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Uneven Technological Development:
The Geographic Evolution of Optics Technologies in the United States, 1976-2010

A thesis submitted in partial satisfaction
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by

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ABSTRACT OF THE THESIS

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

While significant research has examined processes of knowledge production across space, less work has focused on understanding the dynamics of technological change within particular industries. Why do technologies emerge unevenly across space, and how does the evolution of particular knowledge trajectories enable growth in some cities, while constraining growth in others? To better understand these questions, this project uses the optics industry as a case study. Optics is the study of the behavior and transmission of light, and optics technologies have fueled breakthrough innovations in the fields of photography, medical imaging, defense and security, fiber optics and telecommunications, and many other areas. Using USPTO optics patents from 1976 to 2010 and methods drawn from social network analysis and community ecology, I map the evolution of the optics industry across time and space. I find that optics technologies evolve along distinct trajectories over time, and that those trajectories vary from one location to another. This uneven distribution of technologies has important implications for the development of cities and regions, and this research provides an important platform for future studies on the evolution of regional economies.

The thesis of Melissa Haller is approved.

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Introduction: An Evolutionary Perspective of Technological Change

Innovation, or the novel application of economically valuable knowledge, has long been viewed as a key driver of the growth and decline of regional economies (Schumpter, 1942; Solow, 1957; Feldman, 2000). As the decline of traditional manufacturing in the developed world has given rise to economies built around innovative industries, regions increasingly gain competitive advantage by specializing in the production of particular technologies (e.g. biotech, nanotechnology, optics, etc.). The development of technological industries is largely influenced by processes of technological change and the new ideas and flows of knowledge that drive particular development paths; new technologies are continually created through a search for new possibilities and the recombination of old ideas (Nelson and Winter, 1982; Kogut and Zander, 1992). Technological production may also exhibit path dependency, as choices in one time period continually influence the range of technological possibilities in future time periods (Arthur, 1998; David, 1987; Martin and Sunley, 2006). Technologies vary not only across time, but also over space: locations serve as a nexus between people, their ideas and human capital, regional resources, institutions, and organizations. All these characteristics influence the ways in which knowledge is created, borrowed and diffused throughout regional economies. Cognitive, social and spatial forms of proximity interact and guide knowledge production and the trajectories along which that production flows (Boschma, 2005; Leamer and Storper, 2001). This project seeks to understand the role of geography in producing uneven technological development.

While considerable work has been devoted to theorizing the formation, growth, and eventual decline of industries over time, less work has focused on the evolution of industries, or the ways in which the rise and fall of particular technologies drives changes in industry growth over time and space. This paper aims to add to existing research by investigating the evolution of the optics industry in the United States. Optics is the study of the behavior and transmission of light, and optical technologies have fueled breakthrough innovations in the fields of photography, medical imaging, defense and security, fiber optics and telecommunications, and many other areas. Often described as an enabling technology, optics is unique because of the clear synergies that it possesses with other technologically-focused industries; its transformation from an industry built on end-user products (e.g. cameras and eye glasses) to one fueled by components and applications (e.g. fiber optics cable) make it an interesting case study in technological evolution (Feldman and Lendel, 2010).

Using networks built from USPTO data from 1976-2010 and methodological techniques drawn from both network science (Rosvall and Bergstrom, 2008) and evolutionary and community ecology (Anderson and Walsh, 2013), I aim to investigate the following two questions. First, how has the optics industry grown and developed over time? What technologies drive industry growth, and can we identify how they have changed? Second, is the production of different optics technologies shaped by the regions in which they emerge? Can we expect optics technologies to take on different evolutionary paths in different places, thereby contributing to the uneven distribution of technologies and their production across space? In this way, my project seeks to understand both the ways in which the production of optics technologies dynamically unfolds, and how the evolution of optics technologies varies in different places.

The paper is organized in the following way. Section II introduces the theoretical motivation for the paper, drawing on works from economic geography, economics, technology studies, and other related areas. Section III discusses the optics industry and the unique characteristics that make it of particular interest. Section IV outlines the empirical methods used to identify technologies and map their variation across space and time. Section V discusses the key results. I find that, at the national scale, optics technologies generally follow very distinct trajectories over time. While some technologies become more stable over time, many of these trajectories exhibit continuous technological change and variability, illustrating the dynamism of the optics industry's evolutionary history. In addition, my analysis reveals that there is considerable differentiation in the technological structure of the optics industry between key U.S. urban areas. I further find statistically significant differences in the mix of technological categories across cities over time. This suggests that, even within a single industry like optics, technological production likely looks very different from one city to the next, and this has important implications for the industry's evolution over space. Section VI concludes the paper, and discusses implications for future research.

Literature Review

Economic geographers have long recognized the role of knowledge in producing landscapes of uneven technological development (e.g. Maskell and Malmberg, 1999; Frenken and Boschma, 2007; Kogler, Rigby, and Tucker, 2012). As industries increasingly gain success through the production of innovative technologies, knowledge has become more valuable than ever before. Firms, research institutes, universities, and other organizations (henceforth referred to collectively as "organizations") use their knowledge bases, or the knowledge that they can readily draw upon, to invent new technologies and to build or improve upon existing ones. Knowledge is increasingly a source of competitive advantage that organizations can leverage to be successful (Grant, 1996). These knowledge bases can consist of both information (e.g. how to build a technology) and know-how (e.g. how to organize a team), and are the result of people and their interactions: they materialize not only from current employees' or members' levels of expertise, but are also passed down over time from previous members (Kogut and Zander, 1992; Cohen and Levinthal, 1990). Ultimately, under a knowledge-based view of the organization, a key advantage of organizations is their ability to coordinate the specialist knowledge of their members into something greater, and successful organizations do so better than others.

How do organizations learn to create and adopt new technologies? This, again, has much to do with the ability of the organization to coordinate the interactions of its members and their existing knowledge. Cohen and Levinthal (1990) identify one way that organizations learn through their "absorptive capacities," or their ability to recognize the value of new information, assimilate it, and apply it commercially. Whether or not an organization adopts a new idea is highly dependent upon its existing level of related knowledge and the experiences of members; organizations are best positioned to utilize new knowledge when they are familiar with it and have the potential to implement it. Organizations not only adopt new, external knowledge, but they can also create new knowledge. Their ability to do this is often dependent upon their "combinative capabilities", or the capability to exploit an existing knowledge base in order to create something new (Kogut and Zander, 1992, p. 391). Organizations rarely conceive of new ideas from nowhere; innovations are frequently new combinations of existing knowledge bases and incremental learning processes, all of which are coordinated through the organization (p. 392; Schumpeter, 1934).

These ideas can be extended further to understand how organizations and the technologies that they produce *evolve*. An evolutionary view of technological change is one in which new ideas are continually produced and recombined to form new innovations. Building on the knowledge-based view of the organization, evolution explicitly incorporates a time dimension into our understanding of the innovative process. The evolution of technologies is a dynamic process that is both dependent on events in previous time periods and an important determinant of future technological development. Technologies are made up of components that take on different configurations over time; as new combinations of ideas enter dynamic sectors, they often merge with existing ideas and technologies to create entirely new technological configurations. As technologies change in this way over time, they follow distinct paths or trajectories. Tracing the paths that different technologies take is an important step in understanding the rise, growth, and decline of technological industries. How are these new ideas and configurations produced? One way that knowledge is accumulated is through experimentation within the firm, a key focus of evolutionary economic literature.

How does evolution happen? A number of evolutionary economists theorize that firms possess a finite set of behaviors or "routines" that both enable them to operate and restrict their opportunities to adopt new behaviors (Nelson and Winter, 1982; Winter, 2005). Routines can be any of the forms, rules, procedures, conventions, strategies, and technologies that the organization uses on a day to day basis (Levitt and March, 1988). The range of routines available to the organization is conditioned by its existing knowledge base. Similar to genetic inheritance, these routines are maintained and passed down over time by the firm. Firms evolve over time through the process of searching for new routines and ideas in a heterogeneous selection environment. As firms compete, those with routines that are more "fit" tend to survive (note that "fitness" is not the same as "efficiency;" firms may ensure their survival, for example, by capturing a niche market or using other strategies to increase sales), while firms with less fit routines face declining profitability or are pushed out of the market. As a response to declining profitability or uncertainty in their environment, firms may engage in an experimental search process, producing new ideas and routines that build on existing capacities and knowledge in order to become profitable again or adapt to changing conditions. In the case of innovative industries, this search may involve creating new technologies or developing different combinations of existing technological components.

This is, however, not the only way that scholars conceive of economic evolution. Evolutionary ideas have proliferated through parts of economics, management, geography, sociology, and other related disciplines, and conceptions of how ideas, firms, industries, and regions evolve over time have taken numerous forms. Although there is no clear consensus on what we mean when we say that things "evolve," there are similar patterns throughout the literature: most evolutionary theories conceive of economic processes as dynamic; they recognize that choices made in one time period not only influence the next time period, but are often irreversible; and they show how variety and, more specifically, novel ideas, are a primary driver of economic change (Boschma and Martin, 2007). Thus, firms use knowledge and new ideas to gain a competitive advantage over others, industries employ knowledge to grow and forge new paths of development (often at the expense of existing paths), and all of this allows regions and the firms and people within them to capture new waves of economic growth across a heterogeneous economic landscape. Knowledge is often embodied in the creation of a new invention or technology, and the exploitation of new these technologies can give rise to impacts at multiple levels of analysis.

If new ideas are built upon the recombination of existing knowledge and the learning capabilities of organizations, what determines the nature of the technologies that are produced? Ultimately, an organization's ability to recombine ideas is constrained by its ability to process new combinations, and the decision to recombine certain ideas may simultaneously open up new development paths while closing off others (Weitzman, 1998). Along this vein, a number of researchers have conceptualized this process of looking for new combinations as a search across fitness landscapes, operationalizing a concept from evolutionary biology (Kauffman and Johnson, 1991; Levinthal, 1997). Fleming and Sorenson (2001), building on the work of Kauffman (1993), envision technological components as "genes" which are continually recombined through technological evolution, and inventors as continually searching across these landscapes, seeking higher positions (which correspond to greater degrees of success or fitness). The topography of the landscape is then determined by the number of components and the interdependence between them; while increasing component interdependence increases the likelihood of finding synergies between components, very high levels of interdependence make it increasingly difficult to find useful new combinations as components become more similar. Thus, inventors are tasked with sorting through a complex landscape, and moving along one direction or peak meaningfully closes off opportunities in other directions (although such a conceptualization is limited, in that it does not explain how the topography of the landscape was developed in the first place). Social and cognitive constraints, access to resources, risk aversion, and other characteristics further limit an inventor's ability to access the full extent of the landscape, and influence the direction of the inventor's search efforts.

Assuming they cannot visibly see this landscape of invention, how do inventors choose what components to recombine? While many new, recombinative technologies have a minor impact, sometimes technologies can destabilize existing industries or even lead to the growth of new ones, often by reconfiguring the architecture of existing technologies or combining existing knowledge in distant but complementary fields (Hargadon, 1998; Henderson and Clark, 1990). As the above discussion has implied, the full range of possibilities for recombination are influenced by heterogeneity or variety within the existing knowledge base of an organization or location, as new technologies are generally the result of combinations that have not yet been implemented. To this end, variety can be related or unrelated to existing knowledge, and a choice to pursue one type of variety over another is conditioned by inventors' ultimate goals and incentives. 'Related' variety includes ideas that occur in proximate or similar industries and technologies, and is easy to recombine to produce new products, while 'unrelated' variety is more difficult to recombine, and often involves a larger diversification of an organization's knowledge base (Frenken et al., 2007; Content and Frenken, 2016). While related variety enhances the growth of a particular industry and likely involves less risk, unrelated variety may enhance regional diversity but is likely more risky to pursue. When one technological pathway has been exhausted, the organization that is most successful is often the one that is able to combine the most distant technological possibilities in order to forge a new path. However, related technologies are often closer to an organization's existing competencies, and learning new skills and technological areas requires significant time and investments by the organization. Generally, more local search processes are common, as the payoffs for those technologies are much more certain (Stuart and Podolny, 1996).

The search for new ideas can occur locally, within the organization, or globally, through inter-organizational partnerships and networked collaboration structures. A number of authors have written on patterns of search within firms, stressing the importance of organizational boundaries in both constraining and enabling inventor collaboration and the subsequent production of new ideas. Zucker and Darby (1996) imagine institutional boundaries as "information envelopes," protecting a firm's ideas and preventing them from diffusing across organizations. Organizations choose to form partnerships with other organizations in those situations wherein the benefits of collaboration outweigh the costs; often, the obstacles to changing existing firm structures are particularly large. According to Powell, Koput, and Smith-Doerr (1996), such a networked organizational structure is most likely to occur when the knowledge base of an industry is both complex and expanding and the sources of expertise are widely dispersed. In these cases, the incentives to collaborate in order to gain access to information from other organizations are particularly high. The authors' papers find evidence in support of university-firm partnerships and networked collaboration structures, respectively, in some high tech industries like biotechnology (although some industries are more collaborative than others), and later work has further emphasized the importance of technological and industry boundary-spanning in producing high-impact technologies (e.g. Rosenkopf and Nekar, 2001). Overall, a significant body of literature exists which suggests that collaboration structures significantly impact the production of ideas in knowledge-intensive industries.

All of these literatures point to the complex and evolutionary nature of technological change. Not only do future inventions depend on pre-existing ideas, but technological trajectories are continually shaped by inherited behaviors and routines, patterns of search and collaboration, organizational incentives, and our ability to process immense quantities of complex information. Although tracing the evolution of particular technologies or industries over time cannot possibly uncover the wide range of contextual factors that have led to particular instances of technological change or differentiation, being able to delineate technological trajectories over time is an important first step towards understanding why industries and regions have taken on particular forms across time and space. These questions lead to my first two research hypotheses:

H_1: Despite the diversity of optical technologies and applications, the industry can be separated into clear, distinct technological trajectories across time[1]

H_2: Because new ideas are often built on pre-existing, proximate forms of knowledge, these trajectories have been relatively stable over time as a result of continual recombination along existing paths

The Role of Geography

What role, then, can geography play in helping us to understand how technologies evolve over time? Industries, and the technologies they produce, are often linked to particular geographies. Even as the costs of doing business, including transportation and communication costs, continually decline, evidence suggests that industries are more spatially clustered than ever (Porter, 1998). This is increasingly because of the unique benefits of co-location, which include access to resources, human capital, and regional capabilities (Glaeser, 2010; Duranton and Puga, 2003; Storper and Venables, 2004). One particular advantage of place is the ability to communicate and access complex information, particularly in high tech industries: because complex scientific knowledge is often tacit, or cannot be easily written down and diffused, being close to key people with technical knowledge is crucial to developing new technologies within and between organizations (Nelson and Winter, 1982; Polanyi, 1967). Organizations develop new ideas through face-to-face interactions with their members and by building collaborative relationships with other nearby organizations; because of the advantages organizations gain access to as a result of their location, firms are incentivized to concentrate in particular places, creating an uneven geography of industrial location (Maskell and Malmberg, 1999; Storper and

[1] Alternatively, an industry could evolve along complex, interconnected

Venables, 2004). As industries concentrate in regions, their knowledge bases become concentrated in those places as well.

A number of researchers have quantified this local dimension of knowledge production. In their early work, Jaffe, Trajtenberg, and Henderson (1993), followed by Sonn and Storper (2008), studied knowledge spillovers using US patent citations; they ultimately found that citations to US patents were more likely to come from the same state and metropolitan area than what might be expected based on pre-existing research concentrations, evidence of a strong localization of knowledge in the US. Others have continued to pursue work in this research stream: Audretsch and Feldman (1996) echo earlier findings, and further illustrate that the geographic concentration of innovative activity is most likely to occur in industries where knowledge spillovers are greater. From a network perspective, Owen-Smith and Powell (2004) find that the interaction between geographic proximity and organizational form is an important factor in determining the character of knowledge flows. All of these point to the important role of geography in shaping knowledge creation and transmission.

It is worth noting that geographic proximity is not the only mechanism through which knowledge can be transferred, and firms often leverage local and global knowledge sources to produce new ideas. For example, Boschma (2005) suggests that geographical proximity likely does not stimulate knowledge production on its own, but heightens other proximity dimensions, such as cognitive and social proximity, by promoting interactive learning processes. Further, Bathelt, Malmberg, and Maskell (2004) distinguish between different scales of interaction and collaboration: they call “local buzz” the dimension of interaction which occurs among actors embedded in a community by just being there, and “global pipelines” the knowledge that is attained by investing in building channels of communication beyond a firm’s local milieu. They argue that the coexistence of high levels of local buzz and global pipelines provide key advantages which are not available to firms that are less connected. Although knowledge production is likely a complex, multi-dimensional process, geography nevertheless remains an important explanatory variable.

Can the localization of knowledge flows be a bad thing? As many authors have argued, while the geography of technological evolution may facilitate interactive learning processes and opportunities to recombine proximate ideas, it may also create an environment in which the production of new technologies becomes too local. Facing bounded rationality and other cognitive constraints, firms often concentrate their search for new ideas on a restricted range of possibilities (Simon, 1990; Maskell and Malmberg, 2007). The environment in which a firm is located further contributes to this myopic behavior by constraining the nature and variety of ideas that a firm can access locally, and creating isomorphic pressures for emerging firms to conform to the norms established by dominant regional firms (Frenken and Boschma, 2007; DiMaggio and Powell, 1983). Because technological evolution is path dependent, or conditioned on factors including past technological events and existing regional capabilities, regions can become “locked-in” to particular technological trajectories (Grahber, 1993; David, 1985; Arthur, 1988). While lock-in can sometimes be a positive process, it is often associated with a region’s tendency to become “over-reliant on, or dominated by, a particular self-reinforcing industrial-technological path that renders the regional or local economy increasingly structurally and technologically rigid” (Martin and Sunley, 2006, p. 7). Thus, some regional environments may constrain the search for new ideas and lock particular technologies into infertile paths, while others will more readily enable continuous technological growth and development.

It is not known why some paths tend to become more successful than others, and many authors attribute initial path selection to random chance or historical accident rather than rational deliberation; although firms have agency in the decision making process, imperfect information prevents them from being able to make perfectly optimal decisions. In economic geography, this is similar to a "window of locational opportunity" view of industrial location, which suggests that because there is often a gap between the requirements of a new industry and the surrounding environment, infant industries can settle anywhere (Boschma and Frenken, 2003; Scott and Storper, 1987). Both views suggest that random or exogenously determined events can determine or permanently alter a region's potential paths. Others have contested this perspective. For example, Martin (2009) points out that many find that the pre-existing industrial structure of a region can be both a positive or negative determinant of whether a new industry emerges there. He further points out the contradictory logic behind the historical accident assumption; why should history only begin to matter after a technology or industry has been selected for? Can the history of a region be a determining factor for future industrial location? Overall, there is no agreed upon explanation for how path selection occurs, and there is significant space for more research in this area.

Finally, it is important to recognize that path dependency need not be interpreted as an equilibrium process. It need not be the case that regions converge to a stable state at which they become locked into a technological or industrial trajectory; if economic development is a dynamic process, and economic paths are in a continual state of change and transformation, then it seems unlikely that a region could become permanently stuck on one path (Martin and Sunley, 2006). Instead, there remains a possibility that new paths could continually emerge from older paths; regions are complex systems made up of institutions, organizations, individuals, and the composite “organizational elements, structural arrangements, sociocultural norms, and individual rules and procedures” around which these regional systems emerge and are configured (Martin, 2009, p.13). It is possible that new routines and structures are continually layered upon old ones, changing the nature of an existing evolutionary path and potentially converting it to something new, or, like technologies, recombining with old structures to create a novel structural configuration (p.14-15; Boas, 2007; Stark and Bruzst, 2001). Given this, there is no reason to assume that technologies necessarily become locked-into particular technological trajectories either; as regions evolve, the technologies that they produce likely co-evolve with them, and building a new economic path may be associated with new patterns of technological production. This discussion leads to two further hypotheses that will be examined in the analysis below:

H_3: Potential components for recombination differ from one city to another, leading to different evolutionary trajectories

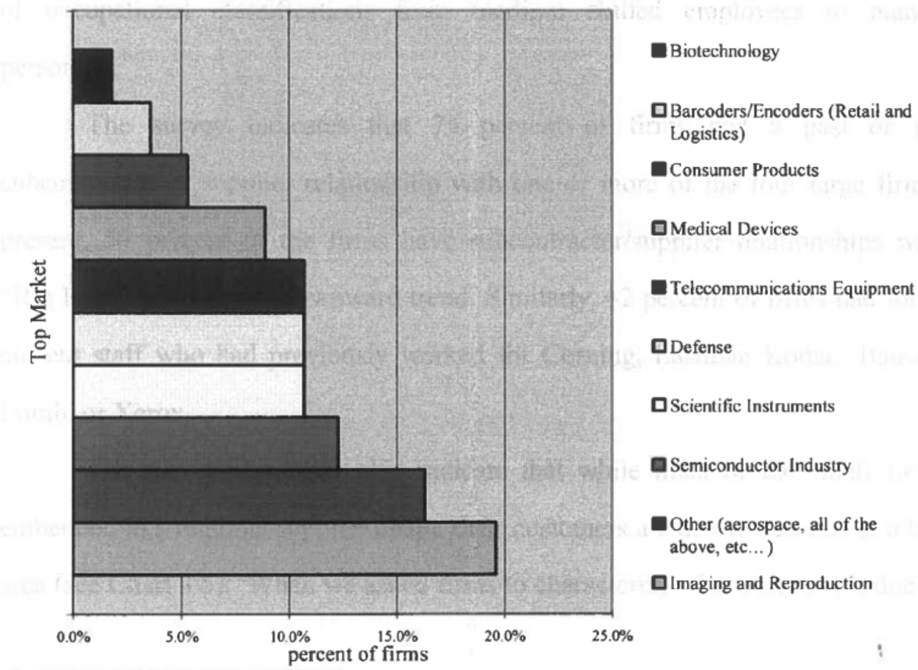
H_4: These differences are persistent over time

Evolutionary Case Study: The Optics Industry

This study considers technological evolution from the perspective of the optics industry. Optics is the field of physics and engineering based around the science of light, and it encompasses a broad range of technologies and applications, including innovations in photonics, opto-electronics, optical discs, photography and imaging, and other related fields which involve “the integration of optical and electronic techniques in the acquisition, processing, communication, storage and display of information,” (Gaschet et al., 2017, p.1). Although early optical technologies, including optical lenses and photographic apparatuses, were prominent in the early 20th century, particularly in Rochester, NY, the home of photography giant Eastman Kodak and lens producer Bausch and Lomb, more recent breakthroughs have transformed the industry (Loudon, 2015). While early optics technologies took advantage of natural lighting to observe objects, leading to the production of technologies like eyeglasses and telescopes, new discoveries have expanded the ways that scientists use and understand light. In particular, the development of the laser in the 1960s by the US military and the discovery of optical waveguide fiber that could carry an unprecedented amount of information in 1970 by researchers at Corning Glass Works revolutionized the applications of optical technologies for the foreseeable future (Hecht, 2016; Alwayn, 2004). Additional innovations in optics include the bar code scanner, the CD player, the laser printer, soft contact lenses, the optical mouse, and the display screens of televisions, computers, and mobile phones (Bass, 2016). Optics technologies have also given rise to important components of medical imaging devices, digital cameras, smart phones, surveillance devices, and a range of other diverse technologies that are prevalent in everyday life (OSA, 2017).

An important characteristic of the optics industry is the fact that optical technologies possess synergies with many related fields. According to Gaschet et al. (2017), optics technologies fall into three primary categories: underlying generic technologies (e.g. optical glasses), key components (lasers), and end-user products and systems (p. 3). As a result, many optical innovations are considered 'enabling technologies,' with a wide array of applications across a variety of different sectors. Recent breakthrough discoveries have enabled optics to develop more applications than ever before. Figure 1 provides an early list of some of the industries within which optics technologies have been most widely adopted, but a modern list would likely include an ever greater variety of industries (Clark, 2004). The diversity of the field has fueled fast growth in optics careers. The International Society for Optical Engineering estimates that optics is growing 3.5 times more quickly than other major industries, making it a promising driver of economic development for many regions (Feldman and Lendel, 2010). These characteristics make it an interesting and case study for understanding the geographic evolution of an industry.

Figure 1: Top Markets for Optics, Imaging, and Photonics Firms
Source: Clark, 2004



However, given the ability of optical technologies to interface within many other fields, this also makes it challenging to define the breadth and scope of the industry. No industry classification fully encompasses all of optics, and capturing optical technologies proves a challenging endeavor (Feldman and Lendel, 2010). How large is the optics industry? In the Optical Society of America, the leading American professional society in optics and photonics, there are 315 firms and 21,000 individual members (OSA, 2018). However, this measure misses any optics firms that do not opt into OSA membership and is likely an underestimate of true industry size. On the other hand, there are 1,070 firms that have produced at least ten patents in optics in the data used for this project (the methods used to collect this data are described in detail below), suggesting that the optics industry might be much larger. However, this may capture firms that do not solely produce optics technologies, and is likely an overestimate of the industry size. Given the diverse nature of the field, measuring the size and scope of the industry is particularly challenging. What firms produce optics technologies, and where are they located? Table 1 lists the top ten firms in the data. Unsurprisingly, the top firms include Eastman Kodak, IBM, Xerox, AT&T, and other industry giants. Geographically, the top optics-producing cities are listed in table 2. The majority of optics patents are produced in California's Bay Area (San Francisco and San Jose) and in major east coast cities (New York, Boston). Rochester, NY, is the smallest city on the list, and much of its patenting is driven by the continued presence of Eastman Kodak and Xerox, among other firms. The industry is also very geographically concentrated; although there are 353 total cities that produce at least one patent in optics, approximately 48% of all patents are produced by the top ten cities.

Table 1: Top 10 Optics Producing Firms

Firm	Number of Patents
Eastman Kodak Company	2276
IBM	2187
General Electric Company	2055
Lucent Technologies Inc.	1760
The US Navy	1447
Xerox Corporation	1383
Intel Corporation	873
AT&T Bell Laboratories	820
Hewlett-Packard Company	799
Corning Incorporated	794

Table 2: Top 10 Optics Producing Cities

City	Number of Patents
San Jose-Sunnyvale-Santa Clara, CA	12365
New York-Northern New Jersey-Long Island, NY-NJ-PA	11662
San Francisco-Oakland-Fremont, CA	8781
Boston-Cambridge-Quincy, MA-NH	7318
Rochester, NY	4122
Minneapolis-St. Paul-Bloomington, MN-WI	3141
Washington-Arlington-Alexandria, DC-VA-MD-WV	3080
Chicago-Joliet-Naperville, IL-IN-WI	3016
San Diego-Carlsbad-San Marcos, CA	2784
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	2721

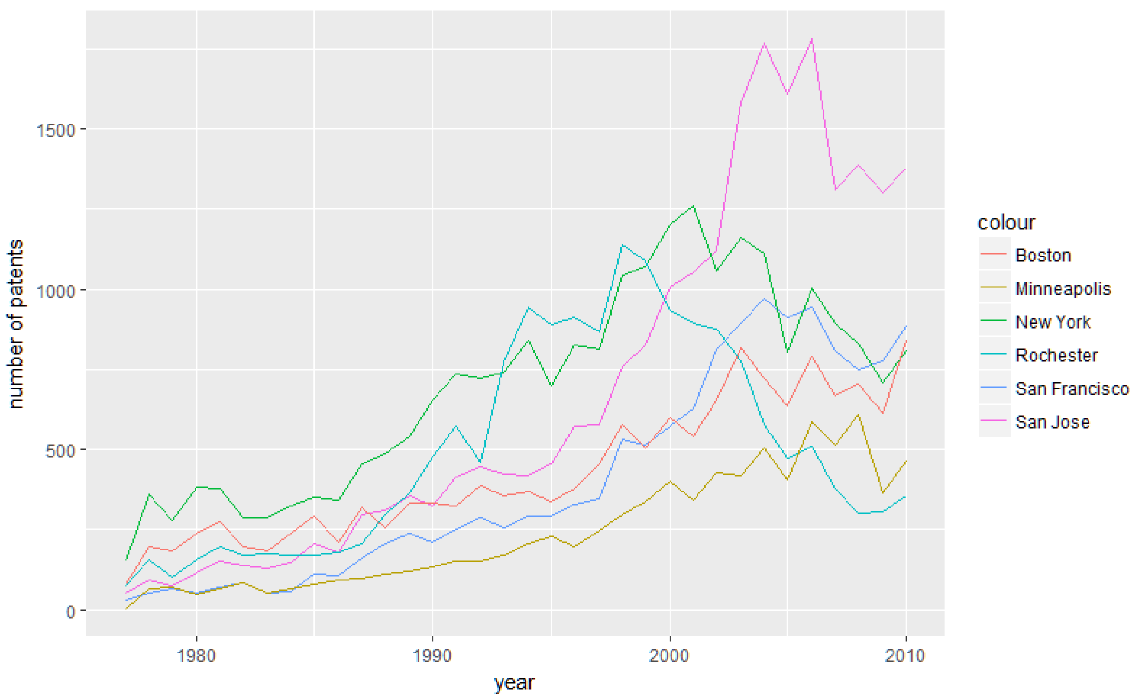


Figure 2: Optics Production in Top US Cities, 1976-2010

How has the geography of the optics industry changed over time? Looking at patent production between 1976 and 2014, figure 2 depicts patenting in the top six cities. Although New York and Rochester lead the industry in the mid 1990s, over time San Jose, and later San Francisco, managed to capture a greater share of optics patents. The decline of the earlier two cities appears to coincide with the rise of the later two. Boston and Minneapolis, by contrast, appear to produce a relatively stable quantity of optics patents over time, with only a modest increase in later years. All of this suggests that the industry is relatively dynamic; while some cities have experienced declines over time, others exhibit clear growth patterns.

A few recent empirical studies have been conducted which investigate the nature and extent of optics clusters in the US and Europe. Most work has focused on delineating the different geographic and structural forms that optics clusters take on. Feldman and Lendel (2010) study the optics industry in the US using patent data to identify emerging optics clusters, and find that optics clusters tend to conform to three general geographic forms: small, specialized metropolitan areas dominated by a few large firms, cities with a few anchor firms and a number of smaller firms that benefit from the presence of local universities, and large urban agglomerations that are known to specialize in innovation more generally. They further find that anchor firms are one of the most important means of building optics clusters. Patterns of search and collaboration have been a particular focus of the literature on optics clusters. Gaschet et al. (2017) study optics clusters in the European Union using patent data, and find that, due to optics' broad applicability and strong synergies with other industries, it tends to cluster in more diverse technological regions that facilitate recombinatory knowledge production and collaboration across firms. Using US patent data for the optical disk industry, Rosenkopf and Nerkar (2006) analyze the role of search patterns in generating high-impact technological breakthroughs. They find that search patterns that span firm boundaries produce the highest impact within the optical disk industry, and that search that spans both firm and technological boundaries has the highest impact beyond the optical disk industry. This suggests that networks of collaboration are key to producing optics innovations, while inward-looking knowledge production is more likely to lead to technological lock-in or "competency traps."

Hendry et al. (2001) use case studies of opto-electronics firms in Wales and Thuringia, Germany to produce a general model of cluster evolution and inter-firm collaboration patterns over time. They find that, while young clusters tend to benefit from local processes of knowledge sharing and proximity to university research labs, as firms mature, they tend to look farther afield, beyond the regional level. However, as the mature firm becomes increasingly global in scope, local knowledge sharing becomes important again. DeMartino et al. (2006) similarly study knowledge sharing and collaborative linkages in the optics sector in Rochester, NY, and find that, as optics firms become increasingly global in scope, local collaboration relations become less significant in favor of more global connections. In contrast, Hassink and Wood (2006) question whether inter-firm collaboration has been over-emphasized in the opto-electronic industry. Studying opto-electronics industry in Germany, they find that, although the industry exhibits considerable geographic clustering, not all optics clusters exhibit strong inter-firm collaboration patterns. Thus, although some optics producers may exhibit strong tendencies towards collaboration and recombinatory knowledge production, it may be difficult to generalize about these patterns. Although all of these studies investigate some of the structural features of the optics industry both broadly and in different regions, none of them explicitly models how the industry has evolved over time and in different places. This project represents an important and novel contribution to existing literature.

Methods

In order to study the evolution of the optics industry over time, this project uses patent data as a proxy for invention. Although patents are not the only way to measure innovative activity, and not all inventions are patented, patent data are a consistent and reliable source of information on firms' inventive activity, and numerous studies have shown that patenting activity strongly correlates with other innovative activities like R&D (Griliches, 1998). Patents are a rich source of technological information, as they contain data on the particular technological classification of each invention, the year of invention, the inventors and assignees of each patent, the abstract and title of the patent, and the geographic location(s) where each patent was created, allowing us to trace the geography of invention over time (USPTO, 2010). Because traditional sector data using NAICS and SIC codes is often only able to capture the geographic distribution of mature industries, patent data uniquely allows for the identification of emerging sectors within the US technology space (Feldmen and Lendel, 2010). Patent data has been used to study the evolution of patent regimes (Lamareoux and Sokoloff, 1996), the technological relatedness of regions (Rigby, 2013; Kogler, Rigby, and Tucker, 2013), the localization of knowledge spillovers (Jaffe et al., 1993; Sonn and Storper, 2008), the evolution of industries (Feldman and Lendel, 2010; Gaschet et al., 2017), and a variety of other research questions.

For this research, data are compiled from the USPTO between 1976 and 2010. Raw data are compiled and assembled from the USPTO's online Patents View service, and contains information on each patent, including the grant date, title, abstract, inventor and assignee IDs and locations, and a variety of other pertinent information. The city or metropolitan statistical area (MSA) for each patent can be assigned based on the location of each inventor on the patent;

because patents often involve the collaboration of multiple inventors, it is possible for the same patent to be assigned to multiple cities. Because there is no pre-existing industrial classification for patent data, patents are compiled using a text-based search of optics-related key words. To do this, I use the patent abstracts, which provide detailed information on the purpose, composition, and technological contribution of each patent. The keyword list is compiled from the Optical Society of America's Optics Classification and Indexing Scheme (OCIS), and only unique, optics-specific words were used[2] (OSA, 2017). Overall, the words refer to very broad optical categories rather than specific optics technologies, in order to ensure that the dataset include a wide diversity of optics technologies, components, and applications. Keywords are presented in table 3 (with suffixes stemmed to allow for better text matching). Using a keyword search on patent abstracts was determined to be the best way to do this because of the diverse nature of optics technologies; only taking optics-related primary classes would likely miss some optical technologies that interface more with other industries, while only looking at patents assigned to optics firms misses optics patents produced by larger firms that span multiple industries. Using optics keywords is a clear way to capture as many technologically relevant patents as possible.

Table 3: Optics Keywords (OSA, 2017)

optic	holograph
photonic	diffract
laser	optoelectronic
photograph	spectroscop
microscop	scattering
x-ray	

After the set of optics patents was selected, I constructed a network from the subclasses assigned to each patent. Networks are appropriate here because they allow us to understand technological evolution from a relational perspective; technologies are not only important on

[2] E.g. many specific optics categories were excluded from the list because the term "optic" captures the majority of optical technologies, including major technologies like fiber optics and optical waveguides; on the other hand, very broad words like "physics" and "measurement" were also excluded from the list

their own, but in the ways that they build upon and relate to other technologies. Co-classification networks allow us to visualize how individual patents relate to other patents, and to construct technological trajectories based on these patterns of relatedness. All patents are assigned to a series of primary and sub USPTO classifications that provide detailed categorical information on the nature of the technology being patented; broadly speaking, primary classes delineate one technology from another, while subclasses delineate "processes, structural features, and functional features of the subject matter encompassed within the scope of a class," (USPTO, 2012). In practice, because there are only 438 primary classifications, and primary classifications are quite stable over time (new technologies are more likely to be placed in existing primary classes than to lead to the introduction of a new primary class, even if the new technology is meaningfully distinct from those that came before it), the coarse nature of the data makes it difficult to distinguish between individual technologies within technological fields without also considering subclass information.

Subclasses provide more detail about the heterogeneity of inventive activity, and new subclasses are continually introduced to capture the novelty of inventions. However, they also exhibit a complex hierarchical structure in which *mainline* or parent subclasses are classified directly beneath the primary class structure, and *indented* subclasses represent the children or descendents of mainline subclasses, indicating that they are related to classes above them in the hierarchy. Because there is a great deal of heterogeneity within the hierarchical structure (some mainline classes have only one or two descendents while others may have as many as fifteen or more), and because the inclusion of all subclasses yields 157,759 possibilities, this analysis is limited to mainline subclasses. A bipartite network is constructed from patent data such that all unique optics patents, i, form a link to all corresponding subclasses, j in an mxn adjacency matrix. A one-mode projection is then performed to construct an *nxn* adjacency matrix which captures the co-occurrence of mainline subclasses on patents, allowing for the construction of a simplified (weighted) network in which connected subclasses are more related than unconnected subclasses. Subclass pairs then represent different components of technologies in the data.

To better understand how the optics industry has evolved, I cannot simply look at the interactions of subclasses over time; not only do individual subclasses represent technological components or processes rather than unique technologies, but the sheer numbers of subclasses that appear on optics technologies in each year (around 3,000 or more) do not lend themselves to meaningful interpretation. An alternative exploratory tool is to group subclasses into technological categories or trajectories. A promising way of doing this is dynamic community detection. Community detection aims to capture the mesoscopic structure of a given network; communities, or modules, are groups of nodes that are strongly connected to each other but sparsely connected to other dense groups in the network (Porter, Onnela, and Mucha, 2009). This research utilizes Rosvall and Bergstrom's (2008) map equation to detect technological communities in the data. The intuition behind the map equation is simple: suppose you take a random walk through the network structure. A community is a collection of nodes in which the walker spends a lot of time before moving on. More formally, the mapping attempts to encode the flow of information in the network in the most efficient way, using unique codes for each node and module to map this flow with the shortest description length possible. Longer codes occur infrequently (and are often nodes), while shorter codes are traversed more frequently (and are often modules) This is accomplished using the following algorithm:

$$L(M) = q_{\curvearrowright} H(\quad) + \sum_{i=1}^{m} p_{\circlearrowright}^{i} H(\varphi^{i}) \tag{1}$$

where the first part of the equation is the entropy of the movement between modules, and the second is the entropy of movements within modules (p. 1120). Here, L(M) is the description length, given the network partitions, M. $q_{\curvearrowright}$ is the probability that the random walk switches modules on any given step. H(Q) is the entropy of the module codes (i.e. the code words used to describe the random walk on the network). $H(\varphi^{i})$ is the entropy of the within-module movements, including the exit code for module i. The weight $p_{\circlearrowright}^{i}$ is the fraction of within-module movements that occur in module i, plus the probability of exiting module i such that $\sum_{i=1}^{m} p_{\circlearrowright}^{i} = 1 + q_{\curvearrowright}$. The best partition of the network is the one in which the description length is minimized. A fast and stochastic search algorithm is employed in which nodes are assigned to modules, and each node is then re-assigned in random sequential order to the neighboring module that results in the largest decrease in description length, a process which is repeated until the model can no longer be improved (Rosvall et al, 2009).

One clear benefit of the map equation is that we can ensure the robustness of communities by performing many iterations of the model using parametric bootstrap resampling of the edges between nodes; this allows the researcher to compare observed network structure to the proportion of bootstrap samples that support the observation, thus assessing the significance of the model and ultimately allowing the most stable community structure that emerges to be selected (Rosvall and Bergstrom, 2010). I am thus likely prevented from selecting a structure which represents a local minimum, rather than the true community structure. The communities are built based on five-year time slices of the network between 1976 and 2010; the best community structure is determined by running 50 iterations of the model. By running the model over different time periods, I can capture the dynamic nature of technological evolution. Based on the discussion above, it is clear that not only does the prevalence of particular subclasses grow and decline over time, but subclasses are also continually recombined in ways that simultaneously lead to the creation of new technological paths while potentially disrupting older trajectories. The map equation uniquely allows me to map the flow of technological trajectories over time, and to visualize the way in which trajectories in time t can either decline, expand, merge with other trajectories, or split into multiple new trajectories in time t+1. An alluvial diagram, which maps the changing community structures over time, can then be used to visualize the movement of subclasses (and the introduction of new ones) from time t to time $t + \Delta t$ (Rosvall and Bergstrom, 2010). The technological trajectories are named by taking the subclass names assigned to each subclass in a given module, and looking at the most frequently used words to determine a common theme in each. The text of each subclass is modified using typical natural language processing techniques: stop words, special characters, punctuation, and white space are removed, and words are stemmed to ensure that similar words with different suffixes are grouped together. I assigned module names with the help of an expert in the optics field to ensure that categories represented relevant technological themes.

The stability of technological trajectories is measured by computing the similarity between modules from one time period to the next. A simple way to do this is to compute the pairwise similarity of each module in time period t to all modules in time period t+1. This can be done by calculating the percentage of subclasses from one time period that appear in the next time period; if a high percentage of subclasses (e.g. >50%) appear in a module in the next time period, we can generally conclude that the modules represent the same community.

The evolution of cities is computed by selecting all patents and their corresponding mainline subclasses on a city-specific basis. The same subclass co-classification networks that were built out for the entire optics industry can then be constructed for each individual city. The map equation algorithm, as outlined above, is then run for each city to determine the city-specific evolution of optics technologies. Because running the algorithm for each individual city would be extremely time consuming, only a few illustrative case studies are selected for alluvial visualization. The top five most productive optics cities are selected for comparison, and communities and their themes are determined in the same way as for the optics industry as a whole. In this way, we can analyze whether technologies evolve in different ways in different geographic locations.

How can this analysis be generalized across cities? Because the mix of subclasses in different locations is a key driver of evolutionary differences, methods that are common in literature on evolutionary ecology are implemented to measure the diversity of technology distributions in cities over time. Just as species biodiversity is a key driver of evolutionary differences in particular locations, and traits at the species level can impact aggregate community structure, the diversity of technological components in particular cities can help us to make sense of evolutionary differences in technologies and the broader evolutionary paths in which they are situated (Legendre and Legendre, 1983; Whitam et al., 2006). As discussed earlier, a lot of new knowledge is simply a recombination of pre-existing, proximate ideas; because the knowledge base of a region conditions its combinative capabilities, we need to understand just how diverse underlying knowledge structures are in different places. However, the number of subclasses in the data (3366) makes this kind of analysis computationally difficult. Additionally, as discussed above, individual subclasses are not necessarily meaningful in discerning differences between the technologies being produced in different places. As an alternative to subclasses, the map equation is run again, this time for all cities across all time periods to ensure concordance between communities in different years. Although aggregating up to the community level reduces the variation that we would expect to see from one city to another, differences in the distribution of communities in each city may be more illustrative of technological diversity, as the 115 communities detected by the algorithm are comprised of unique mixes of subclasses (components) which represent broader technological categories. The distribution of communities in a city, therefore, gives us insight into the technologies being produced there. A "community matrix" is constructed, in which rows are observations for each of the 16 largest optics-producing cities[3] in two time periods, 1980-1985, and 2005-2010[4]. Columns are the individual communities that appear in each city (measured by the number of subclasses on patents that correspond to each community). Using this data structure, zero-corrected[5] Jaccard similarity measures can be calculated for each city pair in each year as follows: (Clarke, Somerfield, and Chapman, 2005)

$$J(X,Y) = \frac{|X \cap Y|}{|X \cup Y|} \tag{2}$$

or the intersection of communities that appear in both cities X and Y divided by the number of communities that appear in either city. Then, to test whether there are significant differences in community diversity within cities and across time, a permutational multivariate analysis of variance (PERMANOVA)[6] test is performed on the resulting Jaccard distance matrix (Anderson,

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[3] These represent all cities with at least 5000 patents in optics across the whole study period; this is a reasonable decision because the inclusion of cities with a large number of zero values could potentially skew the results, and because this study is primarily interested in evolution within large optics clusters.

[4] Rather than use the whole study period, change over time can be demonstrated just as well using an early and a late time period, and using only twelve years reduces the dimensionality of the data to allow for easier data processing.

[5] Similarity has to be zero-corrected because at least one city produces no patents in optics in some years; to deal with this problem, a dummy subclass is added which is equal to 1 for each city-year observation. This does not change the resulting diversity estimations, and allows the research design to remain balanced, which is an assumption of the PERMANOVA test that should not be violated.

[6] Additionally, PERMANOVA is less sensitive to heterogeneity of dispersions within the data, unlike other similar measures like ANOSIM or the Mantel test (Anderson and Walsh, 2013). Because running a test for heterogeneity in dispersions, using the measure developed by Anderson, Ellingsen, and McArdle (2006), indicated significant dispersion in the data, PERMANOVA is likely the best choice of statistical test.

2017; Anderson and Walsh, 2013). The PERMANOVA test is well suited to this kind of analysis rather than a more traditional ANOVA or MANOVA because it is specifically designed to test for differences in a variety of distance measures (beyond simple Euclidean distance), and makes no assumptions about the normality of the data. Instead, p-values are estimated by a random 999 permutation test. The null hypothesis (H_0) for the PERMANOVA test is that the centroids of the groups (in this case, the arithmetic mean of the year observations for each city) are equivalent for all groups; if the means for each city are the same, then there will be no statistically significant differences in the distribution of communities across cities. On the other hand, a rejection of the null hypothesis suggests that there are significant differences in the diversity of subclass distributions across cities, and we should, therefore, expect evolution to look significantly different in different places and different time periods.

Results and Discussion

The results of the community detection are presented below in the alluvial diagram in figure 3. Bars in each year represent the communities detected by the algorithm, and flows between them represent those subclasses or components that persist from one time-period to the next. The size of the bars is determined by a PageRank algorithm, with the most important communities scaled larger than less important communities. For visualization purposes, only those communities with a PageRank of at least three percent are depicted in order to prevent the diagram from becoming overly cluttered. Because many of the larger communities have a PageRank between 10-20%, the largest communities in each time period are of most interest in understanding the evolution of the optics industry. The technological trajectories of the optics industry are colored according to the categories in the time period 2006-2010; colors that go all the way back in time represent components that have persisted from one time-period to the next in the same community. The base color of the alluvial is gray, and gray flows represent communities that emerge in an early time period and decline before reaching the end of the study period. We can, therefore, visualize the growth, persistence, and decline of technological categories in the optics industry.

Some optics technologies emerge in 1976 and are prevalent throughout the study period. Semiconductor design and light detection and control methods are two examples of technological persistence; they likely represent technologies which have been used in a number of applications and have remained foundational in optics over time. Others have a much more turbulent history. The components that make up coating methods in 1976 split and were combined with a number of other technological trajectories over time (e.g. semiconductors, mirror and lens design, etc.) before eventually re-merging and solidifying into a larger coating category. Technologies like laser design begin in 1976 and their components move around over time before dropping out of optics' evolutionary history in 2005. Other new technologies pop up later in time. Components that make up optical communications do not become a prominent technological category until the early 1990s, and medical device optics becomes particularly prominent after the mid-1980s. Additionally, some technologies become completely new categories over time: rather than emerging on their own, fiber optics emerge from earlier technologies dealing with lens and mirror design. While there is a great deal of disorder in the evolution of the optics industry, it is clear that there are distinct patterns that we can trace over time, confirming hypothesis one. It is also clear that components themselves are multi-purpose; organizations and individuals have continuously found new ways to re-purpose components from one technological area to others, suggesting that there are interdependencies between many of the technologies that are prominent in the data.

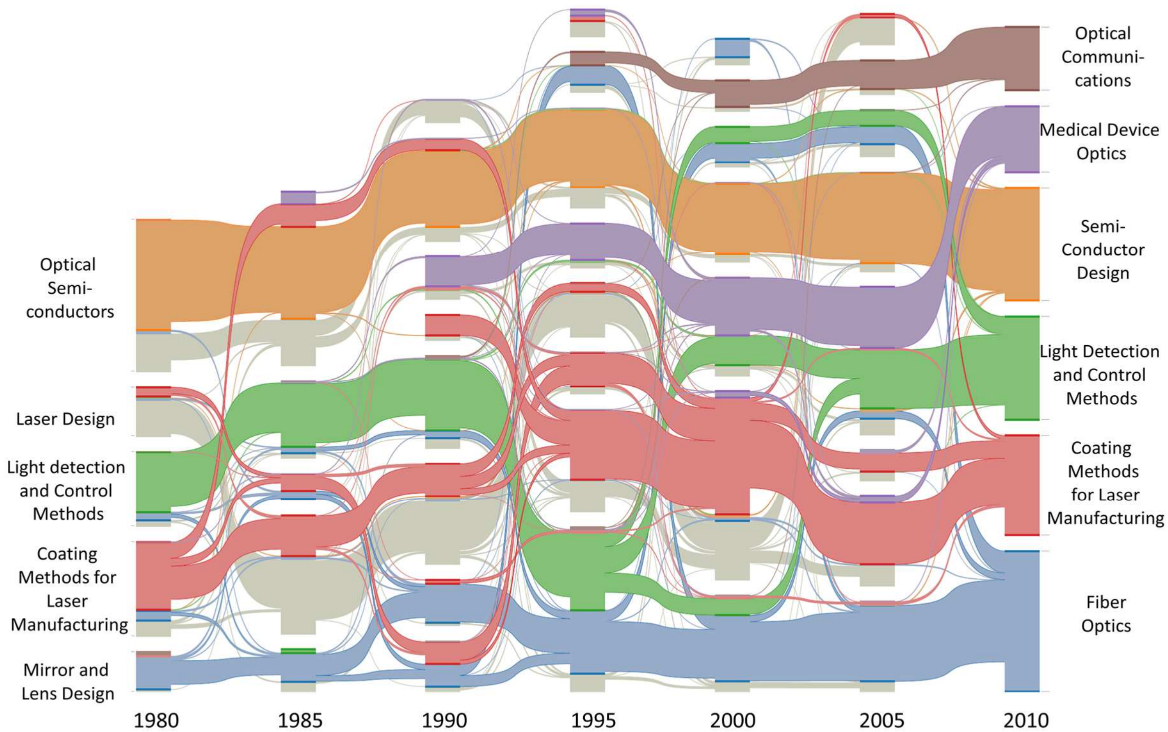


Figure 3: The Evolution of the US Optics Industry, 1976-2010

Table 4 digs deeper into the community structure. Some of the top key words that I identify for each optical category are listed. Although there is some overlap between categories, each appears to make up a unique technological field within optics. The largest category is optical waveguides, with 526 components, followed by semiconductors and lasers. It is important to note that this does not correspond to total patents; while many components may signify many patents, a very complex category may contain many components but few patents, and a simpler technology may have many patents but few components. How similar are communities from one time-period to the next? Do communities change significantly over time? The last three columns of the table calculate the persistence of components across different time periods. As illustrated, there is a lot of variability in the similarity of communities over time. While some trajectories, like semiconductors and fiber optics, become increasingly more similar over time, others continuously incorporate new components. Optical waveguides and silicon photonics are clear examples of this: by 2006-10, less than 40% of components from 2000-05 carry over, suggesting that these fields are continuously combining new components to produce optical technologies. The evolution of optics does not, therefore, look the same for every technology: while some technological paths stabilize over time, others are continuously changing, by branching to form new technologies, incorporating new components, and sometimes even by declining or merging with existing paths. I do not, therefore, find support for hypothesis two. Optical evolution is clearly a diverse and dynamic process.

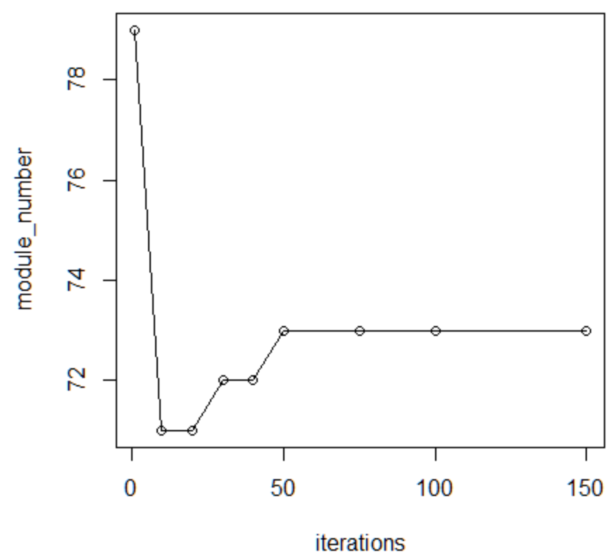
Table 4: Final Optics Communities, and Component Persistence over Time

Category	Key Words	Total Components	1976-1985	1990-1999	2000-2010
Fiber Optics	optical, light, element, waveguide, optic, fiber, plural, reflect, surface, image	526	17%	45%	35%
Optical Semiconductors	semiconductor, layer, structure, device, light, material, substrate, laser, element, optic	282	42%	74%	78%
Light Detection and Control Methods	light, detect, radiate, beam, plural, source, measure, surface, optic, reflect, image	219	30%	--	39%
Coating Methods for Laser Manufacturing	metal, coat, polymer, material, layer, optical, reactant, silicon, atom, group, compound	214	14%	30%	32%
Medical Device Optics	test, measure, optical, acid, carrier, antibodies, optic, nucleic, sample, process, cell	162	--	38%	--
Optical Communications	waveguide, fiber, control, element, feedback, fault, receiver, communication, circuit, transmit, transceiver	106	--	23%	64%

*Communities need to make up at least 50% of a module in order to persist from one time-period to another. In cases where two communities merge into one, the larger of the two is interpreted as the primary community in the module. This is why, for example, medical device optics disappears in some time periods.

How sensitive is the community structure to changes in the model parameters? If subclasses can move from one community to the other depending on the iteration of the map equation algorithm, then there are clear concerns for the validity of this evolutionary model. In order to test the sensitivity of the communities to these changes, the algorithm was run a number of times, varying both the seed value and the number of parametric bootstraps. As the number of bootstraps increases, the number of communities varies and converges on a stable value around 50 bootstraps, regardless of the seed set. This pattern is demonstrated by figure 4 below, which shows the number of bootstraps that were run (iterations) versus the number of modules discovered by the map equation for the 1976-1980 data. Similar patterns are found in the rest of the data. The contents (subclasses) of each community are the same for every successive bootstrap added once convergence is reached. We can generally conclude that the final model is a good representation of the community structure in the data.

Figure 4: Communities per Bootstrap Iteration

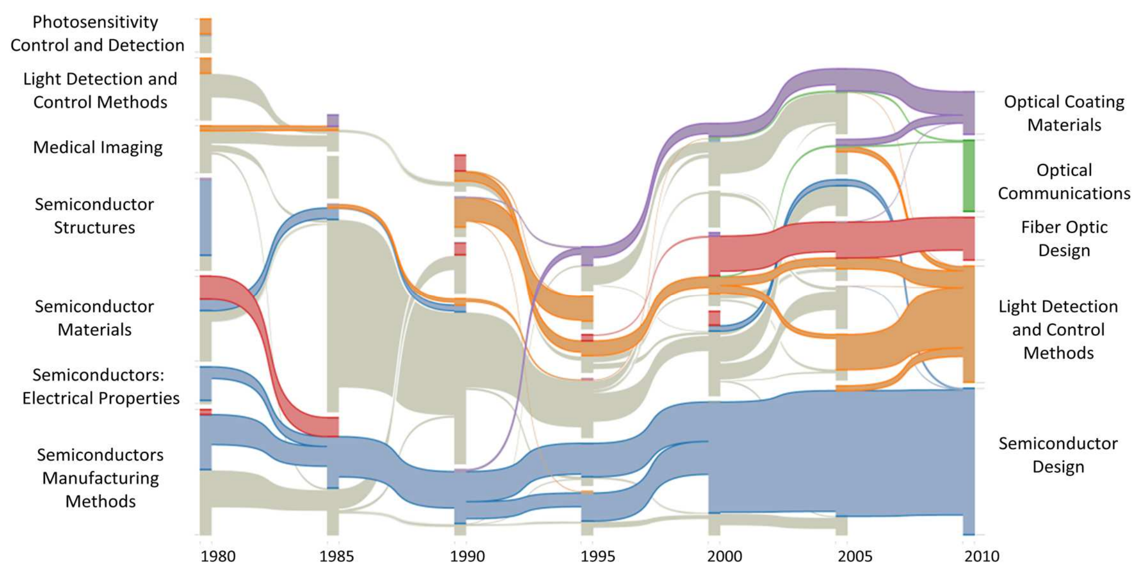


I next look at evolution within individual cities. Using subclass networks at the city level, alluvial diagrams are developed for the top five patenting cities in the data: San Jose, New York, San Francisco, Boston, and Rochester, NY. Figure 5 presents the results of this analysis. There are some commonalities from one city to the next. For example, technological categories dealing with semiconductors, optical coating materials, and light detection and control methods appear in a number of the cities, and generally persist over time. In four of the five cities, categories dealing with fiber optics, optical communications, and optical waveguides emerge later in the period, suggesting that these technologies rise to prominence from about the mid 1990s and onward. The precise nature of these categories differs from one city to the next; some cities produce technologies in multiple categories related to optical communications, while some cities are much less specialized in these types of technologies. The alluvial diagrams are colored according to the sizes of the communities in the period between 2005 and 2010. It is clear that there is a lot of variation in the size and importance of communities from one city to the next; for example, while most cities produce a large quantity of subclasses pertaining to semiconductors, the importance of other communities varies significantly. While some cities like San Jose and New York specialize in fiber optic technologies right away, others, like Boston, do not begin to pick up communications technologies until much later in the time period. There are also clear instances where some technologies rise to prominence and decline or completely drop out of the data by the end of the time period. By illustrating technological change in this way, we can clearly see that there are differences in the evolutionary paths taken from one city to the next, and we can get a better sense of what is happening within each individual city.

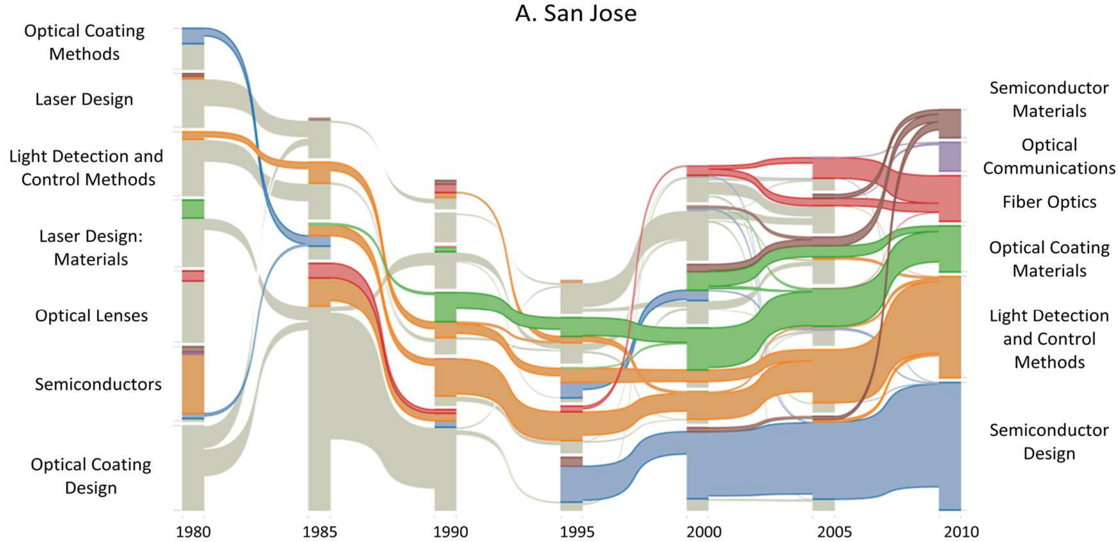
What does evolution look like within each city? San Jose begins 1976 with a number of different categories pertaining to semiconductors and light detection methods; as time goes on, few of the early subclasses persist except those pertaining to semiconductors, which merge into a larger “semiconductor design” category by 2010. Fiber optics becomes prominent in 2000, optical coating methods emerge out of earlier semiconductor technologies, and light detection and control methods become increasingly prominent by 2010. There are a number of technological categories that emerge after 1976, but that do not persist to 2010 (the gray flows), indicating that there has been considerable variability and change in San Jose’s optics sector over time. Despite its close proximity to San Jose, San Francisco seems to have a more diverse optics sector in 1976, specializing in lasers, semiconductors, light detection, and optical coating. Most of the early subclasses are not present later in the time period, suggesting that there is quite a bit of change in the components implemented in optics technologies over time. By 2010, San Francisco looks more similar to San Jose, producing semiconductors, light detection devices, optical coating materials, and fiber optics (after 2000).

New York, on the other hand, has much clearer trajectories over time. In particular, a number of categories relating to semiconductors merge to become one large semiconductor category that appears to be relatively stable over time (with the exception of 1995, in which it briefly splits into two communities). Other technologies exhibit much more variability: the purple trajectory emerges in laser and light detection methods, and proceeds to merge and split a number of times before settling on optical coating materials by 2010. Optical coating processes exhibit a similar pattern, and emerge out of an earlier semiconductor community. This suggests that early technologies are being repurposed or recombined to produce entirely new optical fields. New York also adopts fiber optic technologies earlier than the bay area cities, beginning in 1995 rather than 2000. Like the other three cities, Boston also begins producing semiconductors early on, and continues to produce them through 2010. Like San Jose, Boston is heavily specialized in light detection and control methods. Boston also produces a large number of subclasses in lens and mirror design, and later on produces optical waveguides, illustrating that the city’s optics sector produces a slightly different mix of technologies than the other top cities. Rochester is the most dissimilar of the five cities. Specializing early in lens and camera design (likely influenced by the presence of Eastman Kodak), Rochester follows a relatively turbulent path, which is illustrated by the fact that its trajectories are particularly challenging to trace over time. By 2010, Rochester has moved into coating processes and light detection methods, although camera design persists across the whole time period. While it has diversified its optics sector over time, Rochester still remains heavily tied to its photographic roots. Overall, these small snapshots of each city's optics industry illustrate considerable variation both in the kinds of technologies that different cities specialize in, as well as in the pathways that each city follows from one year to the next.

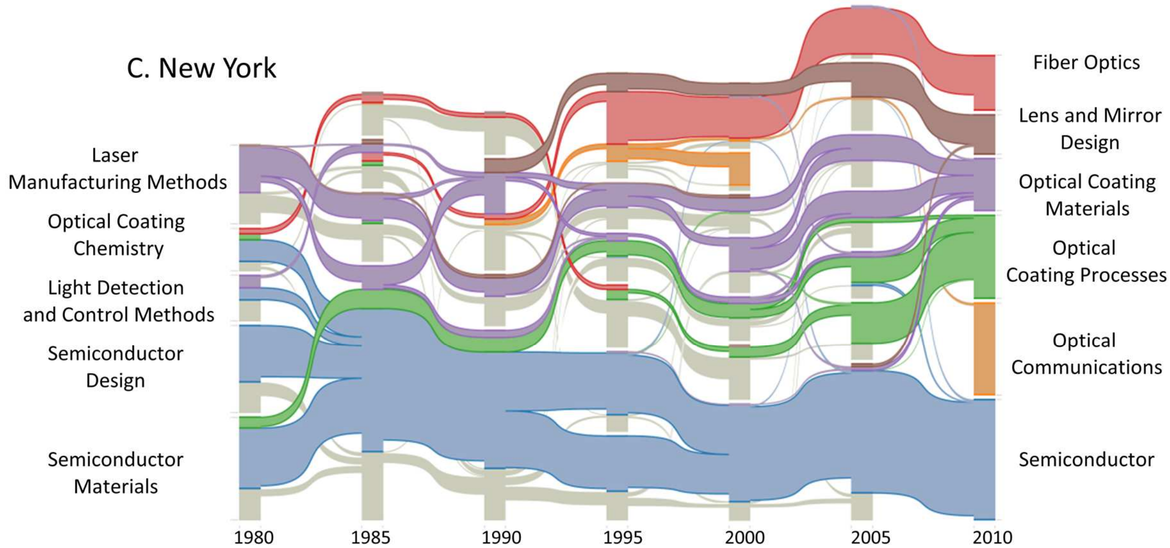
Figure 5: Technological Evolution in Optics by City, 1976-2010

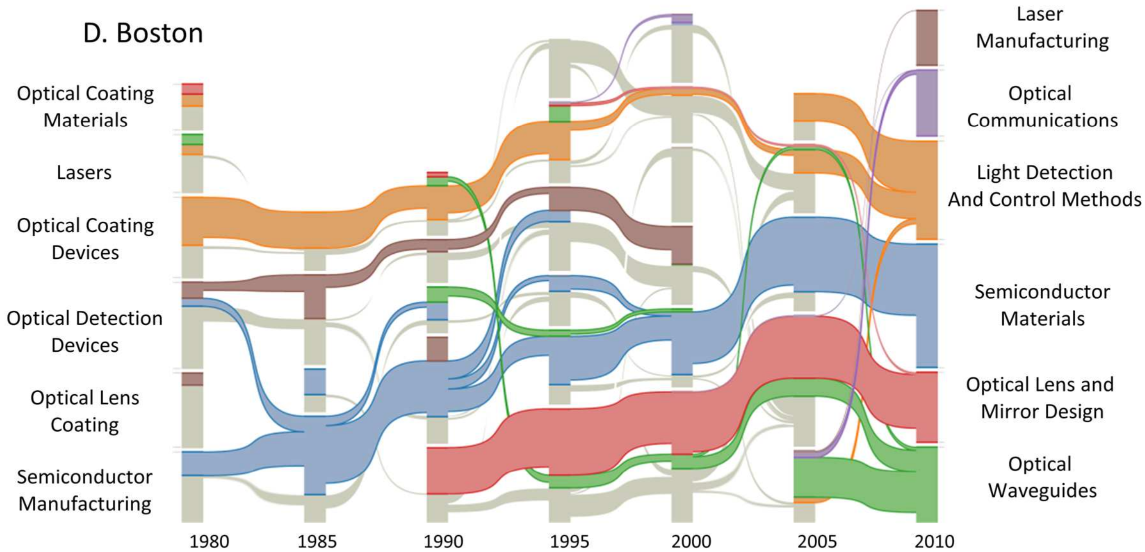


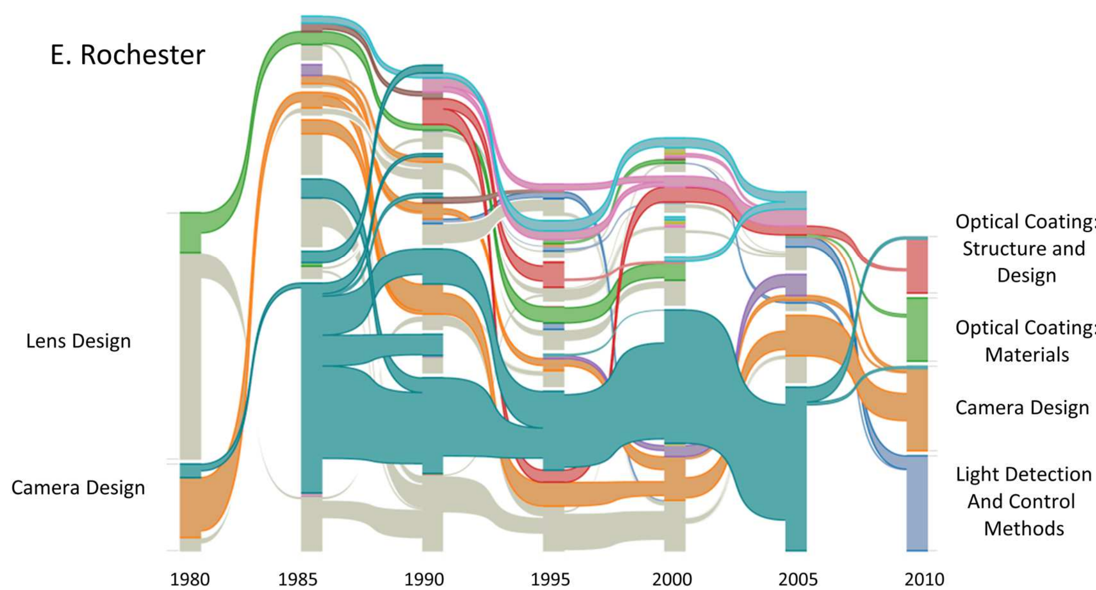
A. San Jose



B. San Francisco


C. New York
Laser Manufacturing Methods
Optical Coating Chemistry
Light Detection and Control Methods
Semiconductor Design
Semiconductor Materials
Fiber Optics
Lens and Mirror Design
Optical Coating Materials
Optical Coating Processes
Optical Communications
Semiconductor
1980
1985
1990
1995
2000
2005
2010


D. Boston
Optical Coating Materials
Lasers
Optical Coating Devices
Optical Detection Devices
Optical Lens Coating
Semiconductor Manufacturing
Laser Manufacturing
Optical Communications
Light Detection And Control Methods
Semiconductor Materials
Optical Lens and Mirror Design
Optical Waveguides
1980
1985
1990
1995
2000
2005
2010


E. Rochester
Lens Design
Camera Design
Optical Coating: Structure and Design
Optical Coating: Materials
Camera Design
Light Detection And Control Methods
1980
1985
1990
1995
2000
2005
2010

The results of the PERMANOVA test are presented in Table 5. Given the significance of both the MSA and year terms, we can generally conclude that there are significant differences in the distribution of communities across places (more specifically, we can reject the null hypothesis: there are significant differences between the centroids of the groups), and that those differences vary across time. But do those differences also persist in cities from one time period to another? To investigate this, an additional PERMANOVA test was run with a "decade"[7] term, as well as an interaction term between cities and decades. Results of this are presented in Table 6. The MSA*Decade term captures whether there are significant differences in centroid values within cities between the two time periods. The significant result suggests not only that there is significant variation between cities and across time, but also that individual cities change significantly over time as well. This upholds both hypotheses 3 and 4, illustrating not only that the top optics cities differ significantly in the mixes of subclasses that they employ in the production of optics technologies, but that these differences are persistent over time, both between and within cities. We would expect, therefore, that the evolutionary trajectories from one city to another likely take on very different forms, and that the nature of the optics technologies produced within cities likely exhibit strong regional differences, depending on the regional distribution of pre-existing technological components, inventors' abilities to create new components or recombine existing ones, and other contextual factors which condition regional organizations' capacity to learn and to produce new technological possibilities.

[7] Because the observations are already city-year observations, using a "year" term here would result in one observation per group, which cannot work because the PERMANOVA must be able to take the average (centroid) within groups.

Table 5: Result of PERMANOVA Test for Spatial Differences

	DF	Sum of Squares	Mean Squares	F	R^2	P (> F)
MSA	15	7.646	0.510	3.502	0.210	0.001***
Year	11	4.797	0.436	3.00	0.132	0.001***
Residuals	165	24.016	0.146		0.659	
Total	191	36.459			1	

Signif. codes: *** = 0.001, ** = 0.01, * = 0.05

Table 6: Result of PERMANOVA Test for Spatial Differences Over Time

	DF	Sums of Squares	Mean Squares	F	R^2	Pr(>F)
MSA	15	7.656	0.510	3.851	0.210	0.001***
Decade	1	3.000	3.000	22.662	0.082	0.001***
MSA*Decade	15	4.635	0.309	2.334	0.127	0.001***
Residuals	160	21.179	0.132		0.581	
Total	191	36.459			1	

Signif. codes: *** = 0.001, ** = 0.01, * = 0.05

These results provide interesting insight into the evolution of a single industry. There are, of course, clear limitations to this kind of project. By studying cities individually, I am assuming that there are no interdependencies between cities; this is likely an unrealistic assumption, because not only do firms often have multiple offices in different locations, but inventors often collaborate across space as well (e.g. Bathelt, Malmberg, and Maskell, 2004). Future work in this area should take these patterns of inter-regional knowledge sharing into account, as they likely also play a role in determining the evolutionary trajectories of technologies. It is also likely the case that the evolution of the optics industry is influenced by other related industries. I limit the scope of this analysis not only to tell a more manageable evolutionary story, but also because identifying other industries that should be taken into account presents clear identification challenges. Further, I am unable to make any statement about why different technological components, and, by extension, the technologies that they comprise, are initially present in some places and not others. This research produces a rich descriptive history of the optics industry, but makes no causal claims about what drives optical evolution, aside from the idea that location conditions recombinatory possibilities. The locational decisions of firms, the influence of universities and research institutes, the presence of key inventors, resources, and funding opportunities, and many other factors likely shape evolutionary processes, and future work should seek to understand the role that these factors play. This research is intended to be a starting point to understanding how industries and regions evolve, which will hopefully spark deeper investigation into evolutionary processes and mechanisms.

Conclusion

As regional economies become increasingly structured around high-tech, innovative industries, there is a growing need for research that seeks to trace and understand how technologies grow, decline, and co-evolve with the growth and decline of cities and regions. This project is a step towards understanding how one particular industry, optics, has changed and evolved over time in US cities. Using patent data from the optics industry and dynamic community detection, I trace the evolution of the optics industry as a whole as well as at individual city levels, and ultimately find that, while some technologies exhibit relatively stable trajectories over time, others are very dynamic, continuously adding new components and combining with other technological paths over time. This creates exciting new possibilities for understanding how industries grow, decline, and change over time. Further, at the city level, there is strong evidence that the evolution of optics technologies exhibits variation from one place to another. Looking at alluvial diagrams in different cities, not only do technological trajectories exhibit very distinct differences, as cities follow unique technological pathways over time, but additional analysis using methods from community ecology suggests that the distribution of technological categories in cities is significantly different over time and space. All of this suggests that we can expect evolution to vary geographically, and that understanding the particularities of place is an important component for understanding why the development of industries is geographically uneven. This project further highlights the fact that much more work is needed in this area to better understand why evolution unfolds the way that it does, and what characteristics allow some cities to capture particularly successful evolutionary paths while others cannot. Even as technologies evolve over time, there is considerable space for future work that seeks to understand the co-evolution of technologies and the places where they are produced. Being able to delineate evolutionary trajectories at different times and in different spatial scales is an important foundational piece for these future analyses.

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