Importance of Localized Learning. *European Urban and Regional Planning Studies* 6.

Maskell, P., and Malamberg, A. (2007). Myopia, Knowledge Development and Cluster Evolution. *Journal of Economic Geography* 7(5).

Massey, D. (1992). Politics and Space / Time. *New Left Review* 196.

Nelson, R., and Winter, S. (1982). *An Evolutionary Theory of Economic Change*. Cambridge: Harvard University Press.

Peri, G. (2005). Determinants of Knowledge Flows and Their Effect on Innovation. *Review of Economics and Statistics* 87(2).

Peters, T. (1992). *Liberation Management: Necessary Disorganization for the Nanosecond Nineties*. New York: Knopf.

Polanyi, M. (1966). *The Tacit Dimension*. Chicago: University of Chicago Press.

Rigby, D. (2015). Technological Relatedness and the Knowledge Space: Entry and Exit of U.S. Cities from Patent Classes. *Regional Studies* 49(11).

Rigby, D., and Essletzbicher, J. (1997). Evolution, Process Variety, and Regional Trajectories of Technological Change in U.S. Manufacturing. *Economic Geography* 73.

Romer, P. (1986). Increasing Returns and Long-Run Growth. *Journal of Political Economy* 94(5).

Romer, P. (1990). Endogenous Technological Change. *Journal of Political Economy* 98(5).

Saxenian, A. (1994). *Regional Advantage: Culture and Competition in Silicon Valley and Route 128.* Cambridge: Harvard University Press.

Schumpeter, J. (1939). *Business Cycles*. New York: McGraw-Hill.

Siggelkow, N., and Rivkin, J. (2006). When Exploration Backfires: Unintended Consequences of Multi-Level Organizational Search. *Academy of Management Journal* 49.

Smith, W.K., and Tushman, M.L. (2005). Managing Strategic Contradictions: A Top Management Model for Managing Innovation Streams. *Organization Science* 16(5).

Song, J., et al. (2003). Learning-by-Hiring: When is Mobility More Likely to Facilitate Interfirm Knowledge Transfer? *Management Science* 49(4).

Sonn, J., and Storper, M. (2008). The Increasing Importance of Geographical Proximity in Knowledge Production. *Environment and Planning A* 40(5).

Sorenson, O., et al. (2006). Complexity Networks and Knowledge Flow. *Research Policy* 35.

Storper, M. (1995). *The Regional World: Territorial Development in a Global Economy.* New York: Guilford Press.

Storper, M. (2015). *The Rise and Fall of Urban Economies: Lessons from San Francisco and Los Angeles*. Palo Alto: Stanford University Press.

Storper, M., and Venables, A. (2004). Buzz: Face-to-face Contact and the Urban Economy. *Journal of Economic Geography* 4(4).

Teece, D. (2007). Explicating Dynamic Capabilities: The Nature and Microfoundations of (Sustainable) Enterprise Performance. *Strategic Management Journal* 28.

Teece, D. (2010). Business Models, Business Strategy, and Innovation. *Long Range Planning* 43.

Watts, D. (1999). Networks, Dynamics, and the Small-World Phenomenon. *American Journal of Sociology* 105(2).

Zucker, L., et al. (2002). Commercializing Knowledge: University Science, Knowledge Capture, and Firm Performance in Biotechnology. *Management Science* 48(1).