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Economic Crises, the Mobility of Displaced Inventors, and Regional Resilience

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy in Geography

by

Melissa N. Haller

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ABSTRACT OF THE DISSERTATION

Economic Crises, the Mobility of Displaced Inventors, and Regional Resilience

by

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Doctor of Philosophy in Geography

University of California, Los Angeles, 2022

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Abstract

In recent decades, the United States and other advanced economies have transitioned from an industrial, manufacturing-based economic system to one structured around high technology industries and the production of knowledge. Under this “knowledge economy”, knowledge becomes the primary basis for an organization’s competitive advantage, and the ability to create and commercialize new knowledge faster than competitors is crucial to any organization’s success. The fast pace of technological change has the tendency to create unprecedented prosperity while displacing ideas (and often firms and industries) that came before through a process of creative destruction. Although a significant body of literature has studied the job loss and “deindustrialization” that occurred as a result of the decline of the US manufacturing sector, considerably less work has studied job loss and economic change within the knowledge economy. This research gap is a principal motivation for this dissertation.

Job loss is studied from the perspective of inventors, or the knowledge workers primarily responsible for the production of new technologies and innovations within firms and organizations. Although not all workers formally patent their ideas, studying the inventors on patents may provide a window into the experiences of knowledge workers more broadly. Chapter 1 examines the mobility of inventors across firms and geographic regions as they leave struggling firms. It assesses not only the characteristics of inventors who patent again after job separation, but also the regional conditions that best promote patenting re-employment within local firms. Chapter 2 expands this analysis by analyzing the adjustment time between an inventor leaving a declining firm and patenting again for a new firm, and the impact of this adjustment on inventors' future patenting careers. The two chapters highlight the possibility of brain drain and regional skill loss that may occur in the aftermath of firm decline. Finally, Chapter 3 examines the impact of inventor mobility on regional innovation and resilience, using Rochester, NY as a case study. This work illustrates some ways that firm decline has the potential to open up new regional growth possibilities, and makes recommendations for policy makers facing these challenges in the future.

The dissertation of Melissa N. Haller is approved.

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Introduction

In recent decades, the United States and other advanced economies have transitioned from an industrial, manufacturing-based economic system to one structured around high technology industries and the production of knowledge. Under this "knowledge economy", knowledge becomes the primary basis for an organization's competitive advantage, and the ability to create and commercialize new knowledge faster than competitors is crucial to any organization's success. The act of creating new knowledge is typically carried out by "knowledge workers", who primarily use knowledge-intensive skill sets in their work instead of performing manual tasks (Ricard, 2020). This includes workers across a broad variety of occupations, including engineers, researchers, scientists, physicians, and programmers. Although knowledge workers once represented a small subset of the American labor force, more workers are earning STEM degrees than ever before, and the size of the knowledge workforce is currently estimated to be 100 million in the US alone and 1 billion worldwide (Graf et al., 2018; Luna-Ostaseski, 2021). Knowledge workers are, therefore, a critical component of the knowledge economy, and are a primary focus of this dissertation.

The knowledge economy, and the capitalist system more broadly, is inherently dynamic: competitive pressures incentivize organizations, firms, and knowledge workers to continually invest in research and development (R&D) activities in order to maintain their competitive advantage (Grant, 1996; Nelson and Winter, 1985). At the same time, the advent of advanced communication and transportation technologies increases the pace at which new forms of knowledge can be codified and transmitted to others, a process which constantly threatens to erode that very competitive edge (Maskell and Malmberg, 1999; Dosi, 1988). This has given rise to a system of constant economic change, as the introduction of new ideas revolutionizes both production and peoples' lives while simultaneously displacing ideas that came before through a process of creative destruction (Schumpeter, 1942). This is not a neutral process, as the destruction of older ideas and technologies often renders some firms and entire industries unable to compete if they cannot adapt to the pace and direction of innovation. As the rate of technological change is seemingly accelerated by the knowledge economy, layoffs and organizational restructuring often occur when firms are not able to maintain their competitiveness. Although a significant body of literature has studied the job loss and "deindustrialization" that occurred as a result of the decline of the US manufacturing sector (e.g. Bluestone and Harrison, 1982; Massey and Meegan, 1987), considerably less work has studied job loss and economic change within the knowledge economy. This research gap is a principal motivation for the chapters that follow.

In recent decades, these kinds of changes have profoundly affected not only individual firms and industries, but economies around the world. The knowledge economy has reconfigured the role and importance of regions in economic development. The most valuable ideas or innovations often start in the form of tacit knowledge, or knowledge that cannot easily be shared or written down (Maskell and Malmberg, 1999; Polanyi, 1966). Once the knowledge becomes codifiable, its value erodes as other firms gain access to it and can incorporate the ideas into their own knowledge base. Because of its nature, tacit knowledge is most easily produced through face-to-face interaction within firm or organizational boundaries, although knowledge spillovers often occur between firms in close proximity to one another (Storper and Venables, 2004; Jaffe et al., 1993). As a result, the process of learning and producing new ideas tends to be concentrated within particular locations, and the monetary benefits of successful innovations are initially very localized. Thus, the emergence of new knowledge is particularly regional in nature.

A second reason that the knowledge economy has a particularly regional character is that knowledge production is dependent upon the regional context in which it takes place. Regions are a nexus of localized capabilities and certain untraded interdependencies which may enhance or detract from the competitiveness of firms and their ability to produce new ideas (Storper, 1995). These factors include infrastructure, resource and institutional endowments, human capital, firms and organizations, networks of interaction and collaboration that influence the day-to-day operations of firms and workers (Malmberg and Maskell, 2003; Hayek, 1960; Putnam, 1993). Much like knowledge, these regional characteristics are unevenly distributed across space, and no two cities or regions are alike.

Finally, the size of a region may influence its innovative potential: when firms in similar industries concentrate in the same place, agglomeration economies emerge from the sharing of resources, the development of specialized infrastructure, the generation of a localized pool of skilled labor, and knowledge spillovers that decrease transaction costs and enhance the efficiency of firm activities (Duranton and Puga, 2003; Krugman, 1991; Ellison and Glaeser, 1994). Larger agglomerations may be particularly conducive to knowledge production both because a) highly skilled knowledge workers are often more likely to move to larger regions to take advantage of wage premiums and better job opportunities and because b) of the combinatorial nature of new ideas: larger regions have larger pools of skilled labor that likely possess a greater variety of skills, capabilities, and ideas, thus increasing the range of technological possibilities that firms and organizations can access and exploit (Nelson and Winter, 1982; Levinthal and March, 1993) (among other reasons).

Although the knowledge economy has created considerable economic opportunity across the United States, it has also given rise to a more spatially uneven economy than ever before, primarily for the reasons mentioned above. As fast growing, “superstar” cities have become hubs for innovation and investment, many other small and medium sized cities have been left behind; evidence suggests that the tendency for large cities to capture new jobs and economic activities has continuously increased over time, leaving “lagging” regions with few opportunities for new growth and development (Balland et al., 2018). As spatial inequality rises, understanding how regions can better prepare for and adapt to economic change is a critical concern for researchers and policy makers today.

In general, the literature on the knowledge economy has focused on how firms and regions can better adapt to the knowledge economy and enhance their innovative capabilities, using large, well-known case studies like Silicon Valley or Boston as models for development policy (e.g. Saxenian, 1996; Owen-Smith and Powell, 2004; Fleming and Frenken, 2006; Gilson, 1999). However, the emergence of a new, successful industry often coincides with the decline or destruction of another. Not only does the loss of a major firm or industry typically cause considerable job loss, but it also can have adverse ripple effects at a regional level: it can entail a loss of regional income, tax revenue, or local consumption spending, a loss of regional human capital if workers move away or switch occupations in order to find re-employment, and additional job losses in related industries or supplier firms, among other impacts. There is a clear need for more work that addresses the destructive side of the knowledge economy, and how knowledge workers and regional economies (especially smaller cities) can adapt and recover from periods of decline. This is the driving force behind this dissertation. In this introductory chapter, I first provide an overview of existing literature on economic decline and creative destruction, job loss and employment transitions, and regional economic resilience in order to introduce some of the key themes of the chapters that follow. I conclude by providing a summary of each chapter, the motivating questions that drive their analysis, and the gap in existing research that each is intended to fill.

I. Background

A. Causes of Economic Decline

While much is known about economic decline, the underlying causes of decline are often contested. Throughout history there have been countless instances of cities rising and falling with the development of industries, as the global economic system is continually revolutionized by new ideas and technologies that transform everyday life (Schumpeter, 1942; Solow, 1957). At its core, capitalism is inherently dynamic, requiring constant competition and experimentation by firms to develop new products, improve processes of production, and fuel new rounds of growth. As a result, the system is always in flux, and capitalist growth brings about both the continual creation of new economic structures and the obsolescence of older industries and technologies (Harvey, 1980). While new industries create prosperity, their success is often concentrated in particular places (namely, big cities), while other places are left behind (Walker and Storper, 1989).

What causes a new industry to form in a particular place? New industries tend to be associated with macro-geographic shifts in the location of production because new "industrial ensembles" have different geographic needs than the industries that came before them (Scott and Storper, 1987). Because of this, these industries have an initial "window of locational opportunity" in which they can generally form in any location, although regional characteristics may make some places more attractive than others (also see Boschma, 1996, and Walker and Storper, 1989). Over time, firms co-locate in particular places to take advantage of economies of scale and the benefits of face to face interaction (Norton and Rees, 1979; Storper and Venables, 2004). Often, new entrants into a growing regional economy are related to existing firms, or are spin-offs from those firms, and the growth of these new companies leads to the development of an industrial cluster (e.g. Golman and Klepper, 2018). As regions specialize in particular industries, they attract specialized workers, both high and low skilled. The most successful of these industries tend to be in larger labor markets, as these decrease the search costs of finding workers best suited to fill job vacancies (Duranton and Puga, 2003). These advantages tend to be further exacerbated as workers sort into labor markets where they perceive they have the best chance of finding a job in their field. As a result, places and the people who live there change as key industries grow; when industries are successful, regions grow and evolve around them.

Industries generally do not continue to grow indefinitely, but eventually become more mature and less dynamic. Sometimes, the forces that catalyze decline are endogenous within the regional economy, or the firm itself. Regionally, the same forces that helped to create a successful industry agglomeration may also derail it: congestion, pollution, rising land costs, and the escalating costs of public services may become a problem if the industry gets too big (Scott and Storper, 1987; Henderson, 1974; Richardson, 1995). Cities have finite geographic space and resources, and cannot grow ad infinitum. Firms may be pushed out of the market if they cannot adapt to these rising challenges. In addition, firms may decline as a result of their own organizational structures and internal inertia. Firm growth typically follows a particular life cycle: drawing on theories from organizational ecology, firms become stable when they are able to build up, reproduce, and improve certain core features and competencies over time, from which they derive their initial competitive advantage (Hannan and Freeman, 1977, 1989; Nelson and Winter, 1982; Heine and Rindfleisch, 2013). Although this stability may initially contribute to the firm’s success and survival, these same characteristics may render a firm unable to adapt to new challenges over time as existing routines and structures potentially become old and obsolete. These characteristics include "sunk costs in plant, equipment, and personnel, the dynamics of political coalitions, and the tendency for precedents to become normative standards," (Hannan and Freeman, 1984, p. 149). If the routines and structures within a firm that once made it successful begin to undermine its efficiency or competitiveness, the firm may begin to decline. Other times, there may be exogenous shocks that force an industry to contract: changes in technology, the introduction of new competitors through trade, recessions, and other shifts in macroeconomic conditions may all play a role (e.g. Bluestone and Harrison, 1982; Martin, Sunley, and Wills, 1993; Autor, Dorn, and Hanson, 2013; Kollmeyer, 2009). Economic decline is a complex and heterogeneous process that effects individual firms, entire industries, and even cities and regional economies in complex and uneven ways.

As prefaced above, one exogenous way in which industries are pushed into periods of decline is through processes of creative destruction and technological change. Creative destruction is a result of the evolutionary nature of capitalism: as new products, technologies, and ideas are continually produced over time, each new industrial "mutation" revolutionizes the economic structure of industries from within. As one new technology emerges, it may disrupt old industries entirely and lead to the creation of new ones. According to Schumpeter (1942), this process of creative destruction is the essential fact about capitalism (p. 82-83). We can see examples of this process throughout history: electric lights replaced gas lamps, the automobile replaced the horse and buggy, the personal computer displaced typewriters. Not all instances of creative destruction are radical: even a seemingly small process innovation may create new competition which commands a decisive cost or quality advantage over other firms in an industry. This may push incumbent firms from the market or force them to substantially cut costs to survive. This may especially be the case if new firms are able to form and take advantage of a new technology before existing firms are able to adapt their structures to the new technological paradigm (Hannan and Freeman, 1984).

Why does “destruction” happen when a new technology is invented? Firms have particular sets of skills which they accumulate over time through their workers. Many of these skills are tacit (Polanyi, 1966; Nelson and Winter, 1982; Maskell and Malmberg, 1999). When a new technology is introduced by a competitor, existing firms may need to produce something new, or replicate the new technology in order to remain competitive. This is especially the case if the new technology is more advanced or efficient than the technologies that the firms were previously producing. However, coming up with something entirely new may be challenging, and replicating a new idea may be equally difficult. Whether or not an incumbent firm can adapt to technological changes depends on how similar the new technology is to what the firm produced before, which determines a firm’s “absorptive capacity”: if the tacit skills required to produce the new technology do not align with the firm’s existing skills, the replica will be imperfect, and the firm will be unable to compete (Levitt and March, 1988; Coen and Levinthal, 1990; Kogut and Zander, 1992; Gertler, 2003). Often, producing a new technology will require a firm to re-train existing workers in a new technology field, or hire new workers who possess the necessary skills, both of which can be a costly endeavor. Thus, only the firms best suited to create and capture this new technology will survive, and less fit firms will contract. In some cases, new technologies are adopted widely, and can have ripple effects across many industries. Technological change has the power to destroy existing industries as it creates new ones.

A number of other explanations have been posed to explain firm decline, especially in the context of trends towards deindustrialization in the late 20th century. One cause is competition from trade. If a firm produces a product that can be made more cheaply elsewhere, trade liberalization may jeopardize the firm's position in the market and its future profits as it is forced to compete with new, lower cost competitors. Evidence suggests that trade is an important factor in explaining manufacturing decline and employment loss across the United States (e.g. Kemeny, Rigby, and Cooke, 2013; Autor, Dorn, and Hanson, 2015; Kollmeyer, 2009; Krugman, 2008). Another common explanation for firm decline is cost escalation. In the 1970s, many firms were facing an aging and energy inefficient capital stock (Bluestone and Harrison, 1982). Finally, some have suggested that changing consumer preferences and consumption patterns, and even the rise of labor unions and increasing upward pressure on wages, have led to considerable economic change (Clark, 1957; Kollmeyer, 2009). While all of these explanations may provide insight into the decline of the manufacturing sector, some may be less fruitful in explaining firm decline in the knowledge economy: for example, because many manufacturing activities are now performed overseas, and US union membership has declined significantly in recent years, cost escalation may not explain the decline of many high technology firms. It is, however, important to recognize that the decline of any firm is likely the result of multiple complex and contingent factors, rather than a single, definite explanation. Although the focus of this dissertation is on the impacts of firm decline rather than its causes, understanding basic theories and explanations for firm or organizational decline provides useful context for the analysis that follows.

B. Job Loss: What do we know?

When a firm experiences a period of decline, it must often invest in labor and cost saving technologies, layoff workers, or close plants entirely in order to cut costs (Massey and Meegan, 1987). Because manufacturing employment in countries like the United States has been hit particularly hard since the 1970s, this has been a focus of much of the literature on employment decline, mass layoffs, and worker transitions. This focus is understandable, as the employment loss in many regions of the country was massive: Rigby (1992) estimates that some US regions lost as much as 56 percent of their manufacturing employment (relative to the rest of the country) from 1950 to 1986, a substantial employment loss. This literature is not limited to traditional manufacturing jobs, however: not only was this period of time devastating for low skilled manufacturing workers but, between 1979 and 1995, displacement rates substantially increased for both skilled, white-collar workers and high-tenured workers, which historically are more stable subsets of the working population (Aaronson and Sullivan, 1998). Overall, both employment growth and employment losses have occurred simultaneously in recent history as advanced economies have transitioned to knowledge-intensive economic activities. This section will focus on insights from this job loss literature, as well as some additional considerations for job loss in the knowledge economy.

How does job loss impact workers? In general, most studies suggest that workers take a pay cut in the initial aftermath of redundancy, and that it often takes time for workers to find new jobs for which they are well-matched. Evidence on earnings losses is mixed, with studies suggesting that workers experience decreased earnings anywhere from three to fifteen years after displacement occurs (Von Wachter, Song, and Manchester, 2009; Burda and Mertens, 1999; Stevens, 1997; Kletzer and Fairlie, 2003). The longer a person remains unemployed, the less likely they are to find employment in the long run (Hein-Weijman, Eriksson, and Henning, 2018). Displacement increases the long-run probability of leaving the labor force, and the drop-out rate is particularly high in the first few years following displacement (Huttunen, Moen, and Salvanes, 2011).

Workers generally have a number of potential options, transition states, or “branching pathways” that they can take in response to job loss: they can pursue local re-employment or self-employment, move to a different location, pursue more diverse economic options (e.g. take on multiple jobs), seek out additional training, retire, or become unemployed or economically inactive (MacKinnon, 2017). The extent to which a worker can redeploy existing skills and competencies in their new job and maintain a similar standard of living as before depends on which pathway they are able to pursue, as well as what kind of economic opportunities they have available to them. Workers generally find re-employment most easily when they can transfer to another plant within the same company (Frederiksen and Nielsen, 2006). Younger workers find re-employment with a higher probability, but are also more likely to transition out of work in favor of seeking additional education. If there are a number of other firms in the same or a related industry within a worker's home city, they are more likely to find re-employment within the first year (Hein-Weijman, Eriksson, and Henning, 2018; Neffke, Otto, and Hidalgo, 2018). However, finding re-employment in the same industry increases a worker's chances of becoming redundant again (Eriksson et al., 2018). However, in cases where most firms in the regional economy are unrelated to the declining firm, workers often have a much more difficult time re-purposing industry specific skills to fit new positions.

A workers' decision to move is dependent on opportunities within the regional economy: similar and related employment opportunities not only increase a worker's probability of finding a new job, but also prevent workers from moving to more distant labor markets in search of re-employment, decreasing the probability of regional "brain drain". For regions that have struggled to adapt to the knowledge economy, this may be a particularly important consideration. More educated workers, including those enrolled in training programs, are significantly more mobile across industries, and also tend to be much more mobile geographically. Less skilled workers tend to be more "sticky" in space (Eriksson et al., 2018). This is likely due to the risks involved with moving: many workers feel a strong sense of geographical attachment to their homes, and researchers estimate that most workers would need to expect a doubling or more of their income in order to even consider switching locations (Dahl and Sorenson, 2009). Wage premiums tend to be higher for highly skilled workers, and workers whose skills are particularly in demand will be more likely to find a high paying job in another city that is a good match for their skills (Wright et al., 2017 Kemeny and Storper, 2012; Scott, 2010). The pressure to move may be particularly high for many workers employed by a declining firm because there may be few employment opportunities locally that are a strong match for their skills, and moving to a larger regional economy may open up significantly more employment options (Wright and Ellis, 2019). Finally, the highest performing workers may be more likely to prioritize job opportunities over other factors like geographical attachment and social ties, causing them to be more likely to consider geographically distant employment opportunities (Martins, 2021). Because of these reasons, regions often lose talented, highly skilled workers after major firm closures, and this may impact economic development possibilities. The impacts of firm decline on knowledge workers' mobility is the primary focus of Chapter 1.

Lastly, the impact of job loss or separation on workers' skills and future job performance may be a particularly important consideration for knowledge workers and their hiring firms. Knowledge workers' primary value added to any organization is their ability to contribute complex knowledge, skills, and expertise to a firm's existing knowledge base. While firm mobility may enhance workers' performance when they switch firms in general (e.g. van der Wouden and Rigby, 2021; Hoisl, 2009), an involuntary move may have the opposite effect. Any job change will involve the redundancy of some of the worker's skills, as no two jobs will make use of a worker's skills in identical ways: when a worker starts a new job, they may find that some existing skills are not useful in the new occupation, while some additional skills may need to be learned (Poletaev and Robinson, 2008; Nedelkoska et al., 2015). If there are few job opportunities in the same field or industry locally, skill loss or decay may be even greater if a worker switches into a new field or occupation. Thus, not only does job separation pose significant costs to the worker in the form of a loss in wages and a costly job search period, but it may also negatively impact the workers' skill retention and their ability to employ those skills in their new job. This focus on job separation and knowledge workers' skills is explored in more detail in Chapter 2.

C. Innovation and Regional Resilience

Finally, a rapidly growing body of literature is focused on regional resilience or recovery in the face of a major economic shock. This literature is particularly helpful in understanding how regions, and the organizations and workers who live there, respond and adapt to the decline of a major firm or industry. There has been considerable debate around what constitutes resilience and how it ought to be measured. For example, Martin and Simmie (2010) outline four primary approaches to understanding resilience. The first is 'engineering resilience': this conceptualizes a regional economy or cluster of firms as existing near an equilibrium or steady state. Resilience, then, is the ability of the system to resist a negative shock and return to the pre-existing equilibrium state. "Equilibrium" here is used similarly to its usage in mainstream economics. This form of resilience, however, does not leave space for adaptation, and instead assumes that there is one singular state to which a system will continually return; this limits its usefulness in understanding real-world scenarios, which are typically varied, complex, and ever-changing. A second, similar conceptualization is 'ecological resilience', which is focused on whether a shock causes a system to move to another regime of behavior. A 'resilient' system or region, then, is one which is able to absorb a relatively large shock without changing its structure. As Martin and Simmie point out, such a conceptualization also seems to assume that there is one equilibrium state to which a system must return, thus similarly closing off the potential for adaption or the development of new states.

A third view builds on these previous conceptualizations by allowing there to be more than one possible state: in this 'punctuated equilibrium' view, a system moves through a succession of stable forms that are triggered by economic shocks or perturbations. While this version feels closer to the real world and the tendency for regions or systems to change form or adapt in response to shocks, it continues to rely on the concept of equilibrium, which may not be a realistic interpretation of economic change. As the authors point out, it is unlikely that regional economies ever truly reach a point of equilibrium. The capitalist economic system is constantly changing and in flux, and regions and their unique constellation of industrial, technological, labor force, and institutional structures, are constantly asked to respond and adapt to these changes. To reflect this aspect of economic change, this dissertation adopts an 'evolutionary' model of resilience (Simmie and Martin, 2009; Martin and Sunley, 2015; Pendall et al., 2008; Boschma, 2014; Christopherson et al., 2010). Under this conception of resilience, resilience is considered 'an ongoing process rather than a recovery to a stable equilibrium state' (Simmie and Martin, 2010, p. 31). This view of resilience recognizes that regions are dynamic; rather than conform to a singular state, a region is a complex system of economic agents that can adapt within a preconceived path, or develop new paths in response to a shock (Grabher, 1993). An evolutionary view of resilience also recognizes the role that the past plays in determining future outcomes, 'not only in terms of constraints but also in terms of opportunities, as it sets the scope for re-orientating technologies, skills and institutions in regions" (Boschma, 2014). Finally, it is important to note that this type of resilience does not necessarily prescribe a particular metric for determining whether a region is resilient: while resilience might mean that a region is able to return to or even surpass previous indicators of economic health, a resilient region might also be one that is able to successfully foster the growth of new industries or diversify into new knowledge domains.

What factors potentially enhance a region's economic resilience in response to a major shock (like the closure of a large firm)? When an economic pathway is threatened or declines, a resilient region is typically one whose economic agents are able to chart a dynamic new growth path by diversifying into new industries or products. For organizations in the knowledge economy, this often involves recombining existing skills or sourcing new, external knowledge in order to shift their technological or productive focus away from the old path and into a new one. The knowledge base of regional economic actors, therefore, plays a key role in the process of regional adaptation. In his summary of the literature on evolutionary resilience, Boschma (2014) identifies three key features that augment this adaptive process. First, industrial variety has been identified as one component that may improve resilience outcomes; in particular, related variety, or the presence of a number of industries that share similar skills, may enhance resilience by providing a large pool of shared resources or knowledge that can be used to build and develop new growth paths; a sector-specific shock, however, may negatively impact many related industries at once (Boschma, 2014; Frenken et al., 2007). In this case, the presence of many unrelated industries may be beneficial for resilience, as unrelated industries are generally protected from a shock that only impacts one industry, and may also provide declining industries with access to new, external knowledge.

In addition, the structure of regional knowledge networks may enhance resilience and adaptability. This feature is addressed in greater depth in Chapter 3. Networks between organizations and workers may impact resilience because, on one hand, actors in a tight-knit network of interaction or collaboration may be better suited to work together to overcome a regional shock. On the other hand, particularly cohesive network structures may present limited opportunities for knowledge recombination or the development of new growth paths. In these cases, a more diffuse network, or a network with access to more distant collaborative partners, may enable regions to overcome this shortcoming (Boschma, 2014; Crespo et al., 2013). Finally, regional institutional structures may strengthen a region's response to a major shock. In particular, the flexibility of local institutions may either enhance or impede regional efforts to chart a new growth path. In highly specialized regions, more specialized institutions may develop which cannot easily adjust or adapt to new economic structures; local leaders or organizations may even become rigid or hostile to change. This is often referred to as 'institutional lock-in' (Grabher, 1993; Neffke et al., 2011). In more diversified regions, or in regions with weaker institutions, it may be easier to promote institutional change, thus creating an institutional environment that better supports the creation of new ideas and new growth possibilities. In summary, each region will contain different endowments of technological and industrial variety, networks of interaction and collaboration, and institutional structures, and the characteristics of these features as well as their interaction are argued to be some of the key determinants of a region's adaptive capacity.

II. Overview of the Dissertation

In this dissertation, I focus on the ways that organizational decline impacts both the career trajectories of knowledge workers and the economic resilience of regional economies. I study this primarily through the lens of inventors and invention: inventors are the scientists, engineers, and researchers who produce new technologies in the form of patents. Patent data are readily available from the United States Patent and Trademark Office (USPTO), and are the most accessible and complete source of historical data that we have on innovation in the United States (Hall et al., 2001). Each patent contains information on the patent's inventors, the organization to which the patent is assigned, the location of both the organization and inventor, the dates that the patent was filed and granted, the length of the patent, the technology classification codes for the patent (using both the US Patent Classification (USPC) and the globally-used Cooperative Patent Classification (CPC) system), the description of the invention, and often an image or diagram of the invention.

Patent data are, therefore, a rich source of information on the technologies produced by organizations (assignees), the ideas and technological content that are embodied by an invention, and the geography of innovation and technological production across the US. Because multiple inventors are often listed on a patent, the data contain valuable information on inventor collaboration which can be used to identify or map collaboration networks. Since the production of new ideas and technologies is a driving force behind the knowledge economy, inventors are a key population of knowledge workers, and the experiences of inventors may provide a window into the experiences of knowledge workers more broadly. There are also serious limitations to using this type of data because not all inventions are patented and not all inventors patent their technologies; these limitations are discussed with greater depth in Chapter 1. However, because data on organizations' R&D activities is otherwise not easily or publicly available, patent data was determined to be the best source of data for this research. Patent data are used in conjunction with Census data on regional economic indicators, as well as original survey and interview data collected from workers who left a major declining firm. An overview of the specific research questions and methods covered by each chapter is provided below.

Chapter 1 is focused on the mobility of inventors who leave declining firms. In this chapter, I ask, how do knowledge workers respond or adapt to job separation? What characteristics are associated with patenting again for a new firm or moving to a new city after separating from a firm in decline? And what regional economic characteristics are associated with higher rates of re-employment of inventors in patenting roles? To examine these questions, I compiled a large dataset of inventors working for a diverse sample of firms in decline that either a) went bankrupt, b) merged with another firm, c) were acquired by another firm, or d) underwent internal restructuring or laid off workers. Using this data, I investigate these questions using linear probability models to assess the inventor and region-level characteristics that influence an inventor's probability of patenting again and moving after separating from the declining firm. While there is a large body of literature on inventor mobility more generally, I argue that inventors working for a declining firm are systematically different from those who choose to switch firms voluntarily or during a period of relative firm growth. In these instances, inventors either lose their jobs at the declining firm or are incentivized to leave, and likely would not have left the firm otherwise. By focusing on these inventors, I fill an important gap in existing literature. This chapter also contributes to current debates on the role of variety in enhancing rates of re-employment after an economic shock: I investigate whether related or unrelated variety improve an inventor's probability of finding a new, patenting position locally, and whether either type of variety decreases the probability that an inventor moves to a new city to seek re-employment. Because promoting and retaining a labor force with a diversity of skills and capabilities may be one strategy that can help regions adapt to a major shock, preventing "brain drain" or the outmigration of knowledge workers may be an important consideration for local policy makers.

Chapter 2 extends the analysis in Chapter 1 by analyzing the impacts of job separation on an inventor's future career performance. I ask the following questions: first, how does job separation impact knowledge workers' productivity and future career performance? In particular, how does the length of the gap period between patenting for a declining firm and subsequently producing a patent for a new firm influence an inventor's future productivity? Second, how do common re-employment strategies, like moving to a new city or switching into a new technology area, further impact an inventor's future performance? Third, is this "gap period" geographically uneven? In other words, do inventors have an easier time finding comparable re-employment in some cities compared to others? Using the data collected for Chapter 1, I investigate these questions first using a survival model to understand the individual-level characteristics and strategies and are associated with finding a new, patenting position more quickly. Second, using propensity-score weighted regression, I test the effects of a) taking time away from patenting and b) switching industries or regions on inventors' future patenting performance. While considerable research has examined the impacts of firm and geographic mobility on inventors' performance more broadly (e.g. Hoisl, 2009; van der Wouden and Rigby, 2020; Miguelez, 2019), this is the first study to examine the impacts of mobility on performance in the context of job separation. While mobility in general often enhances the productivity of inventors, I hypothesized that mobility as a result of job separation from a declining firm would likely have the opposite effect: because searching for a job after a layoff event (or in anticipation of one) is particularly costly, inventors in declining firms will be more likely to accept patenting positions that are not a strong match for their skills, or to even accept a position that requires them to take time away from patenting. Using patent data to explore the impacts of this disruption on inventors' skills enables me to test this hypothesis, contributing to a growing body of research on job separation and skill loss or mismatch (e.g. Poletaev and Robinson, 2008; Nedelkoska et al., 2015). This analysis also has implications for regions, as large-scale job loss or separation and its resulting effects on inventor productivity may have ripple effects throughout the knowledge economy: displaced workers need to find re-employment, and the quality of the re-employment match experienced by knowledge workers may impact regional levels of human capital. If significant workers switch occupations or transition into lower quality employment, productive skills and capabilities may be lost or deteriorate in the transition. The loss of a large local firm may, therefore, not only negatively impact employment and other economic indicators in the immediate aftermath of firm closure, but may also close off some future technological possibilities for a region as skills are lost through disuse or redundancy.

While Chapters 1 and 2 focus on the impacts of firm decline on individual inventors, Chapter 3 considers the impacts of firm decline on regional economic resilience, using Rochester, NY as a case study. The economy of Rochester, NY experienced a considerable economic downturn beginning in the late 1990s, as the three largest firms in the city, Eastman Kodak, Xerox, and Bausch and Lomb (referred to as KXB), all experienced simultaneous declines, laying off thousands of workers. Accounting for 60% of regional employment, the city looked like it would not recover; in recent years, however, the economy is performing much better than expected, and has generally returned to pre-downturn levels of growth and employment. The city has also remained highly innovative, and has experienced considerable growth in high tech firms and patenting. I focus on the resilience of Rochester's high-tech sector from a network perspective. I hypothesized that the widespread job loss caused by KXB's decline both reconfigured the economic base of the region and caused an influx of skilled inventors into smaller and emerging firms in the region, thus enhancing their skills and innovative possibilities. Thus, the destruction of the city's existing economic base created a foundation upon which the city could rebuild and begin to chart a new growth path. Based on this, Chapter 3 explores the following questions: first, how can regions prepare for these kinds of shocks, and in what ways can the loss of a major firm open up new opportunities for path creation? Second, and more specifically, how do networks of inter-firm mobility grow and evolve as laid off knowledge workers obtain re-employment, and does firm membership in these networks enhance regional innovation and patenting? To study these questions, I first collected survey data from former Eastman Kodak inventors to better understand the values and motivations that drove their job search and the decision to stay (or leave) Rochester. This analysis provides helpful context for the second half of the chapter, in which I use methods from social network analysis and patent data to study a) the emergence of networks of inter-firm mobility that were created by inventors leaving KXB to patent for other firms, and b) whether a firm's position in these networks enhances its future patenting output. As Boschma (2014) points out, networks of mobility and knowledge sharing between firms may be an important component of regional resilience, but empirical studies testing this theory are limited. This chapter directly contributes to the literature on regional resilience by studying this issue from the perspective of innovation in Rochester, thus filling a critical research gap. This chapter also concludes with broader lessons for cities undergoing periods of economic decline.

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Chapter 1: Firm Decline and The Mobility of US Inventors

The US has experienced considerable economic dislocation in the last half century. Former industrial regions have been hit particularly hard as the US economy has transitioned from manufacturing-based to more knowledge-intensive activities in recent decades. Forces such as globalization, technological change, and automation have displaced workers of all skill levels and occupations (Bluestone and Harrison, 1982; Massey and Meegan, 1982; Moretti 2012). In this chapter, I focus on the impact of job displacement on inventors. Inventors are the scientists, engineers, and researchers that produce new innovations and technologies within firms and other organizations. Understanding how inventors are affected by economic decline is particularly important for a few reasons: First, as more workers enter STEM fields than ever before, the experiences of inventors may be increasingly relevant to a growing proportion of the US workforce (Fry et al., 2021).

Secondly, the experiences of inventors may be relevant to regional fortunes. New technologies represent an important source of economic value and competitive advantage for regional economies, and technologies are increasingly produced by teams of inventors (Kelly et al., 2018; Romer, 1986; Akcigit et al., 2017; Lamoreaux and Sokoloff, 2005; Crescenzi et al., 2016). The decline of a major firm typically displaces hundreds of inventors, and it often takes years for them to resume patenting (if they ever patent again) (Haller, Chapter 2). Additionally, evidence suggests that knowledge workers have high rates of geographic mobility, especially in response to economic shocks (Dahl and Sorenson, 2009; Wright and Ellis, 2019). If inventors are incentivized to seek re-employment elsewhere, this “brain drain” could be detrimental to regional innovation outcomes[1]. Therefore, tracing inventors' patterns of firm and geographic mobility after a period of economic decline is broadly of interest to cities and policy makers.

In this chapter[2], I examine the mobility of inventors after a firm enters a period of significant decline or goes bankrupt. I use US Patent and Trademark Office (USPTO) patent data to trace the inventors from declining firms as they patent for new firms and relocate to new regions. Using a novel dataset on 110 major US firms that declined between 1976 and 2015, I investigate firstly, which inventors most successfully find re-employment after working for a declining firm. Using a linear probability model, I assess the types of skills and characteristics that best enable inventors to obtain new jobs in patenting positions. Secondly, I consider the extent to which inventors change location to find re-employment, and whether regional characteristics influence patterns of inventor mobility. Patent data uniquely allow me to trace inventors across firms and regions as they resume patenting post displacement. To my knowledge, this is the first research to examine the mobility of inventors from this context.

The chapter is structured in the following way: first, I review previous research on employment transitions and mass layoffs in order to build the theoretical foundations of the chapter. Next, I discuss the data and methods that are used for analysis. Finally, I present the results, discuss their significance, and highlight avenues for future research. Results suggest that an inventor's collaboration networks and the diversity of the technologies she produces are the most consistent determinants of finding a new, patenting position in another firm; more productive inventors are also significantly more likely to seek employment elsewhere when a firm declines. These results are compared to inventors who move during economically favorable

[1] Although this paper does not investigate the impact of inventor out-migration on innovation more broadly. This is an important goal for future research.
[2] A version of this chapter has been accepted for publication in *Environment and Planning A*.

circumstances, in growth periods, and the same characteristics are insignificant. Despite clear inter-firm and regional differences, these results are consistent in all models. The results suggest that inventors with fewer co-inventors and those who produce more specialized technologies have more challenging transitions after displacement, and are more likely to stop patenting altogether. From a regional perspective, the technological diversity of a city significantly influences whether inventors move away to seek out patenting positions or patent again locally.

I. Literature Review

Displacement: Impacts and Reemployment

Technological change and increasing global competition continually transform the economic conditions and opportunities faced by firms. A large portion of job loss over the past few decades has impacted low-skill and low-wage workers, particularly in the face of labor-saving technological change and increasing incentives to offshore production processes (Autor et al., 2003; Krugman, 2008; Baily and Lawrence, 2004). However, decline at the firm level often causes job loss across all occupations and skill levels, especially when plants are closed or many workers are laid off (Bluestone and Harrison, 1982; Massey and Meegan, 1982; Moretti 2012). For example, evidence suggests that offshoring is increasingly leading to job loss amongst high skilled workers in tradeable and service-based industries (Jensen et al., 2005). Although considerable work has focused on job loss and employment transitions in general, comparatively fewer studies have considered the impact of economic redundancy on knowledge workers (and, more specifically, inventors).

There has been considerable research on employment transitions after mass layoffs. After being laid off, workers typically must choose between several potential strategies, including finding work in the same industry, transitioning into a new industry, seeking additional training, and exiting the labor force (MacKinnon, 2017). The majority of workers find re-employment within the first year of redundancy (Eriksson et al., 2018); however, they often do not immediately find a position that is equivalent to their previous job, or in the same industry (Bailey, Chapain, and de Ruyter, 2012). Re-employed workers typically experience earnings losses, although evidence is mixed: studies suggest that workers experience decreased earnings anywhere from three to fifteen years after displacement occurs (Von Wachter, Song, and Manchester, 2009; Burda and Mertens, 2001; Stevens, 1997; Kletzer and Fairlie, 2003).

Individual characteristics, such as age and education level, are also important determinants of re-employment. Younger workers find re-employment with a higher probability, but are also more likely to transition out of work in favor of seeking additional education (Quintini and Venn, 2013). One reason that older workers may have a more difficult re-employment search is because firm-specific human capital is accumulated over time; older workers' skills may be less transferable to new jobs and occupations than younger workers (Kletzer, 1998). Older workers may also have higher pay expectations. Finally, they may also be more likely to opt into retirement in the aftermath of displacement or job separation, rather than face a long and potentially costly job search. This leads to the first hypothesis:

H1: Inventors who patent for a firm longer will be less likely to find re-employment in a patenting position

Additionally, human capital and education are positively associated with re-employment, and workers with lower levels of education tend to have a particularly difficult re-employment search (Lynch, 1986; Riddell and Song, 2011). Although we cannot directly observe the education level of inventors, we can use patent information to proxy for their skills. Using technology classes on inventions, we can determine the kinds of technologies inventors produce, the range or diversity of technical skills exhibited by an invention, and other important information. Displaced workers typically have a longer re-employment search if their skills are not in demand (Quintini and Venn, 2013); by extension, workers with skills that are more broadly applicable across industries, those who specialize in growing skill areas, and those whose skills are particularly valuable or exceptional may have a higher probability of finding re-employment. This leads to the following hypothesis:

H2: Inventors with skills in more diverse technology areas, those who specialize in growing technology areas, and those whose skills are more valuable or rare will all be more likely to find re-employment in a patenting job.

The region where workers live is especially important to re-employment, as regions have differential capacities to absorb redundant workers (Hein-Weijman et al. 2018). Regional employment opportunities may impact whether a worker chooses to remain in the same industry, or transition into a new one. In general, workers are more mobile across firms in regions with either strong localization economies (a large concentration of firms in the same industry) or urbanization economies (a large concentration of firms in diverse industries); there are comparatively fewer opportunities for mobility in regions where one or a few firms dominate the local labor market (Eriksson et al., 2007). In other words, the existence of both related and unrelated variety may enhance re-employment opportunities for displaced inventors: research generally suggests that employment growth is higher in regions with a high concentration of related industries. However, unemployment rates are typically lower in the aftermath of an industry or firm-level economic shock when a region has a high concentration of unrelated economic activities, as most local firms will be protected from the shock (Frenken et al., 2007; Content and Frenken, 2016; Boschma and Iammarino, 2009; Hartog et al., 2012). After displacement, if there are other firms in the same or a related industry within a worker's home city, redundant workers are more likely to find re-employment locally within the first year (Neffke et al., 2018). However, finding re-employment in the same industry often increases a worker's chances of becoming redundant again (Eriksson and Hane-Weijman, 2017). By contrast, in cases where most firms in the regional economy are unrelated to the declining firm, time to re-employment may be prolonged, but there may be more local job opportunities. This leads to the following hypotheses:

H3: Inventors are more likely to be re-employed in a patenting position in their home region when there is a higher concentration of firms that produce similar technologies.

H4: Inventors are also more likely to be re-employed in a patenting position in their home region when there is a higher concentration of unrelated variety

Access to employment opportunities often depends on connections. Over 50% of jobs are attained in part through social networks, and these networks can include professional connections, friends, family, and other acquaintances (Granovetter, 1995). Knowing a person in an organization can vastly increase the amount of information that a job-seeker has about that organization, and having a high-quality connection can increase the odds of finding a high-quality position (Montgomery, 1991; Fernandez, Castilla, and Moore, 2000; Fountain, 2004).

The importance of the strength of ties is often debated: while having many weak ties may provide job seekers with a wealth of information on many organizations, the probability of being hired by an organization may increase with the strength of the tie (and, thus, the strength of the interpersonal relationship) (Granovetter, 1973; Yakubovich, 2016; Van Hoye et al., 2009). Existing literature on employment and networks remains underdeveloped, particularly because information on a job seekers' networks is often not readily available in economic data. Few studies have considered, for example, how the role of networks varies across industries and geography, and this is a key contribution of this research.

Networks may be a particularly important consideration in the case of inventors. Invention increasingly occurs among teams of inventors, and the average size of these teams has increased over time (Wuchty et al., 2007; Crescenzi et al., 2016). No single inventor typically has all of the knowledge required to produce an innovation; rather, inventors take on specific roles in the innovative process, and work together to combine expertise and ideas. Over their careers, inventors build co-invention relationships both within their firms and across organizations. The number of connections an inventor has, the strength of those ties, and the cohesion of the broader network are all factors that may enhance a firm's innovative capacity (Innocenti et al., 2020; van der Wouden and Rigby, 2019). When an inventor is displaced from a job, or leaves voluntarily, these networks may also be beneficial: on the one hand, having more connections in both nearby and more distant firms may provide inventors with more information about potential job opportunities. Inventors may also be more or less willing to move to find re-employment, depending on their level of embeddedness in regional co-invention networks. On the other hand, inventors with more geographically dispersed co-inventor networks (often those in more specialized industries), may be more likely to move to a new region. This leads to the next hypotheses:

H5: Inventors with more co-inventors, and a stronger position within a firm's co-inventor network, will be more likely to be re-employed in a patenting position.

H6: Inventors who have stronger connections to the local firm network will be less likely to move to a new region to seek re-employment. Inventors with more geographically distant connections will be more likely to move to a new region.

Displacement and Geographic Mobility

If the regional economy offers few re-employment opportunities, workers will likely have to relocate to find new jobs. In general, workers only move when the benefits outweigh the costs; Dahl and Sorenson (2009) estimate that the average worker needs to expect a near doubling in income to justify even a short move. Between 2006 and 2007, only 14.14% of workers moved in the United States, and 64% of those moves were within the same county. Evidence suggests that highly educated workers are more likely to move. There are two key reasons for this: first, wage premiums are highest in large and fast-growing urban agglomerations. Research in urban economics has verified the link between population density and wages (Combes et al., 2010; Glaeser and Mare, 1994). On one hand, workers move to these locations because they expect to receive the highest wages there. On the other hand, as larger, more productive firms cluster in big cities, increasing pressures from agglomeration drive up the cost of living; highly skilled workers who expect the largest wage premiums are able to move into those cities, while less skilled, workers in low-wage occupations may find high-cost regions inaccessible (Venables, 2011; Andersson et al. 2007).

Secondly, alongside wage expectations, individuals generally move to locations where they believe they can find a job that is a strong match for their skills (Duranton and Puga, 2004). Workers with advanced degrees have a higher probability of finding a good match in large urban agglomerations: as the number of agents (firms and workers) increases, the expected quality of each employer-employee match improves (Wright et al., 2017 Kemeny and Storper, 2012; Scott, 2010). Skilled workers in smaller cities may, therefore, have clear incentives to move to larger and more dynamic regions in the face of an economic shock, particularly if they believe their skills are in high demand elsewhere. Employment is the strongest determinant of movement for skilled workers during recessionary periods, suggesting that mobility and out-migration rates may be higher for cities undergoing periods of economic decline (Wright and Ellis, 2019). This leads to an additional hypothesis:

H7: More skilled inventors will be more likely to change location to seek re-employment in a new region.

Whether inventors are able to find re-employment locally has important implications for regions. Knowledge and innovation are key sources of competitive advantage for firms (Grant, 1996; Lucas, 1988; etc.), and the most innovative regions are often the most economically successful (Verspagen, 2006; Romer, 1986; Solow, 1957). Patents are a primary mechanism for measuring and tracing innovation (Trajtenberg and Jaffe, 2002), and the inventors on patents drive the production of ideas and technologies that patents represent. Moreover, inventors and their webs of interaction between and across firms further influence regional knowledge production; inventors are important not only for their individual inventive capabilities, but also for their position in networks of collaboration (Van der Wouden and Rigby, 2019; Fleming, King, and Juda, 2007; Lobo and Strumsky, 2008). Literature on inventor mobility suggests that the movement of inventors impacts firm productivity, knowledge production and diffusion, network formation and collaboration rates, and other important aspects of firm and regional performance (Singh and Agrawal, 2011; Breschi and Lissoni, 2006; Almeida and Kogut, 1999; Hoisl, 2009).

When talented people leave their home regions, they take their ideas, capabilities, and relational capital with them. While their new firm may benefit immensely from this move, the home region's economic future may be negatively impacted if it cannot offset this loss. As a result, people, and their movements across firms and space, matter greatly for economic outcomes. In the following analysis, I consider, first, how skills, productivity, and networks influence the employment transitions of inventors to determine which characteristics are most important for finding re-employment in the face of economic decline. Secondly, my work also aims to consider the regional characteristics that best enable inventors to find re-employment locally. While previous research has considered the determinants of inventor mobility in general, no other study has focused specifically on inventor mobility in response to firm decline. Because the mobility of inventors across firms and regions is a crucial component in understanding patterns of economic change, this research is an important contribution to the literature on inventor mobilities, innovation, and regional economic development.

II. Materials and Methods

Research on employment transitions is challenging because detailed information on workers and their locations is not readily available. While most census data do not trace individual workers over time, LEHD data from the Census is available publicly in limited years, and detailed microdata which traces workers over time is difficult to access (Longitudinal Employer-Household Dynamics, 2019). For this reason, patent data are uniquely suited to studying inventors and their mobility.

Using patent records, I am able to identify inventors, the firms that they work for, their location, and the years in which they are actively patenting. When an inventor leaves a firm, new employers are identified by tracing their patenting activity in subsequent years. Because multiple inventors are often listed on a patent, networks of collaboration and co-invention can be built into the analysis. Although this cannot account for all of an inventor's social connections, it is a useful starting point.

There are limitations to using patent data: inventors who retire or stop patenting cannot be traced. Often, in the face of redundancy, workers change occupations. Such strategies may help inventors to overcome the negative consequences of unemployment, but cannot be considered in this research. Finally, not every firm patents. Patenting requires that inventors describe the production of a new technology in detail; therefore, secrecy is an important opportunity cost of engaging in the patenting process, discouraging some firms from patenting (Hall et al. 2001). Producing new inventions and patenting them requires access to significant capital and funding, and is typically more easily accessible to larger, more established firms

(Lamoreaux and Sokoloff, 2005). Some industries value patents much more highly than others; for example, patents may be more valuable to firms that produce pharmaceuticals or semiconductors, while firms that produce beverages, or those in the software industry, may place less competitive value on patents (Shackelford and Jankowski, 2021; Sukhatme and Cramer, 2019). While patents are one of the most comprehensive and accessible data sources on innovation and inventors, it is important to note that many highly innovative firms and workers are not captured by these data.

The analysis is based on a dataset of 110 firms from USPTO data. Data was sourced from the USPTO's PatentsView database[3], and covers the years 1976-2015. While this analysis cannot provide a long-run perspective on inventor mobility, the years covered represent a significant period of economic and technological change in the United States economy. Not only did the US shift from manufacturing to high tech industries after 1975, but it also underwent multiple recessions and economic downturns which negatively impacted firms and workers. To compile the data, all firms in the United States with at least 100 inventors were selected. Next, the number of inventors in each year was aggregated by assignee (firm owner), and the sample was limited to firms whose total number of inventors had declined by at least fifty percent. This yields approximately 900 firms. However, assignee names are often not consistently listed, and a decline in inventors may also occur when a firm changes its name. To ensure that this was not the case, assignee names were manually inspected to ensure that firms in the final sample had either a) gone bankrupt or shuttered completely (12 firms), b) were acquired by a larger firm (63 firms), c) merged with another firm (22 firms) or d) declined more generally, either laying off

[3] Note that PatentsView uses a disambiguation algorithm to ensure that the IDs for inventors and assignees are consistent from 1976 to the present. This allows me to trace individual inventors across time and space using a unique ID for each individual inventor.

workers or restructuring from within while staying open and maintaining ownership (13 firms). Although mergers and acquisitions (M&As) are not necessarily a sign of firm "decline" in a traditional sense, they still represent a significant workforce disruption: evidence suggests that, on average, roughly 30% of the existing workforce is typically deemed redundant as a result of a merger or acquisition event, and this tended to be the case for the firms in the sample (Marks et al., 2017). As such, these firms were also included in order to build a large and diverse database of inventors. A list of all firms in the data, and a more detailed description of the data collection process, can be found in the Appendix. The final dataset contains one observation for each inventor; because inventors often do not patent consistently across years, and drop out of the data for multiple years at a time, it is not straightforward to construct a panel dataset using inventors. Instead, each observation includes information on whether an inventor patented again or moved to a new city after working for one of the declining firms, along with a vector of innovation related characteristics tied to the inventor and original employer (firm), as well as characteristics of the region in which the inventor patented. The independent variables are motivated by both data availability and insights from theory and previous work. These include variables that measure characteristics of inventors' position in collaboration networks, quantify aspects of the technologies that inventors produce, and control for other general inventor characteristics that impact mobility. Regional variables at the Core-Based Statistical Area (CBSA) level aim to capture the diversity of technologies produced within the city, as well as other general economic characteristics. The dependent variable in the first set of regressions, *new firm*, takes the value 1 if an inventor switches firms after leaving one of the declining firms, and a 0 otherwise. In the second set of regressions, *Move* similarly takes the value 1 if a person leaves the home city, and 0 otherwise, and this model is only estimated for the subsample of inventors who patent for a new firm. Regression using a linear probability model with fixed effects is used to determine each variable's effect on moving or patenting for a new firm. The following regression equations are estimated[4]:

$$New\_firm = \beta_0 + \beta_1 network_{itfc} + \beta_2 technology_{itfc} + \beta_3 other_{itfc} + \delta_c + \gamma_t + \alpha_f + \varepsilon_{cf} \quad (1)$$

$$Move = \beta_0 + \beta_1 network_{itfc} + \beta_2 technology_{itfc} + \beta_3 other_{itfc} + \beta_4 CBSA_{itc} + \gamma_t + \alpha_f + \varepsilon_{cf} \quad (2)$$

where *network*, *technology*, and *other* are vectors of individual inventor characteristics calculated across the time period in which an inventor patented for the declining firm. For example, *average patents* is the average number of patents that the inventor produced per year while she worked for the declining firm. CBSA is a vector of region-level characteristics, calculated for the region in which an inventor, *i*, worked during the last year she patented for a declining firm, *t*. Because we know the region, firm, and years in which an inventor patented for a declining firm, and these factors likely influence their ability to find re-employment, δ_c is a CBSA fixed effect, γ_t is a fixed effect for the last year in which an inventor patented for the declining firm, and α_f is a firm-level fixed effect. The CBSA fixed effect is included in the New Firm model to control for differences across CBSAs, while the individual CBSA characteristics are included in the Move model. Because the characteristics of a region likely impact whether an inventor finds re-employment locally, or chooses to move away, using more detailed city-level characteristics in the Move model better allows me to disentangle which factors are the most important determinants of whether an inventor stays in the home region. Errors are clustered by CBSA and Firm.

[4] All analysis is conducted using R statistical software, and the igraph (Csardi and Nepusz, 2006), dplyr (Wickham et al., 2021), and ggplot2 (Wickham, 2016) packages were used throughout.

Network Variables: *Degree centrality* measures the total number of collaborators that an inventor has within her immediate (firm-specific) collaboration network. This is an aggregate count of an inventor's connections. While having more connections may be beneficial, having a small number of highly influential connections may be just as advantageous. *Eigenvector centrality* measures how connected an inventor is to well-connected individuals within her firm. If her connections are also very well-connected, she will have higher eigenvector centrality. *Local/Global Ratio* measures the number of connections that a person has within her home city relative to her geographically distant connections; values greater than 1 indicate that an inventor's connections are more geographically centralized within her home CBSA.

Technology Variables: *Technological diversity* uses the patent classes on an inventor's patents to calculate the entropy of the technologies being produced; if an inventor produces technologies that are spread out across many patent classes, that inventor's patent portfolio is more diverse, and the entropy value is higher. Shannon entropy for each inventor, i, is calculated as follows:

$$\text{Entropy}_i = -\sum_{ij}(p_{ij} \log (p_{ij})) \quad (3)$$

where p is the proportion of patents in each technology class, j, that the inventor produced while working for a declining firm (Guevara et al., 2016). *Technology growth* examines an inventor's technologies in relation to aggregate technological demand: using all USPTO patents, the average growth in a technology class in the year an inventor was displaced is computed. Using the set of all technologies produced by the inventor while working for a focal firm, the weighted average technology class growth is calculated. *Ubiquity* measures how common or rare an inventor's technology portfolio is, given the distribution of technologies across US cities. This is computed by finding the number of US CBSAs in which a technology class is present. Then, the ubiquity scores for each class on each of an inventor's patents are calculated by multiplying the ubiquity of a class by the proportion of an inventor's patent portfolio that is in each class, and these values are summed for each inventor. This is used to find a weighted average of the ubiquity of an inventor's technologies. Because more tacit or rare knowledge cannot easily be codified or shared across long distances, it is often the basis of regional competitive advantage (Maskell and Malmberg, 1999; Hausmann and Hidalgo, 2010). While, on one hand, less ubiquitous skills may be more valuable, on the other hand there may be more employment opportunities in more ubiquitous technology areas.

Other Individual Characteristics: *Total years* captures the total number of years that inventor patented for a declining firm, and is a proxy for experience and firm tenure. *Average patents* counts the average number of patents produced per year by an inventor, and captures inventor productivity. *Citations* measures the average number of citations that an inventors' patents receive while working for the focal firm, and measures the relative value of the inventor's technologies. *Prior Firm Mobility* and *Prior City Mobility* variables control for the number of times an inventor moved prior to leaving the declining firm, as some inventors may generally have a higher preference for mobility.

Region Controls: Because the characteristics of the city in which an inventor lives impact her employment opportunities, a series of variables at the CBSA-level are included in the regression. The first set of variables is intended to capture technological variety in a region; based on the literature, both related and unrelated variety may be beneficial for displaced inventors. *Unrelated Variety* measures the entropy of patent classes, which are aggregated up to 36 broad technology areas (as defined by Hall et al., 2001) in a CBSA in a given year based on the measure developed by Frenken et al. (2007). Each of the broad technology areas groups together related USPTO technology classes, and the diversity of patenting across each broad technology area is a representation of how diverse a region's patent base is across unrelated technologies. In other words, higher values of this measure indicate that a region specializes in a range of technologically diverse and unrelated technology areas. This is also a proxy for urbanization economies. *Average technology concentration* measures the relative concentration of the technological field in which an inventor specializes in a region. A location quotient is computed for each technology area, j, in each CBSA, c, and year, t. The weighted mean is computed using the location quotients and the percent of an inventor's, i, patent portfolio in each area. It is computed as follows:

$$\text{Average Technology Concentration } i = \sum \frac{a_{ji}}{a_i} * \frac{\frac{a_{j,c,t}}{a_{c,t}}}{\frac{a_{j,us,t}}{a_{us,t}}} \qquad (2)$$

where *a* represents the number of patents in a technology area, i indicates patent counts for the individual inventor, c indicates patent counts at the CBSA level, and *US* indicates patent counts at the national level. A high value indicates that there is a high concentration of technologies in a region that are similar to an inventor's technologies, relative to the US concentration. This proxies for localization economies, or related variety.

Finally, a series of variables are included to capture potential employment opportunities in a given region. *Region Size* measures the number of patenting firms in a region (CBSA) in the final year that an inventor patented for a declining firm. Using employment data from the Bureau of Economic Analysis (2019), *employment share* measures each CBSA's share of total US employment in the displacement year; inventors may have an easier transition in larger regional economies that have more jobs overall. *Employment Growth* measures each CBSA's employment growth, averaged over rolling five-year periods. Additionally, some regions may specifically have more employment opportunities for inventors than others. Although factors like

R&D spending or human capital may be good proxies for growth in innovation-driven or knowledge intensive activities in a region, for simplicity I measure growth in patenting jobs more directly. *Average inventor growth* measures a CBSA's average growth in inventors over a rolling five-year period. For reference, Table 1.1 summarizes the independent variables in the model, and what those variables mean.

Table 1.1: Independent Variable Definitions

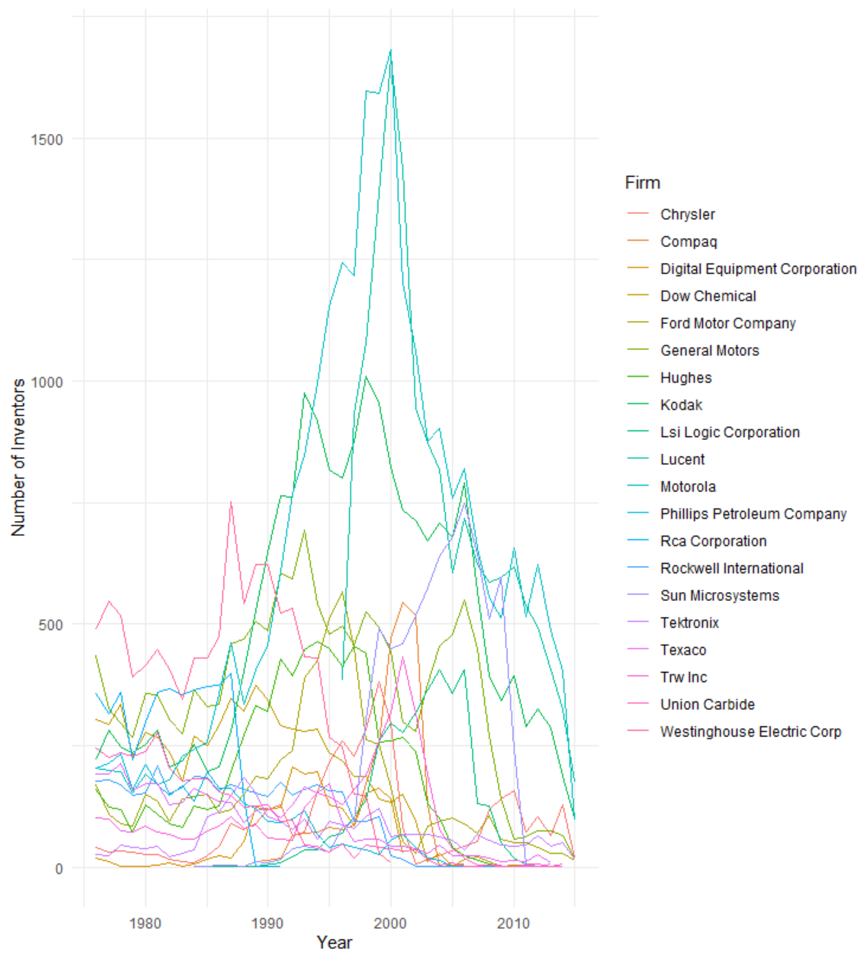
Variable Category	Variable Name	Definition
Dependent Variables	New Firm (Decline)	This variable equals 1 if a) the inventor produced their last patent for the declining firm during its decline period and 2) the inventor patented again for a new firm. It equals 0 otherwise.
	Move (Decline)	This variable equals 1 if a) the inventor produced their last patent for the declining firm during its decline period, 2) the inventor patented again after leaving the firm, and 3) they produced a patent in a new city. It equals 0 otherwise.
Network Variables	Degree Centrality	Total number of co-inventors
	Eigenvector Centrality	A measure of how well-connected an inventor's co-inventors are. Higher eigenvector centrality indicates an inventor's connections are more influential
	Local/Global Ratio	Total co-inventors within the home firm divided by total co-inventors outside of the home CBSA. Higher values indicate that an inventor's connections are more geographically centralized
Technology Variables	Technological Diversity	Higher values indicate that an inventor both a) patents across many technology classes and b) that their patents are not heavily concentrated in any one class. More generally, higher values indicate that an inventor's patent portfolio is more diverse technologically.
	(Weighted) Technology Growth	Average technology class growth over a five-year period, weighted by how many patents an inventor produced in each class. Higher values suggest that an inventor patents in high-growth technology areas
	Ubiquity	A measure of the geographic "rareness" of an inventor's technologies, weighted by the number of patents in each class. Lower values correspond to more rare technologies.
Other Inventor Characteristics	Total Years	Total years patenting for the declining firm
	Last Year Patenting	The last year that an inventor patented for the declining firm. This variable was used to create year fixed-effects in the regression models.
	Average Patents	Average number of patents produced per year (for the declining firm); proxies for patenting productivity
	Average Citations	Average number of citations per patent
	Prior Move	Has the inventor moved before? 1 for yes, 0 for no
	Prior Firm	Has the inventor patented for another firm before? 1 for yes, 0 for no

City (CBSA) Characteristics	Firms	Total patenting assignees (firms or organizations) in a CBSA in a given year
	Employment Growth	CBSA employment growth, calculated over rolling 5-year periods
	Employment Share	Fraction of total US employment by CBSA in a given year
	Technology Concentration (or Related Variety)	Share of patents in 36 technology areas in a CBSA (relative to US average). Weighted average is calculated for each inventor-CBSA-year pairing. Higher values indicate that, in a CBSA, there is a high concentration of patenting activity that is similar to the inventor's technologies
	Unrelated Variety	Diversity of technologies produced in a CBSA, calculated using 36 broad (unrelated) technology areas. Higher values indicate a more diverse technology base in a city or region
	Inventor Growth	Average growth in inventors in a CBSA, calculated over 5-year periods

Figure 1.1 graphs the number of inventors in the largest twenty firms in the dataset over time. Most firms employ the largest number of inventors by the 1990s and begin to decline thereafter. Across the full sample of firms, 1994 is the average peak patenting year, and most inventors are displaced during the subsequent twenty-year period. Importantly, all firms in the sample exhibit a clear pattern of initial growth followed by a period of decline. This information is used in the regression models to compare inventors who patent for a new firm or move to a new city during periods of growth and decline. To measure this, a variable, *decline,* takes the value 1 after the number of inventors in a firm begins to decline, and this variable is interacted with *new firm* and *move* to isolate the inventors who move during this firm-specific downturn. Using this information, the regressions are also run separately for inventors who leave the firm or move during periods of firm growth compared to all other inventors in the sample; these inventors are more likely to have moved voluntarily, either to seek better wages or benefits elsewhere, or for personal reasons. By contrast, inventors who leave when the firm is declining are more likely to do so involuntarily, as a result of displacement, or voluntarily to avoid a potential layoff. In either case, the inventor's motivation for leaving the firm is likely quite different from an inventor who leaves when the firm is growing. Isolating these two groups of

inventors using dummy variables allows me to assess whether these inventors exhibit characteristics that are significantly different from other inventors in the sample. A more detailed description of the dependent variables and their construction can be found in Table A1 in the Appendix. In all regressions, the control group consists of the other inventors in the full sample. In the *New firm* regressions, this consists of the inventors who never patented for a new firm, as well as those who patented for a new firm during the other time period (e.g. for the decline models, inventors who patented for a new firm during the growth period would be in the control group). The *Move* models follow the same pattern, but inventors who never patented again are removed from the sample: because we cannot say whether an inventor who never patented again moved or not, including this group in the model could potentially bias the results.

Figure 1.1: Inventors Over Time in the Largest 20 Firms, 1976-2015



It is important to acknowledge that there is a great deal of heterogeneity that I cannot account for in my model. Inventors may choose to leave a firm for many reasons, including social factors like family obligations or higher pay expectations elsewhere. I cannot observe why an inventor leaves one firm to work for another, and this may introduce some bias into my model. By controlling for the total number of years that an inventor worked for a firm, as well as the number of co-inventors or formal collaborative connections that an inventor has, I can proxy for some social factors: for example, inventors who have lived in a region for a long time, or who have more local co-inventors may be more embedded in or connected to the community in which they live. However, additional research is needed to better disentangle the factors that influence an inventor's decision to move. I also cannot observe why an inventor does or does not patent again: while some inventors may retire, exit the labor force, or transition into new occupations following displacement, I cannot trace these inventors after they stop patenting. Further, patent data does not contain demographic information for inventors: characteristics like age, gender, race, and education level may also play a role in determining an inventor's employment outcomes, but I cannot include this information in my models. Nonetheless, results from the regressions should still provide valuable insight into the characteristics and factors that influence inventors' employment transitions.

Table 1.2 presents summary statistics for the inventor characteristics in the data. Table 1.2A presents summary statistics for the entire dataset, while Table 1.2B presents summary statistics by inventor groups. In Table 1.2B, column 1 presents means for the entire dataset, columns 2 and 3 present means for inventors who work for new firms during periods of firms decline and growth, respectively, and columns 4 and 5 present means for inventors who move to new geographic locations during periods of firm decline and growth. On average, most inventors start patenting for the declining firm in 1993 and stop patenting after 1995, and most inventors patent for 3 and a half years total. Inventors who patent for new firms during periods of decline work for the declining firm 2.2 years longer, on average, than those who leave during growth periods. Those who leave during growth periods may have a greater propensity for firm mobility in general. Inventors who leave during the stage of firm decline also have slightly higher average citations than inventors who leave during growth periods, or do not patent again, they produce slightly more patents, they have a higher quantity and quality of connections, and they patent in technologies that are more diverse. This may be a result of their tenure in the firm: by working for the declining firm longer, they have more opportunities to produce patents and collaborate with other inventors, which may enhance their firm-specific skills and productivity.

Table 1.2A: Inventor Descriptive Statistics (Full Dataset)

Variable	Mean	Standard Deviation	Minimum	Maximum
Last Year Patenting	1995.45	9.83	1976	2015
Total Years Patenting	3.60	4.59	1	39
Global/Local Ratio	2.03	2.43	0	64
Degree Centrality	3.68	4.79	0	143
Eigenvector Centrality	0.009	0.07	0	1
Diversity	0.64	0.59	0	3.39
Average Patents	1.04	0.58	0.06	14.40
Ubiquity	403.79	122.16	6	695
Growth (Weighted)	3.18	33.87	-0.76	956
Average Citations	9.87	15.18	0	1005
Prior Move	0.10	0.30	0	1

Prior Firm	0.20	0.40	0	1
CBSA: Firms	647.24	739.67	1	3095
CBSA: Unrelated Variety	2.91	0.30	0.0	3.30
CBSA: Employment Growth	0.01	0.02	-0.06	0.12
CBSA: Employment Share	0.018	0.02	0.00004	0.08
CBSA: Technology Concentration	1.55	2.02	0.003	129.8097
CBSA: Average Inventor Growth	0.05	0.08	-0.5	3.70
New Firm (Decline)	0.25	0.44	0	1
New Firm (Growth)	0.17	0.38	0	1
Move (Decline)	0.07	0.25	0	1
Move (Growth)	0.05	0.21	0	1

Table 1.2B: Descriptive Statistics by Inventor Mobility

	All Data	New Firm (Decline)	New Firm (Growth)	Move (Decline)	Move (Growth)
First Year	1992.86	1996.10	1991.48	1995.81	1991.09
Last Year	1995.45	2000.14	1993.31	1999.21	1992.74
Total Years	3.60	5.04	2.83	4.39	2.65
Local/Global Ratio	2.03	2.55	1.72	2.21	1.56
Degree	3.68	5.50	3.04	4.99	2.90
Eigenvector	0.01	0.02	0.01	0.02	0.01
Diversity	0.64	0.77	0.61	0.74	0.60
Average Patents	1.04	1.13	1.10	1.18	1.14
Total Patents	3.24	5.32	2.62	5.00	2.68
Ubiquity	403.79	403.47	399.34	400.66	393.23
(Weighted) Tech Growth	3.18	1.72	5.43	1.98	6.70
Average Citations	9.87	11.47	9.42	10.69	9.29
Prior Firm	0.20	0.33	0.27	0.38	0.30
Prior Move	0.10	0.19	0.12	0.34	0.22

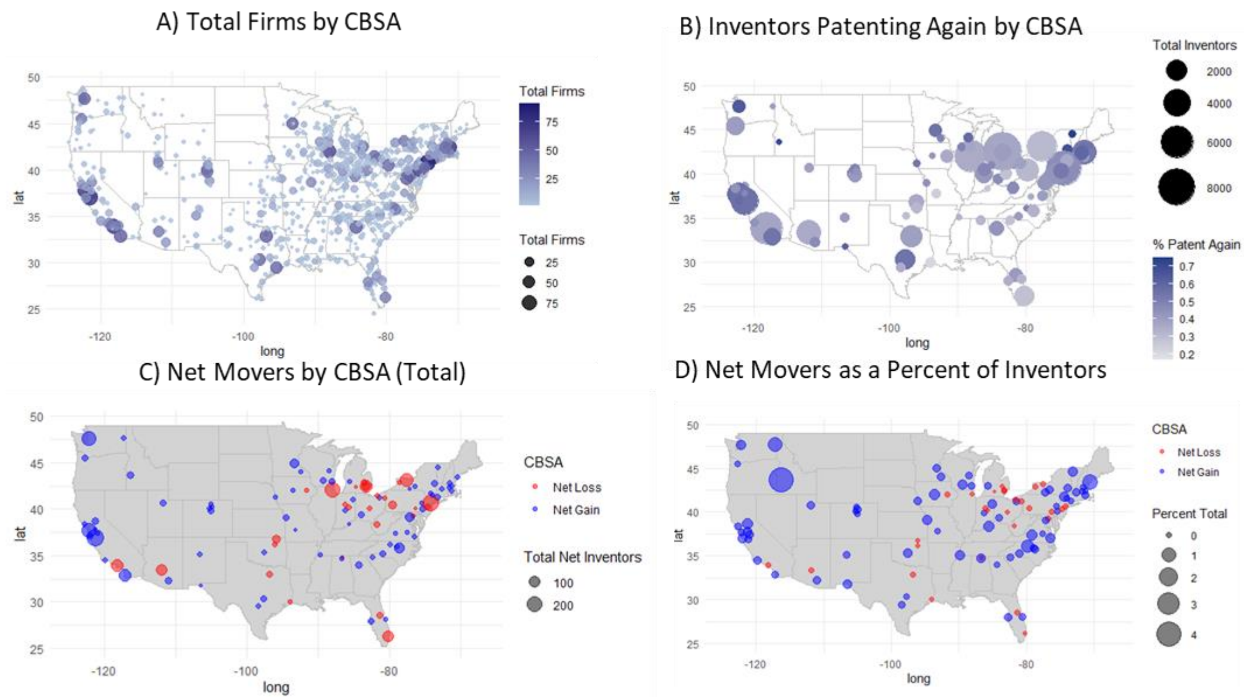
CBSA: Firms	647.24	780.34	628.29	774.99	633.05
CBSA: Unrelated Variety	2.91	2.90	2.95	2.89	2.95
CBSA: Employment Growth	0.01	0.01	0.02	0.01	0.02
CBSA: Employment Share	0.02	0.02	0.02	0.02	0.02
CBSA: Tech Concentration	1.55	1.36	1.60	1.36	1.57
CBSA: Inventor Growth	0.05	0.05	0.06	0.05	0.06

The table presents means for each variable. The data is subset by a) whether an inventor moves to a new firm during a period of firm decline, b) whether an inventor moves to a new firm during a period of firm growth, c) whether an inventor moves to a new CBSA during a period of firm decline, and d) whether an inventor moves to a new CBSA during a period of firm growth.

The geography of inventor mobility is mapped in Figure 1.2. Panel A maps the declining firms in the dataset, and points are sized by the number of firms in each CBSA. In general, the largest concentrations of declining firms in the data are located along the East and West coasts, and in the former industrial cities in the Midwest. There are a few clusters of firms in Texas, Florida, Georgia, and Colorado. The map in panel B focuses on inventors by CBSA. Points are sized by the number of inventors in each CBSA, while the color gradient represents the percent of inventors in each CBSA who patent again. While many of the large CBSAs in the rust belt region of the Northeast and Midwest have large number of inventors who never patented again, inventors in tech hubs like Silicon Valley, Seattle, Austin, and New York are much more likely to patent after a layoff event. Panels C and D map the geographic mobility of inventors by depicting net gains and losses of inventors at the CBSA level as they move post displacement. Panel C depicts total net gains and losses, and the points in the panel are sized by net movers as a percentage of the total inventors from the sample in a CBSA. Cities in blue gain more inventors than they lose, while cities in red lose more inventors than they gain. While larger CBSAs in the Northeast and Midwest (particularly the old industrial region of the US) appear to experience the largest net losses in inventors, west coast cities like San Francisco and Seattle experience large net gains. There is considerable variation amongst smaller US CBSAs, although more small

CBSAs gain inventors than lose them. Turning to panel D, we see that most net gains and losses are relatively small, compared to the population of inventors by CBSA in the sample. Some small CBSAs experience large net gains of inventors: for example, Boise, ID and Portland, ME gain more inventors than they originally had in the sample.

Figure 1.2: Inventor and Firm Locations



Note: Figure A maps the total number of firms in each CBSA (Core-Based Statistical Area) in the sample. Figure B maps the number of inventors who patent again by their home CBSA; the size of the points indicate the total inventors in the sample in a CBSA, while the color gradient shows the percent of those inventors who patent again. Figures C and D depict the geographic mobility of inventors by the net migration flows of inventors into and out of CBSAs. In figure C, blue CBSAs indicate that more inventors in the sample moved into a city than left, while red CBSAs indicate that more inventors left a CBSA than moved in. Points are sized by the total net movers. Figure D illustrates this as well, but points are sized by net movers as a percentage of the total inventors from the sample in a CBSA. CBSAs pictured in figures C and D represent only those locations where inventors in the sample have moved over time.

III. Results

The determinants of patenting again for a new firm are considered more formally. Linear probability regression is performed with firm, displacement-year, and CBSA-level fixed effects to control for differences across firms. Table 1.3 presents the results from the main regressions. In regression 1, the dependent variable (new firm) takes the value 1 when inventors switch to new firms during periods of firm decline. In regression 2, the dependent variable (new firm) takes the value 1 when inventors switch to new firms during periods of firm growth. Regressions 3 and 4 follow the same pattern for the dependent variable *Move.* All inventor-level control variables are included in the models, and region-level control variables are included in the Move models.

More generally, the regressions test the effect of each independent variable on an inventor's probability of either patenting in a new firm or moving to a new city. The values in Table 1.3 present the size of this effect: for example, in Column 1, each additional year that an inventor worked for a firm increases their probability of patenting for a new firm by 0.004, or 0.4%, holding all other variables constant. Stars indicate whether the effect of each variable is statistically significant, and the values in parentheses are the standard error for each variable. Positive values of the regression coefficient indicate that the independent variable increases the probability of patenting again, while negative values indicate that the variable decreases this probability. In the following discussion, I focus on whether the effect of each variable increases or decreases the probability of moving to a new firm or city.

Overall, approximately 23,300 inventors in the sample (25 percent) patent for new firms during periods of decline, compared with 15,500 (17 percent) during periods of growth. The regressions reveal key patterns among inventors who patent again during periods of firm decline. First, I do not find support for hypothesis 1: the total number of years that an inventor patented for a declining firm is positively associated with patenting again for a new firm. It may be that the skills and experience gained during an inventor's tenure at the firm are valuable as the inventor searches for re-employment. I find partial support for hypothesis 2: inventors who produce more diverse technologies, who are more productive (have higher average patents), and whose technologies are more rare (or less ubiquitous) have a higher probability of patenting again in the aftermath of firm decline. Whether or not an inventor patents in a growing technology area does not appear to have a significant effect. The results also support hypothesis 5: having more co-inventors is strongly associated with patenting again, while having more influential co-inventors (eignenvector centrality) is weakly significant, but positively associated with patenting for a new firm. The local/global ratio is insignificant, suggesting that the quantity of connections may be more important than their geographic distribution.

The results also suggest that inventors who patent for new firms during periods of firm decline are different from those who patent for new firms while the firm is performing well: in the growth model, eigenvector centrality is negative and significant, while degree centrality is negative and insignificant. This suggests that inventors who have more influential network connections are less likely to leave the firm during growth periods. Inventors who produce more patents per year, on average, are likely to patent for a new firm during this time, suggesting that the most productive inventors tend to be more mobile across firms in general.

Table 1.3: Determinants of Inventor Mobility

Variable	(1) New Firm (Decline)	(2) New Firm (Growth)	(3) Move (Decline)	(4) Move (Growth)
Intercept	0.480***	-0.210**	0.276***	0.020
	(0.075)	(0.070)	(0.046)	(0.046)
Total Years	0.004**	0.003***	-0.005***	-0.0003
	(0.002)	(0.001)	(0.001)	(0.0005)
Local/Global Ratio	-0.002	0.001	-0.0005	-0.0004
	(0.002)	(0.001)	(0.001)	(0.0009)
Degree	0.005***	-0.001	-0.001	-0.0005
	(0.001)	(0.001)	(0.0006)	(0.0003)
Eigenvector	0.078*	-0.078**	0.045*	-0.009
	(0.047)	(0.034)	(0.025)	(0.024)
Tech Diversity	0.035***	-0.001	0.009***	-0.010**
	(0.006)	(0.004)	(0.003)	(0.004)
Average Patents	0.039***	0.014***	0.015***	0.004
	(0.003)	(0.005)	(0.004)	(0.003)
Ubiquity	-0.0001***	-0.00002	-0.00001	0.000004
	(0.0002)	(0.00003)	(0.00001)	(0.00002)
Weighted Tech Growth	-0.0001	0.00001	-0.00004	0.0001*
	(0.0001)	(0.00006)	(0.00005)	(0.00007)
Average Citations	0.0002	-0.0001	-0.0003***	0.00001
	(0.0002)	(0.0001)	(0.0001)	(0.00008)
Prior Move	0.020**	-0.028***	0.197***	0.080***
	(0.006)	(0.006)	(0.013)	(0.009)
Prior Firm	0.090***	0.074***	-0.029***	-0.0006
	(0.008)	(0.007)	(0.007)	(0.003)
Move	0.317***	0.264***	--	--
	(0.026)	(0.026)		
CBSA: Firms	--	--	-0.000004	-0.00002**
			(0.000008)	(0.000008)
CBSA: Unrelated Variety	--	--	-0.059***	0.031**
			(0.013)	(0.013)
CBSA: Employment Growth	--	--	0.055	-0.702**
			(0.337)	(0.273)
CBSA: Employment Share	--	--	0.251	0.525**
			(0.300)	(0.231)
CBSA: Tech Concentration	--	--	-0.004***	0.004**
			(0.001)	(0.002)
Inventor Growth			-0.069**	0.055*
			(0.036)	(0.031)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	No	No
Observations	91,489	91,489	38,731	38,731
R-Squared	0.296	0.201	0.118	0.124

Significance Levels: * < 0.1, ** < 0.05, *** < 0.01

What inventor characteristics are good predictors of whether an inventor moves away from the city in which they were originally employed? Considerably fewer inventors move to patent for new firms: around 6,000 (or 7 percent) move while the firm is in a period of decline, while around 4,000 (or 5 percent) move during growth periods. Focusing on inventors who move during periods of firm decline, the results clearly support hypothesis 3: the concentration of similar technologies to the inventor's patenting portfolio (related variety) is negative and highly significant, suggesting that inventors are less likely to leave regions where there may be more related patenting opportunities. Interestingly, the results also support hypothesis 4: unrelated variety is negative and highly significant. Taken together, these results suggest that having a high concentration of *both* related and unrelated variety (localization and urbanization economies, respectively) may improve an inventor's chances of finding re-employment locally.

Additionally, the results generally do not support hypothesis 6: during periods of firm decline, inventors with more influential local connections are more likely to move away to seek re-employment, while degree centrality does not have a significant effect. However, inventors who have patented for their firm longer are significantly less likely to move, which may weakly support this hypothesis: inventors who have spent a longer time in one firm have also had more time to build up ties and connections locally (within and outside of their professional life), compared with those who only patented for a few years. Longer firm tenure may also enable inventors to accumulate firm-specific skills and human capital, which may be valuable to future employers in the local labor market. Finally, the results support hypothesis 7. Not only are inventors who are more productive and who produce more diverse technologies more likely to patent for a new firm, but they are also more likely to move to a new city, especially after being displaced by a declining firm.

One potential problem with this model is the construction of the network variables: on one hand, ties created within an organization may persist for the entire duration that an inventor remains within that organization. On the other hand, if an inventor moves around within the company and forms new collaboration ties, ties made early in their career may decay over time. This phenomenon of tie decay has been identified by a number of researchers (e.g. Uzzi and Spiro, 2005; Fleming, King, and Juda, 2007). To test whether the timing of network ties matters for an inventors' future career transitions, I rebuild the network variables using only the last five years that an inventor worked for the declining firm; I use these variables as a robustness check in regressions in Table 1.4. In regression 1, degree centrality remains a strong predictor of patenting again for a new firm after a period of firm decline. In regression 3, the local/global ratio becomes negative and statistically significant, while degree centrality becomes positive and weakly significant. It may be that case that inventors with a greater number of connections formed within the last five years are more likely to move during decline periods; however, if inventors have more local connections than geographically distant ones, they may be more connected to the local community, decreasing their probability of moving. This may provide additional support for hypothesis 6. Eigenvector centrality remains positive and statistically significant.

Table 1.4: Network Variable Robustness Check

Variable	(1) New Firm (Decline)	(2) New Firm (Growth)	(3) Move (Decline)	(4) Move (Growth)
Intercept	0.457***	-0.203***	0.284***	0.020
	(0.074)	(0.070)	(0.046)	(0.045)
Total Years	0.005***	0.003***	-0.005***	-0.0003
	(0.001)	(0.001)	(0.001)	(0.0006)
Local/Global 5	-0.002	0.003	-0.005**	-0.0005
	(0.002)	(0.003)	(0.002)	(0.001)
Degree 5	0.014***	-0.002	0.002*	-0.002***
	(0.001)	(0.001)	(0.001)	(0.0009)
Eigenvector 5	0.037	-0.061*	0.062**	-0.011
	(0.045)	(0.037)	(0.027)	(0.022)
Tech Diversity	0.030***	-0.0004	0.008**	-0.009**
	(0.005)	(0.003)	(0.004)	(0.004)
Average Patents	0.036***	0.014***	0.011***	0.006**
	(0.004)	(0.004)	(0.003)	(0.003)
Ubiquity	-0.0001***	-0.00002	-0.00002	0.000005
	(0.00002)	(0.00003)	(0.00001)	(0.00002)
Weighted Tech Growth	-0.0001	0.00001	-0.00004	0.0001*
	(0.0001)	(0.00006)	(0.00005)	(0.00007)
Average Citations	0.0001	-0.0001	-0.0003***	0.00003
	(0.0002)	(0.0001)	(0.0001)	(0.00008)
Prior Move	0.019***	-0.027***	0.195***	0.080***
	(0.007)	(0.006)	(0.013)	(0.009)
Prior Firm	0.088***	0.075***	-0.029***	-0.0003
	(0.008)	(0.007)	(0.007)	(0.003)
Move	0.315***	0.265***	--	--
	(0.026)	(0.026)		
CBSA: Firms	--	--	-0.000004	-0.00002***
			(0.000007)	(0.000008)
CBSA: Unrelated Variety	--	--	-0.060***	0.031**
			(0.013)	(0.013)
CBSA: Employment Growth	--	--	0.081	-0.700**
			(0.300)	(0.270)
CBSA: Employment Share	--	--	0.283	0.525**
			(0.334)	(0.229)
CBSA: Tech Concentration	--	--	-0.004***	0.004***
			(0.001)	(0.002)
Inventor Growth			-0.070**	0.055*
			(0.036)	(0.031)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	No	No
Observations	91,489	91,489	38,731	38,731
R-Squared	0.300	0.201	0.118	0.124

Significance Levels: * < 0.1, ** < 0.05, *** < 0.01

IV. Discussion

This chapter investigated the individual and regional characteristics that enable inventors to get back to work after displacement. As the United States and other nations transition towards economies built around knowledge-intensive industries, the importance of scientists, engineers, and researchers in regional labor markets has increased in recent years. Considerable research has focused on and debated the role of these workers in economic development strategies, and whether (or not) and how cities should prioritize attracting them (e.g. Florida, 2002, Storper and Scott, 2008; Glaeser and Mare, 1994; Peck, 2005; Kotkin, 2020). However, less work has examined how these workers respond to economic shocks. When a major firm declines and sheds significant numbers of workers, there are often major consequences for cities and regions. Not only do layoffs leave many workers unemployed for a period of time, but they may also induce workers to move to new labor markets if there are not suitable employment opportunities locally. Widespread unemployment and out-migration may induce a loss of regional income and consumption expenditure, put increasing pressure on social safety nets and local resources, and reduce rates of homeownership and educational attainment, among other negative consequences (Davis and Von Wachter, 2011). Out-migration may further divest regions of valuable knowledge, skills, and human capital. It is, therefore, in the best interest of regions to better understand which knowledge workers are able to find comparable re-employment locally, and the regional characteristics that promote the most successful re-employment outcomes.

Using patent data on inventors from 110 US firms that have declined, I used a linear probability model to assess the probability that inventors patent again for another firm or move to another metropolitan area for work. In periods of firm decline, an inventor's collaborative relationships appear to be one of the strongest predictors of transitioning to a new firm. In particular, the quantity of connections (degree centrality) an inventor has improves her chances of patenting again. Further, forming more local than distant ties may decrease an inventor's probability of moving away, particularly when those ties are formed in the last five years at the declining firm. Connections are key sources of information for inventors, and may be a means of helping them to find new jobs during periods of economic crisis. Although my model cannot measure this directly, inventors who have worked for a firm longer may also be more attached to or embedded within their local community, further decreasing their propensity to move.

The diversity of technologies that an inventor produces is a key determinant of firm and geographic mobility. Inventors with diverse technological skill sets may have a much easier time transferring their skills to new industries and occupations following displacement. On the other hand, inventors with more specialized skill sets may have fewer employment opportunities that are well-matched to their skills, particularly if they are displaced as a result of an occupation or industry-wide shock. Inventors with more diverse skill sets are also more likely to move away when their firm declines. This suggests that regions may lose technological diversity when a major firm lays off workers, although quantifying the aggregate effects of inventor mobility at the regional level is beyond the scope of this chapter.

The ubiquity or geographic rareness of an inventors' skillsets also appears to play an important role in transitioning into a new firm. While, on the one hand, the tacit nature of some knowledge allows firms to build and sustain a competitive advantage, on the other hand, possession of such knowledge may make an inventor even more valuable to other firms who want to access that information. Finally, inventors who are more productive at patenting are more likely to transition into a new patenting job following displacement, but are also more likely to move to a new CBSA. In general, the results of this analysis suggest that the same characteristics that help inventors to transition into new patenting careers are also positively associated with geographic mobility.

The characteristics of regions are significant determinants of whether an inventor was able to find a patenting position locally. In particular, this research contributes to discussions on whether variety enhances a city's ability to absorb a major employment shock (Frenken et al., 2007; Hane-Weijman et al, 2018). Both related and unrelated variety significantly increased an inventor's chances of patenting in a new job locally, while inventors were more likely to move away from regions with lower levels of variety. While cities with a large concentration of activities that are related to an inventor's skills may have more re-employment opportunities that are a good match for her current skillset, a high concentration of unrelated variety indicates that there may be more employment opportunities for inventors who are willing to transition into new occupations and technology areas. In the event of an industry-specific shock, finding employment in a new industry may be an attractive option for inventors. Intuitively, living in cities with more employment opportunities in general, as well as cities with strong growth in inventors, decreased an inventor's chances of moving away. All of this suggests that inventors in smaller and more specialized cities are likely to have a more difficult re-employment search, compared to inventors in larger and more diverse regional economies.

There are clear limitations to this analysis. As discussed earlier, inventors who do not patent again, and workers who do not patent, cannot be considered by this analysis. Demographic characteristics and other factors that impact re-employment probabilities cannot be measured using patent data, and an inventor's motivation for moving or staying cannot be captured by this analysis. Further, these results may not be representative of all firms that decline. At the same time, the results remain robust after controlling for interfirm and interregional differences, suggesting that inventors behave in similar ways when faced with potential redundancy. Finally, this research has focused exclusively on individual inventors. Future research should investigate the consequences of firm decline and inventor mobility for broader processes of innovation and regional economic development.

My findings have important implications for regional development policy. While particularly skilled inventors are more likely to patent again, other inventors may struggle considerably more in the re-employment search. Less experienced inventors, those with weaker network connections, and those who were more specialized in within a company may face greater challenges. Further, inventors who are unable or unwilling to move after displacement may have access to fewer employment opportunities, especially in regions with less diversified economies. These inventors may require more re-employment assistance than others. Additionally, this work finds that the most skilled and productive inventors are often incentivized to move away after leaving a declining firm. This "brain drain" may divest struggling regions of valuable inventive skills and human capital. Programs aimed at retaining skilled inventors, or at retraining and upskilling inventors who do not move, may help to offset these losses.

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Chapter 2: Firm Decline, the Patent Gap, and Inventor Performance

Human capital and innovation are increasingly recognized as key drivers of economic growth and prosperity (Moretti, 2013). Maintaining a highly skilled labor force is one way that regions can attract and retain new firms and industries, and is strongly associated with regional productivity and income growth (Hanushek and Woessmann, 2008; Storper and Scott, 2009; Florida et al., 2008; Faggian et al., 2019). In the face of an economic shock like the closure of a major firm, a highly skilled and innovative labor force may also be key to creating and attracting new economic opportunities and recovering more quickly (Balland et al., 2015). While considerable attention has been paid to the factors that enhance workers' skills within firms, networks, and regions, less work has examined workers' skills and capabilities in response to shocks. If a worker is displaced, does she lose skills while she searches for another job, or while she acclimates to her new job? When skilled workers experience significant disruptions to their careers, whether through substantial changes to their work environment, occupational switches, or job separation in general, this has the potential to impact their skill retention and future job performance. Job loss may be particularly harmful, as any time out of work leaves valuable skills and competencies unused by the worker, and a worker's existing skills may not be effectively utilized by employment in a new job (Nedelkoska et al., 2015). This chapter focuses on how different aspects of knowledge workers' skills and performance are impacted by job displacement, and argues that these individual-level impacts are important considerations for both firms and regions.

Because inventors, engineers, corporate scientists, and other knowledge workers are the producers of new technologies and innovations, the impact of job loss on their future performance is particularly relevant to economic development outcomes. An inventor's ability to produce new technologies not only depends on her own human capital, but on other external factors that influence her inventive capabilities. These factors include the organizational and regional environment in which she is embedded, and the dynamics of her R&D team and collaborative relationships (Grant, 1996; Paruchuri et al, 2006; Frank, 1985; Brown and Duguid, 2001). Job loss dislocates the inventor from this familiar context, and requires her to adapt to an entirely new environment as she becomes re-employed. Further, time away from patenting may be particularly harmful, as valuable skills acquired on the job are likely to deteriorate over time through disuse or redundancy (Nedelkoska et al., 2015). Displacement, and the resulting gap between job separation and patenting again, may, therefore, significantly impact the future productivity and patenting output of inventors. While existing research has examined inventor performance in response to other kinds of disruptions (e.g. firm acquisitions – Kapoor and Lim, 2007; Ernst and Vitt, 2000; mobility in general – Hoisl, 2009; van der Wouden and Rigby, 2020; Miguelez, 2019), this chapter considers inventor performance as a result of job separation, and is among the first to do so. Understanding how job separation impacts inventor performance is valuable information not only for researchers who wish to understand the effects of economic shocks on the dynamics of innovation, but also for firms as they make critical hiring decisions.

I use United States Patent and Trademark Office (USPTO) data on nearly 20,000 inventors from declining US firms to investigate the impacts of job separation. Firm decline here is defined as a significant and persistent downturn in patenting output over time; such a downturn typically coincides with bankruptcy, acquisition by a larger firm, or eventual closure. Because many inventors are often displaced at once when a firm declines, the resulting aggregate impacts on inventor performance could have ripple effects at local and regional scales. The chapter investigates three related questions. First, what characteristics of inventors determine the length of the “patenting gap”, or the time between being dislocated from a patenting position at a declining firm and producing a subsequent patent for a new firm? This “gap” period is approximate since an inventor may have been working for a firm for a period of time prior to patenting. Second, does this “patenting gap” vary across space? If inventors patent again much more slowly in some regions than in others, the negative impacts of displacement may be particularly acute in those places. Lastly, and most importantly, how does displacement, and the resulting time away from patenting, impact inventors’ future inventive performance? Patent data uniquely allow me to investigate inventors’ productivity, the diversity of technical skills they possess, their co-inventor ties, and other characteristics of inventive activity that may be negatively impacted by the patent gap.

The chapter proceeds as follows: section two provides an overview of the existing literature on displacement, re-employment quality, and the impacts of career disruption on worker performance. Section three briefly discusses a case study of inventors from a declining firm, in order to better contextualize this “gap” period. Section four describes the construction of the data set, the methods used, and the results. Section five concludes the chapter and discusses directions for future research. In general, I find that taking more than a year away from patenting after displacement has a significant negative impact on inventors’ future patenting productivity, the diversity of technologies they produce, and their co-invention networks. This suggests that displacement significantly impacts inventor performance, skill use and retention, and relational capita. From the perspective of a future hiring firm, providing inventors with targeted resources and support to get back to patenting more quickly may mitigate these negative impacts. I further find that the patenting gap is significantly longer in many smaller US cities, while inventors in larger regional economies tend to patent again more quickly. In general, this research highlights the importance not only of re-employment in response to displacement, but the transition time associated with a career disruption, and its impacts on patenting and innovation.

I. Literature Review

As the US and other countries have transitioned to economies centered around knowledge-intensive activities, rapid technological change has catalyzed job loss in both skilled and unskilled occupations (Jensen et al., 2005). A considerable body of research has examined both the impacts of this displacement on workers and workers' transition to re-employment (e.g. Brand, 2015; Von Wachter et al., 2009; Von Wachter, Song, and Manchester, 2009). Finding re-employment after a layoff or a period of significant firm decline is often more challenging than voluntarily separating from a job under normal conditions for several reasons. First, there is the possibility that being laid off or working for a struggling firm is perceived as a negative signal for worker performance. This may discourage future employers from hiring displaced workers, or increase the probability that a worker accepts a job that is a poor match for her skills (Biewen and Steffes, 2010).

Second, large-scale displacement often occurs during recessionary periods, and many workers are made redundant at once, simultaneously increasing the number of job seekers and decreasing the number of available jobs. When the supply of job seekers increases rapidly, not only does finding employment become more competitive, but research also suggests that some companies raise skill requirements in direct response to the supply shock, making the job search more challenging for many workers (Modestino et al., 2020). Third, displaced workers face particularly large financial and personal pressures to find re-employment after a layoff. Periods of unemployment are individually costly, and workers facing high pressures to find a new job may be forced to take on unsatisfactory employment if there are few high-quality positions available (Leana and Feldman, 1995). If a worker experiences a particularly long period of unemployment, or if she transitions into lower quality employment, this may have significant negative consequences for her future job performance and her quality of life more broadly.

Because corporate scientists and engineers play an important role in regional processes of innovation and R&D, the impacts of displacement on inventors are of particular interest to both firms and regional economies (Lamoreaux and Sokoloff, 2005). However, there is limited research on how job loss or separation, and the duration of time away from patenting, impact inventor performance. Displacement may negatively impact inventors' patenting output for several reasons. First, an inventor's productivity may be a direct result of the firm environment in which she works. Drawing on the knowledge-based view of the firm, innovative performance is influenced by a firm's ability to coordinate the specialist knowledge of its members through its routines and operating procedures (Grant, 1996; Nelson and Winter, 1985). Successful innovation requires more than knowledge itself: knowledge must be assembled and recombined into a usable form. The processes that facilitate this knowledge production form the context in which each individual knowledge worker carries out her own routine. This context will involve a familiar physical setting, colleagues, communication flow, norms, and even emotional support amongst members (Paruchuri et al., 2006; Keller, 1986). A displaced inventor is no longer embedded within this familiar firm environment, and working for a new firm post displacement requires adaptation to an entirely new set of norms, practices, and expectations. Not only can an inventor's performance be diminished while she acclimates to this new organizational environment, but also the new firm environment may never facilitate the same innovative performance that an inventor was able to exhibit while employed by the previous firm.

An inventor's skills and expertise may not be well matched to the core competencies of the new firm. This may especially be the case if an inventor was displaced as a result of an industry or occupation-wide shock; there may be few employment opportunities in the same scientific or technological realm in which the inventor was previously employed. As a result, the quality of the match between the inventor and the new employer may be sub-optimal, influencing future performance (Audretsch et el., 2021). Workers accumulate industry, occupation, and firm-specific human capital over the course of their careers (Neal, 1995; Parent, 2000; Kambourov and Manovskii, 2009; Campbell et al., 2014). Transitioning into a new job after displacement often involves both the redundancy of some skills that are not useful in the new occupation, as well as a need to acquire new skills that are specific to the new occupation and firm environment (Poletaev and Robinson, 2008; Nedelkoska et al., 2015). Skill mismatch in the new occupation may further stunt the inventor's ability to acquire new skills (Guvenen et al., 2020).

Not only can existing skills be a poor fit for an inventor's new job, but displacement often causes the loss or deterioration of some skills over time, particularly as a result of skill mismatch or redundancy. Skill loss is an important and often overlooked consequence of job loss: recent work by Nedelkoska et al. (2015) has suggested that the loss of skills following job displacement may be one of the primary driving forces behind the large and sustained earnings losses that many displaced workers experience (e.g. Von Wachter et al., 2009; Davis and Von Wachter, 2011). Following re-employment, the extent to which previous skills are utilized and new skills are learned can have a large impact on the magnitude and duration of the earnings loss. Because time away from patenting likely causes some deterioration of accumulated skills, and most job or occupational switches will involve some degree of skill mismatch, the technologies produced by the inventor post-displacement may exhibit lower levels of technical diversity. This leads to the following first hypothesis:

H1: Job separation, and time away from patenting, will negatively impact the diversity of technical skills that an inventor employs in future patenting jobs.

Displacement may further impact an inventor's future productivity by severing existing collaborative relationships. Invention increasingly occurs among teams of inventors, and the average size of these teams has increased over time (Wuchty, 2007; Crescenzi et al., 2016). No single inventor typically has all of the knowledge required to produce an innovation; rather, inventors take on specific roles in the innovative process, and work together to combine expertise and ideas (Brown and Duguid, 2001). The most successful firms employ teams of workers or inventors whose skills are highly complementary, and effective teams often develop team or colleague-specific human capital, along with firm-specific human capital, over time (Neffke, 2019; Campbell et al., 2013; Groysberg, 2010). Job displacement also separates the inventor from her existing collaboration networks, and relationships with other inventors may decay over time as an inventor searches for re-employment or transitions into a new firm. If the inventor's new firm does not engage in inter-firm collaboration, the inventor may need to build an entirely new network of collaboration within the new firm's organizational boundaries. An inventor may also experience a considerable loss of status in her collaboration network, particularly as she transitions into a new firm in which her role in the network is not yet established (Paruchuri et al, 2006; Frank, 1985). This may further decrease her innovative performance. These claims underpin the next hypothesis:

H2: Job separation, and the duration of time before patenting again, will negatively impact the number of co-inventors that an inventor collaborates with over the course of her future employment.

The extent of these negative impacts will likely vary across space. Regions have differential capacities to absorb redundant workers that vary by both the size of the regional labor market and the types of employment opportunities available. Displaced workers are most likely to find re-employment within the first year when there are regional opportunities in the same industry as their previous firm, or in related industries (Neffke et al., 2016; Eriksson et al., 2018; Macaluso, 2017). By contrast, in cases where most firms in the regional economy are unrelated to the declining firm, or when most job opportunities have skill requirements that are more remote from a worker's skillsets, time to re-employment may be prolonged, as there may be few local opportunities that are a good match for displaced workers' skills. The quality of the employment match also likely influences the time that it takes an inventor to begin patenting again for a new firm; occupational switches may require considerable on-the-job training before an inventor is able to engage in R&D activities. Although moving to a new city may be one way to gain access to more suitable employment opportunities, research suggests that most workers prefer not to move, and it often takes a near doubling in income to incentivize a move (Dahl and Sorenson, 2009). Instead, workers who wish to remain in their home city may transition into new or more distant occupations, and the resulting skill mismatch may further negatively impact the workers' performance. In the case of inventors, finding re-employment may be considerably easier in places where there are jobs in technology fields within which the inventor has experience. This leads to two additional hypotheses that will be tested in this chapter:

H3: Because regions have differing employment opportunities, the gap between job separation and patenting again will vary from one city to the next.

H4: When inventors are unable to find jobs in the same technological field, patenting in more distant technology fields after job separation will decrease their future performance.

Finally, while a job in a new city may be a strong match for the inventor's skills, relocating may still pose significant consequences for an inventor's future performance and productivity. Like firms, regions also have their own unique mix of agents, industries, norms and conventions, institutions, and infrastructures in place that facilitate the production of new knowledge and innovation. The co-location of these features and their interaction form a region's "untraded interdependencies", which are foundational to processes of learning and innovation within regional economies (Storper, 1995). This is highlighted by the large body of literature that finds that knowledge does not travel well across space, particularly the highly complex knowledge that is produced by inventors (Gertler, 1995; Jaffe et al., 1993; Maskell and Malberg, 1999; Storper and Venables, 2004). An inventor who moves must adapt to this new regional setting as she simultaneously acclimates to the environment of her new firm. Further, because the localization of knowledge is heavily influenced by regional networks of collaboration, an inventor's ability to integrate with local collaboration and knowledge-sharing networks may also impact her innovative performance (Breschi and Lissoni, 2009). Because this regional and territorial specificity impacts the evolution of inventors' organizational routines and knowledge accumulation, I hypothesize that geography may function as an additional source of specific human capital that is lost or deteriorates when an inventor moves away; in addition, adapting to a new regional environment may also be a barrier to an inventor's future innovative performance. This leads to an additional hypothesis:

H5: Moving to a new city after job separation will significantly decrease an inventor's future performance.

The duration of time away from patenting is of particular interest in this chapter because it a) likely intensifies many of the negative factors associated with displacement, and b) may be a direct and observable result of the quality of an inventor's match with her new position. In the case of a high-quality employment match, an inventor will likely be able to resume patenting right away (potentially in a year or less after leaving the previous firm). On the other hand, inventors whose occupational or organizational environment is sufficiently different from their previous position will likely experience a larger adjustment period and, therefore, a larger gap in patenting. Any deterioration or redundancy of skills or connections that occurs while the inventor is not patenting may further influence her future patenting output as well. All of these confounding effects lead to one final and more general hypothesis:

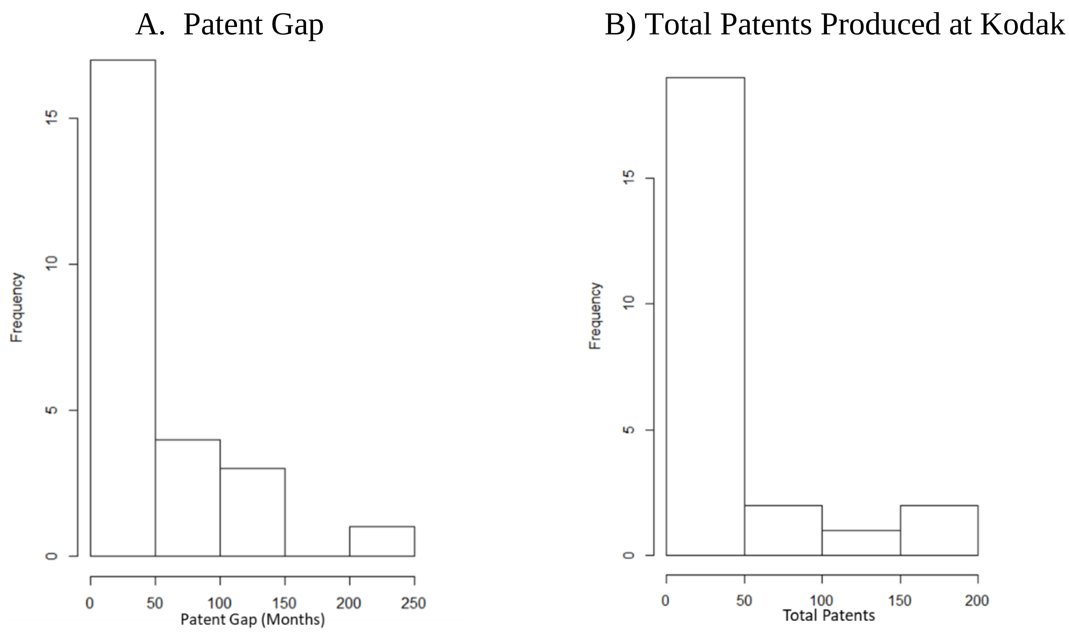
H6: Job separation, and each additional year away from patenting, will significantly decrease an inventor's overall productivity and patenting output over the course of her career.

II. The Patent Gap in Context

What does this "gap" period typically look like for inventors, and what factors influence the length of the gap? To better understand the patent gap in context, I conducted survey research with inventors from one of the largest firms in the data, Eastman Kodak Company. While Kodak was previously one of the largest and most innovative companies in the United States, ranking as one of the top ten US patenting firms for many years, the company experienced a long period of firm decline and ultimately declared bankruptcy in 2012. A case study was selected to enable me to target many inventors at once using active Kodak alumni groups on both LinkedIn and

Facebook to circulate the survey. The survey was constructed with three parts: the first asked basic demographic questions (gender, age, education), and questions relating to an inventor's employment at Kodak. The second section focused on employment after Kodak and the inventor's decision to move to find re-employment. The third section focused specifically on patenting, and asked inventors to answer questions related to whether they patented again after exiting Kodak, and the challenges or barriers they faced to patenting again. A detailed list of survey questions can be found in Appendix B of this dissertation. At the time of writing, 71 inventors responded, 31 of whom patented again after leaving Kodak. While the sample is not intended to be representative of all Kodak inventors, it provides an illustrative snapshot of select inventors' experiences. The sample itself reflects a diverse group of inventors: respondents who patented again produced between 3 and 206 patents during their time at Kodak, with an average of 44.33 total patents per person. Similarly, the "patent gap" period ranges from one month or less to nearly seventeen years, with an average gap of 3.2 years. Figure 2.1 presents histograms for the patent gap and total patents across the entire sample. Respondents were asked to provide their names so that I could both match their responses to US Patent and Trademark Office data, and obtain their employment history from LinkedIn.

Figure 2.1: Total Patents and Patent Gap for Select Kodak Inventors



The results of the survey suggest that the "gap" period primarily represents a period of adjustment as an inventor adapts to her new firm: all 31 inventors surveyed were re-employed in patenting and R&D related occupations in less than one year, with the majority finding re-employment immediately after leaving Kodak. The inventors worked for Kodak for an average of 20 years, and most were highly educated, having obtained a Master's degree or PhD. Most reported finding re-employment in a job that was very similar to their position at Kodak, and a few (7 respondents) reported starting new companies that were similar to the work they did at Kodak. Only 5 of the inventors reported switching occupations or technology areas altogether. One inventor reported returning to school to attain an additional degree. 9 inventors moved to new cities to take advantage of employment opportunities outside of Eastman Kodak's headquarters in Rochester, NY. Inventors who moved appear to have a larger gap period than those who stayed in Rochester, although the sample is too small to make any generalizations about this group. None of the inventors sought additional education between jobs, or spent more than a few weeks unemployed. When asked about the challenges that they faced to producing new patents, inventors generally reported that access to resources and adapting to their new firm were primary barriers to new patent production: 45 percent of respondents reported that their new firm did not have as many resources for patenting and R&D as Eastman Kodak. 48 percent reported that they needed to gain significant experience at their new firm in order to successfully patent again, while 26 percent reported needing to learn more about their new field or technical area in order to produce patents. About 10 percent of the sample also reported needing to get to know their co-workers better before producing new patents. In general, these responses suggest that the "patent gap" may represent a period of learning, adaptation, and adjustment to the inventor's new organizational environment, rather than a period of unemployment or time away from the labor force. However, these descriptives cannot account for the experiences of all inventors, and inventors in other firms or regions may have responded to these survey questions differently.

III. Data, Methods, and Descriptive Statistics

USPTO data from 1976-2014 are used to follow inventors as they move from one patenting position to the next. Data is obtained from the PatentsView database. Using patent records, I am able to identify inventors, the firms that they work for, the types of technologies they produce (i.e. using patent classes) the years in which they are actively patenting, and their collaborators. When an inventor separates from a firm, new employers are identified by tracing the inventor's patenting activity in subsequent years[5]. Patent data are particularly useful because they allow examination of changes in an inventor's technology portfolio from one firm to the

[5] Note that PatentsView uses an inventor disambiguation algorithm to ensure that inventors can be accurately traced over time using one unique Inventor ID.

next. However, there are limitations to using patent data: inventors who retire or switch into non-patenting occupations cannot be traced. In the latter cases, inventors who switch to non-patenting occupations and never patent again also cannot be traced in this analysis. In these cases, much of an inventor's occupation-specific human capital that was gained through the production of technologies is likely lost as the inventor transitions into a new occupation entirely. Finally, not every firm patents. Patenting requires that inventors describe the production of a new technology in detail; therefore, secrecy is an important opportunity cost of engaging in the patenting process, discouraging some firms from patenting at all (Hall, Jaffe, and Trajtenburg, 2001).

One key benefit of patent data is the ability to directly observe the technical expertise embodied in inventions. The patent classes on each patent enable us to disambiguate the breadth and depth of inventors' technical knowledge with considerable detail. If periods of unemployment or time away from patenting impact the retention of skills and future inventor performance, this can be measured if inventors patent after the displacement event. This is a key benefit over occupational data, in which the specific skills that workers use in their occupation are typically not measured; instead, researchers proxy for workplace skills by tracking occupations and assuming the typical skill requirements for each occupation (e.g. years of education, technical, cognitive, physical skills, etc.) (Quintini and Venn, 2013). While this is useful as an approximation, it cannot account for any variation in skill use within occupations, while patent data can provide this information within technological fields with considerable detail.

Unfortunately, on additional limitation of patent data is that it does not identify why an inventor leaves one firm to patent for another. We do know, however, whether an inventor works for a firm in decline. I limit my analytical sample to inventors who were displaced from or voluntarily left declining firms, using the following steps. First, all firms with at least 100 inventors were selected. This was to avoid cases where the loss of only a few inventors potentially looked like decline, but was not. Second, the number of inventors in each year was aggregated by assignee (typically a firm or academic institution), and the sample was limited to firms whose total number of inventors had declined by at least fifty percent, indicating that inventors were likely displaced. This yielded approximately 900 firms. Assignee names are often not consistently listed, and a decline in inventors may also occur when a firm changes its name. To ensure that this was not the case, assignee names were manually inspected to ensure that firms in the final sample had either a) gone bankrupt or shuttered completely, b) declined and were acquired by a larger firm, c) merged with another firm (as a result of poor firm performance) or d) declined more generally, either laying off workers or restructuring from within. After eliminating firms from the sample that did not meet this criteria, the final sample contains 111 firms. Lastly, only inventors who worked for a declining firm while it was continually losing inventors were selected; these inventors are most likely to have been displaced (or to have left voluntarily to avoid displacement), while inventors who leave during periods of firm growth likely have other incentives for mobility. A more detailed description of the data collection process can be found in the Appendix. This process generated approximately 90,000 inventors classified as displaced according to the criteria above.

Using these data, several variables are constructed to assess inventors' transition period after leaving a declining firm, and its impacts on their future performance. *Patent Gap*, the dependent variable of interest, is measured by calculating the number of months between an inventor's last patent for a declining firm (by application date) and her first patent for a new firm. Because many inventors are hired and begin patenting again the first year after displacement, measuring the gap in months better captures this variation in timing. Throughout this analysis, a patent gap of one year or less is typically viewed as a strong or high-quality match between the inventor and her new firm.

Variables that capture inventor characteristics and aspects of an inventors' performance are calculated both over the time period in which an inventor worked for the declining firm, as well as over the course of the inventor's subsequent patenting career (if that inventor patents again). These variables include *total patents*, *average patents per year* (a proxy for inventor productivity), and *total years patenting*.

Three variables are constructed which proxy for the value of an inventor's patents: first, since more valuable patents tend to be cited by future patents more frequently, *average citations per patent* is calculated. Next, more valuable patents are likely produced in growing technology areas. This is captured by calculating the average rate of growth in each USPC technology class in the year an inventor was displaced by a firm, and computing a weighted average based on the number of times each technology class appears on an inventor's patents (*weighted growth)*. Lastly, the final measure of value accounts for the fact that valuable knowledge tends to be concentrated in specific locations. Because successful technologies and industries often grow out of initially geographically rare or tacit technological knowledge, a measure of *average ubiquity* for inventors' technologies is also constructed (Maskell and Malmberg, 1999; Hausman and Hidalgo, 2010). This variable is calculated as the number of US Core Based Statistical Areas (CBSAs) where the location quotient is greater than one for each technology class, divided by the total number of US CBSAs. A weighted average is then computed for each technology class across all of an inventor's patents. Higher values indicate that an inventor's technologies are produced in more geographically common classes, while lower values indicate that an inventor's technologies are rarer (and potentially more valuable). Inventors with geographically rare knowledge may be particularly valuable to firms or regions that wish to move into new technology areas, or that wish to imitate the success of specific places.

The *diversity* of an inventor's technologies is also an important consideration. On one hand, producing a more diverse range of technologies may aid an inventor in finding re-employment sooner, particularly if the inventor transitions out of a declining industry and must switch to a new technological field. Diverse skillsets may also be attractive to firms; existing research finds that R&D teams with diverse expertise tend to be better equipped to find solutions internally (Dixon, 1999; Hoisl et al., 2017), and experience improved performance overall (Horowitz and Horowitz, 2007). On the other hand, any loss of industry-specific human capital while an inventor is not patenting may cause a loss in the diversity of her future technologies. Diversity is calculated as the entropy of technology classes across an inventor's patents, following Frenken et al. (2007). High values indicate both that an inventor is producing technologies in many technology classes, and that her technologies are spread out across those classes; lower values indicate that an inventor produces a smaller, more specialized range of technologies, and those technologies are heavily concentrated within a few classes.

The *technological similarity* of an inventor's patents before and after displacement is another outcome of interest for two reasons. First, being willing to switch into a new industry or technological field may enable an inventor to patent again sooner. Secondly, the opposite may be true: the longer an inventor stops patenting after displacement, the more likely they are to patent in unrelated or technologically distant fields. This may be the case 1) because it takes time to attain the skills necessary to patent in a new technological field and 2) because inventors who spend more time away from patenting may be incentivized to consider patenting positions outside their area of expertise. Technological similarity is measured crudely using 36 broad technology areas as identified by Hall et al. (2001) (see Appendix for a detailed breakdown of each technology area). Patent classes within each technology area are generally highly related to one another, and utilize similar skill sets. This is preferable to using mainline patent classes themselves, as many patent classes are highly related to one another, and producing technologies in different classes may not be a good representation of whether an inventor switched industries or technology areas after displacement. Similarity is calculated as the number of technology areas in which an inventor was active in both at time t (after displacement) and at time t-1 (before displacement), divided by the total number of technology areas in which an inventor was active in t-1. For example, if an inventor specialized in two broad areas while they worked for a declining firm, and they only patent in one of those areas after displacement, their new patents are 50% similar to their former patents.

Because an inventors' connections may help them to find comparable re-employment more quickly, variables that capture aspects of inventors' collaboration networks are also included in the models. *Degree centrality* measures the total number of firm-specific collaborators that an inventor had while working for the declining firm, while *eigenvector centrality* measures how well connected an inventor's collaborators are (similarly to the Google PageRank algorithm). *Outside inventors* measure how many collaborators an inventor had outside the (declining) firm and city where they worked at time period t. Having more connections, more highly connected connections, and more geographically distant connections may all positively influence an inventor's ability to find re-employment after displacement by increasing her access to information on employment opportunities.

Lastly, geographic mobility may be an important determinant of the patenting gap. Whether an inventor moves, and how far they are willing to move, may vastly increase their access to patenting opportunities. This is especially the case if there are few employment alternatives locally, or if regional employment opportunities are typically in unrelated industries (Neffke et al. 2018; Eriksson et al, 2018). To capture this, *move* takes the value one if an inventor moves to a new CBSA after leaving the declining firm, and a zero otherwise. *Move distance* measures the total miles that an inventor moved after displacement, based on their locations on new patents. Economic opportunity in the home city or region may also influence the patenting gap; another variable, *city size*, captures the number of distinct assignees (patenting firms or organizations) in a region to broadly account for this.

Finally, I consider the legal environment of each inventor's home state at the time of displacement. Specifically, I focus on non-compete agreements: a non-compete agreement is a contract between an employer and employee in which an employee agrees not to work for a competing firm within a specific time period and geographic location (Garmaise, 2011). In the US, the enforcement of non-compete agreements varies considerably across states. It is likely that living in a state with strict enforcement of non-competes would vastly reduce an inventor's mobility in the aftermath of job separation, increasing the length of the patent gap (Marx at al., 2009; Balland et al., 2015). To control for this effect, I employ a non-competition enforcement index developed by Garmaise (2011) for US states. This index is based on an extensive survey by Malsberger (2004), who identifies 12 key dimensions of non-competition law in the USA. A detailed description of these dimensions can be found in Garmaise (2011). The index can potentially range from 0 (low enforcement) to 12 (high enforcement). Although the Garmaise index was only computed for 1992-2004, state-level enforcement of non-competes does not change significantly over time. Inventors were matched to a non-compete index score based on the last year that they patented for a declining firm, and the state in which they lived at the time of patenting.

Table 2.1 summarizes each variable by the inventor patent gap; for simplicity, this variable is aggregated into years. The differences in characteristics between inventors who patented again in less than a year and those who resume patenting after a year or more are striking. While working for the declining firm (the first group of rows), inventors who patented again the fastest produced more diverse technologies, had more collaborators (internally and externally), had more citations, and were more productive. The non-compete index is approximately the same across year groups, suggesting that it may not meaningfully impact the patent gap. After patenting again post displacement (the second group of rows), inventors who patent again the fastest continued to be more productive and to produce more diverse technologies. They are also slightly more likely to move. Across their entire patenting career, inventors with the shortest patenting gap also patent in more cities and firms, and they have more collaborators in total, than inventors with longer gap periods. Inventors with a gap of four or more years, however, appear to be equally as likely to move as inventors with a gap of one year or less. For most variables, inventors who start patenting within one year perform the best, and there is a clear drop off with each subsequent year that an inventor goes without patenting after displacement. The similarity of technologies produced before and after displacement also declines with the size of the patenting gap. Initial descriptives indicate that the patenting gap is highly correlated with both positive patenting characteristics and positive patenting outcomes post displacement.

Table 2.1: Descriptive Statistics by Patenting Gap (years)

	< than 1	1-2	2-3	3-4	4 or more
Last Year	2002.04	2000.09	1999.68	1999.45	1995.88
Eigen Centrality	0.03	0.02	0.01	0.02	0.01
Degree Centrality	6.42	5.32	5.02	4.73	3.99
Diversity	0.84	0.78	0.76	0.77	0.68
Productivity	1.28	1.14	1.10	1.04	1.01
Outside Connections	2.05	1.67	1.54	1.45	1.16
Tech Growth	0.29	0.28	0.27	0.28	0.26
Ubiquity	402.99	405.58	403.65	401.05	400.57
Avg Citations	12.22	11.18	11.21	11.34	9.81
Move	0.30	0.27	0.26	0.24	0.30
Patenting Years After	9.47	8.43	7.51	7.43	6.00
Productivity After	1.59	1.00	0.94	0.90	0.76
Diversity After	1.62	1.49	1.43	1.44	1.35
Avg Citations After	19.62	17.69	18.39	17.09	17.43
Degree After	20.36	11.77	10.74	9.90	7.57
Similarity (After)	0.60	0.57	0.55	0.53	0.45
Total Collabs	32.17	19.64	17.75	16.72	12.90
Total Cities	1.95	1.72	1.62	1.61	1.57
Total Firms	5.89	4.28	3.86	3.68	3.22
Total Observations	4665.00	3159.00	2300.00	1615.00	5935.00

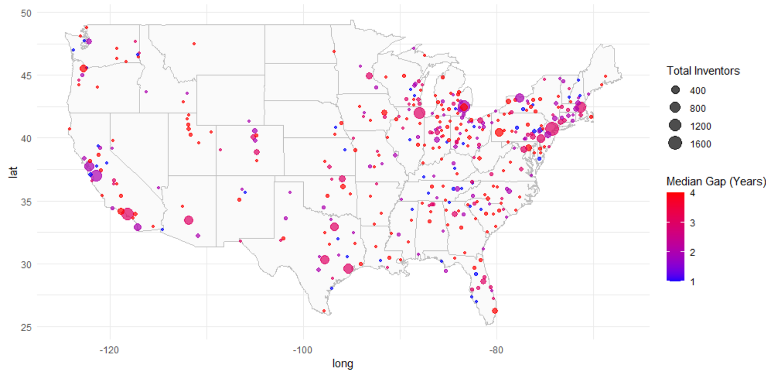
Note: gray boxes indicate groups of variables. Group 1 are variables calculated while the inventor worked for a declining firm, group 2 are variables calculated after, and group three are variables calculated across the entire patenting career. The final row shows the total number of inventors in each category; of the over 90,000 inventors in the sample, only 17,674 inventors patent again after leaving a firm during a period of firm decline.

Lastly, Figure 2.2 explores whether the length of the patenting gap varies, on average, geographically. This addresses research question two. If inventors in some places take longer to begin patenting again compared with others, the impacts may be more pronounced in those locations. Because inventors with particularly large patent gaps tend to skew the mean, panel A shows the median patent gap for each US CBSA. Blue indicates a lower median patent gap (approximately 0-2 years), red indicates a high median patent gap (four or more years), and purple indicates that a city is somewhere in between. There is no clear regional concentration of patent gap values; rather, the patent gap appears to vary significantly within regions. For example, while the Bay Area and San Diego in California appear to have the lower median patent gaps, Los Angeles inventors experience a higher gap period, while the surrounding CBSAs are particularly high. Seattle, Detroit, Rochester, NY, and a handful of other cities also have lower median gaps. Although there is quite a bit of variation, smaller CBSAs appear to have higher median patent gaps in general.

Panel B quantifies the significance of the geographic variation in the patent gap. This map illustrates whether the gap in each CBSA is significantly different from the median value for the US (3.3 years). A one sample t-test is used for each CBSA. Colored cities are significantly different from the median; red cities have patenting gaps that are significantly higher than 3.3, while blue cities have gaps that are significantly lower. Larger CBSAs appear to be more likely to negatively deviate from the median; inventors more than likely have an easier time securing a new, patenting position in larger, more diverse regions, lowering the patent gap. In contrast, a number of medium-sized CBSAs in the Northeast, Midwest, and the South appear to have significantly higher median patent gaps. Cities in gray do not deviate from the median; a number of cities of different sizes fall into this category. This confirms hypothesis 3: that the patenting gap, on average, varies significantly from one city to the next.

Figure 2.2: Geography of the Patent Gap

A) Median Patent Gap in US CBSAs, 1976-2015



B) Significance of Patent Gaps in US CBSAs, 1976-2015

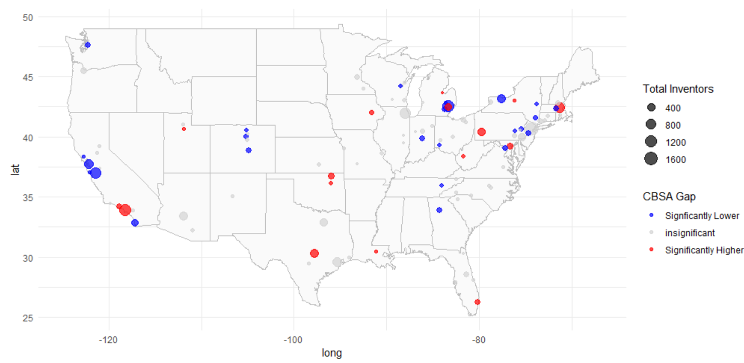


Figure 2A maps the median patent gap for inventors located in each US CBSA. Points are sized by the total inventors from the sample in each CBSA, and the color corresponds to the median patent gap. Figure 2B maps the same US CBSAs. The color corresponds to whether the median patent gap in each CBSA is significantly lower or higher than the US median.

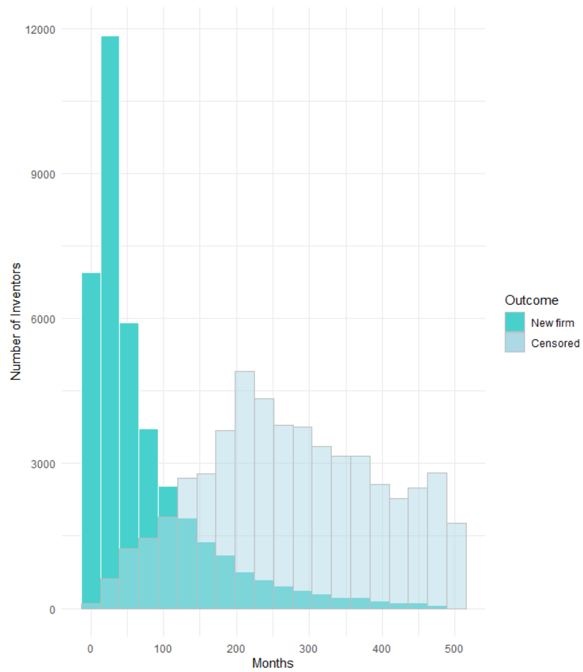
IV. Results Part A: Determinants of the Patent Gap

Next, the determinants of the patent gap and its impacts on future inventive performance are considered more formally. First, survival analysis is used to answer the first primary research question: what characteristics of inventors determine the length of the "patenting gap" or the time between being displaced from a patenting position at a declining firm and finding a new patenting position for another firm? Survival analysis is an attractive way to model the data for two reasons: first, because it is designed specifically to handle time-to-event data, which is precisely how the *patent gap* variable is structured, and secondly because not all inventors ever patent again, and these inventors may have systematically different characteristics than those who do patent again. In a standard regression model for count data, these observations would likely be dropped, while survival analysis allows me to explicitly include these inventors in the model as “censored data”. First, a Cox Proportional Hazards model is used, which is the most commonly used model in survival analysis (e.g. see Cox, 1972; Therneau, 2021; Therneau and Grambsch, 2000; Diez, 2013; Fox and Weisberg, 2018). In a Cox model, the hazard rate, h(t/z) is modeled as a function of the years, t, since an inventor last patented and a vector of inventor covariates, z, written as:

$$h(t/z) = h_0\ (t) exp\ \{\beta'\ z\} \tag{1}$$

where $h_0(t)$ is the baseline hazard function, which represents the direct impact of the time since an inventor last patented on the probability of patenting again, and β is a vector of parameters (one for each of the regressors in the model). The data are structured such that the right hand side takes both a variable, *patent gap*, which indicates the number of months since an inventor last patented, and *new firm*, which takes a 1 if the inventor patents again for a new firm, and a 0 if the inventor does not (and thus, is considered “censored data”). Figure 2.3 visualizes this structure of the data; of those who patent again for a new firm, most of them patent again in the first few years. 22,107 inventors are included in the model as the treatment group (the inventors who patent again), while the remaining 67,776 are included as censored data (for a total of 89,883 inventors in the full sample). The Cox model is run with all pre-displacement covariates, as well as the geographic mobility variables and the similarity measure. A strong assumption of the Cox model is that the hazard rates are proportional, meaning that they are constant over time. One way to test for this assumption is to check the Schoenfield residuals of each variable; if the slope of the plot is zero, then the assumption is met (Therneau, 2021). Running this test on the data, I find that a number of the variables violate this assumption, making a Cox model invalid for my data.

Figure 2.3: Patent Gap Data Structure



The histogram shows the distribution of inventors in the dataset by patent gap (measured in months). The dark histogram represents inventors who patented again after displacement; here, months measures the time between displacement and patenting for a new firm. The lighter histogram represents inventors who never patented again (censored data); months measures the time between displacement and the last time period in the data (December 2015).

One way around this problem is to use an accelerated failure time model (AFT), which relaxes the proportional hazard assumption and allows for constant, increasing, or decreasing hazard rate. There are a number of distributions that can be used to fit the hazard function, and typically a modeler will try different distributions and choose the model which has the lowest Akaike Information Criteria (AIC) (e.g. see Rodriguez, 2010; Faruk, 2018; Wei, 1992). Table 2.2 presents the results of this analysis for my model. Based on this information, a Log-Logistic distribution is the most appropriate fit. Table 2.3 displays the results of the AFT Log-Logistic model.

Table 2.2: Assessing Hazard Model Fit

Model	AIC
Cox PH	793815
Weibull	476273
Exponential	480137
Log-Normal	476832
Log-Log	476259
Gaussian	551531

Table 2.2 presents the Akaike information criterion for different specifications of the survival model. A lower AIC indicates a better model fit.

Table 2.3: Accelerated Failure Time Model Results

Variable	Time to Patenting Again
Intercept	64.270*** (1.613)
Patent Starting Year	-0.029*** (0.001)
Eigenvector Centrality	-0.987*** (0.094)
Degree Centrality	-0.044*** (0.002)
Technological Diversity	-0.394*** (0.013)
Average Patents	-0.162*** (0.013)
Outside Connections	-0.058*** (0.004)
Weighted Technology Growth	-0.0001 (0.0002)
Ubiquity	0.0002*** (0.0001)
Distance (Km)	-0.001*** (0.00001)
City Size (Assignees)	-0.0001*** (0.0001)
Technological Similarity	-3.382*** (0.023)
Non-Compete Score	0.017*** (0.004)
Log(Scale)	-0.058*** (0.005)
Observations	89,883

Note: A negative coefficient on the independent variable suggests that a higher value of the variable will decrease the number of months it takes an inventor to patent again. Note that there are nearly 90,000 observations because inventors who never patent again are included in this model as "censored data". Standard errors are shown in parentheses.
Significance Levels: * < 0.1, ** < 0.05, *** < 0.01

A negative coefficient in the log-logistic model suggests that an increase in the variable will decrease the number of months it will take an inventor to patent again. Similarity, eigenvector centrality, technological diversity, and patenting productivity have the largest negative effects, suggesting that producing similar technologies post displacement, having more well-connected co-inventors, specializing in more diverse technologies, and producing more patents per year may significantly reduce the number of months that it takes an inventor to patent again for another firm. Moving a farther distance is also a significant negative determinant of the patenting gap, suggesting a willingness to move longer distances from the home city is a positive strategy for inventors. Having a greater number of local and non-local co-inventors and living in a city with more firms also reduces the patent gap. The first year that an inventor ever produced a patent was also included in the model to control for patenting experience; experience also has a significant negative impact on size of the patent gap. Additionally, the coefficient on the noncompete score has a positive and statistically significant coefficient; this suggests that living in a state with stricter non-compete compliance may increase the time to patenting again.

V. Results Part B: Impact of the Patent Gap

Next, the focus is turned toward the last research question: how does displacement, and the resulting time away from patenting (the patent gap), impact inventors' future patenting performance? In this section, I directly test the six hypotheses presented in the literature review. Based on insights from previous work, I consider the impacts of the "patent gap" on, first, patenting productivity, using patenting output per year. Secondly, because time away from patenting may lead to a deterioration of skills over time, I consider the impacts on the diversity of skills (technology classes) utilized in the post-displacement position. Third, I consider the impacts on the value of an inventor's future patents, measured using forward citations. And finally, because displacement may impact an inventors' relational capital, I consider the impacts on the total number of co-inventor ties after leaving the declining firm. Table 2.4 summarizes these primary dependent variables.

Table 2.4: Primary Dependent Variables

Variable	Description
Productivity	Patents per Year
Diversity	Measured as the entropy of USPTO mainline classes on an inventor's patents. Higher values indicate that an inventor both a) patents across many technology classes and b) that their patents are not heavily concentrated in any one class. More generally, higher values indicate that an inventor's patent portfolio is more diverse technologically.
Citations	Measured as the average number of forward citations per patent that an inventor's patents receive
Relational Capital	Measured as the total number of co-inventors with which an inventor patents

This table describes the primary dependent variables for the propensity score matching models. Note that these characteristics are measured across the patents that an inventor produced after leaving the declining firm. During this time, the inventor may patent for multiple firms and across multiple locations.

Based on the descriptive statistics in Table 2.1, a clear endogeneity problem arises for this analysis: while, on one hand, the length of the patenting gap may influence future patenting outcomes, on the other, inventors who already performed well may continue to perform well post displacement, regardless of the length of the patent gap. In the latter case, any correlation of a shorter patenting gap with future patenting outcomes may simply be a reflection of inventors' underlying characteristics, rather than a direct impact of time away from patenting itself. To address this endogeneity problem, the following analysis employs propensity score matching to test for the impact of the patenting gap on performance.

The goal of propensity score matching is to take two groups, a treatment and control group (in this case, for example, inventors who patent again in less than one year and those who take a year or more to patent again), and match them based on several covariates (Austin, 2011; Greifer, 2015; Olmos & Govindasamy, 2015; Ho et al., 2011). In the absence of the ability to run a natural experiment, this quasi-experimental approach seeks to compare individuals with the "treatment" to individuals with similar underlying characteristics pre-displacement who did not receive the "treatment". Matched individuals in each group are assumed to be equally likely to have received the treatment, thus allowing us to isolate the effects of the treatment on the treated group. The propensity score, then, is "the probability of treatment assignment conditional on observed baseline characteristics" (Austin, 2011).

The first step in propensity score matching is to compute the propensity scores using logistic regression, with the treatment as the dependent variable. In the first model, the dependent variable is whether an inventor patented again in one year or less, which indicates that the inventor was likely able to find re-employment that was a strong match for her skills and capabilities. A value of one indicates that an inventor did find a patenting position within one year, and a zero indicates that the inventor did not. Structuring the model in this way allows us to compare inventors who patented in one year or less with inventors in the sample with similar characteristics who did not patent again in that time frame. We can also compare inventors who patented again in two or three years with those who took longer. I do not compute the model for inventors who patent in four or more years, as the control group is significantly reduced with each additional gap year. In order to maximize the quality of the matches, the control group must be sufficiently large relative to the treatment group.

The covariates used to perform the matching include indicators of patenting performance pre-displacement (e.g. network statistics, technological diversity, productivity), the last year an inventor patented for a declining firm (since the probability of patenting again likely varies over time), and whether an inventor was mobile across firms and cities prior to working for the declining firm (prior mobility may also be a good predictor of moving to a new firm). Because the ease of finding a new patenting position also likely varies across industries and technology areas, inventors are also matched by their mix of technological expertise. This is calculated by finding the percentage of each inventor's patenting portfolio before displacement that is in each of six broad technological categories by Hall et al. (2001). If, for example, 50 percent of the technologies produced by inventors in the treatment group, on average, are in Computers and Communications, the goal is to construct a control group that matches this distribution. Lastly, inventors are matched by the total duration they spend patenting after displacement. This is key because the number of years that an inventor patents may confound the effects of the treatment; patenting longer enables inventors to acquire more skills and expertise, and may improve patenting performance. If patenting again more quickly simply enables inventors to patent for a longer period of time, this may be the true cause of improved patenting performance, rather than a mitigated loss of human capital during the gap period.

To illustrate the success of the matching step, the results of the matching for inventors who did patent again in one year or less are shown in Table 2.5. Full matching is used to match every treated unit to at least one control and every control to at least one treated unit; this type of matching created much better balance between the treatment and control groups than other matching methods (e.g. nearest neighbor) (Hansen, 2004; Greifer, 2015). When balanced matches are achieved, the resulting model is robust, even to misspecification. In general, the means differ by less than 0.1 for most variables, suggesting that the matching was successful. Last Year, Ubiquity, Average Citations, and Years Post Displacement differ the most between the treatment and control samples; these variables exhibit more variation across inventors than other variables in the model, and were particularly challenging to match. After running multiple matching algorithms, the full matching algorithm appeared to minimize the differences between these variables best. The quality of the matches was very high for all model specifications. Note that, for the PSM models, only inventors who patented again after leaving the declining firm are included, for a total sample of 17,674 inventors.

Table 2.5: Balance of Matches (Patent Gap = 1 Year or Less)

Variable	Mean (Treated)	Mean (Control)	Difference
Degree centrality	6.423	6.548	-0.125
Eigen centrality	0.028	0.031	-0.003
Diversity	0.842	0.790	0.052
Productivity	1.281	1.372	-0.091
Last Year	1999.593	2000.692	-1.099
Worked for Prior Firms?	0.473	0.449	0.024
Lived in Prior Cities?	0.275	0.269	0.006
Ubiquity	402.986	402.243	0.743
Average Citations	12.225	12.916	-0.691
Years Post Displacement	9.467	8.401	1.066
Chemical	0.161	0.142	0.019
Computers & Communications	0.357	0.421	-0.064
Drugs & Medical	0.053	0.048	0.005
Electrical & Electronic	0.222	0.205	0.017
Mechanical	0.132	0.121	0.011
Others	0.076	0.063	0.013
Observations	4665	13009	

Matches are balanced if the means for the treatment and control group are relatively equal (or if the differences between the treatment and control samples are minimized). Note that the table shows the quality of matching for inventors whose patenting gap is 1 year or less with those inventors whose patent gap is longer. The quality of the matching is similarly balanced each time the matching is performed.

Using the matched data, linear regression is then used to determine the average treatment affect across the new analytical sample. While regressing the treatment (the patent gap) on the variables of interest (measures of patenting performance) may be sufficient using the matched sample, covariates are also included in the model. These include both the matching characteristics, as well as some career-spanning variables, including the total number of firms and cities in which an inventor worked and lived across their entire career. The latter variables are useful because mobility across firms and cities may be one mechanism through which inventors learn new ideas and technologies, impacting their patenting performance independently of the patenting gap (Van der Wouden and Rigby, 2020; Hoisl, 2009; Cappelli et al, 2019; Toth and Lengyel, 2021). The former covariates are included for two reasons: first, they can increase precision in the effect estimate, and second, they may reduce the bias due to residual imbalance, and make the effect estimate "doubly robust" (Greifer, 2015). Because the impact of the covariates is not relevant to the research question, Table 2.6 presents only the average treatment effect on the treated (ATT, or the coefficient on the treatment variable) that results from the regression. Standard errors are clustered by matching pairs. For example, in Table 2.6, column 1, the interpretation is as follows: patenting again in a year or less (and thus, finding re-employment that is a strong match for patenting ability) is associated with an increase or decrease in technological diversity, productivity, average citations, and co-inventors.

In addition to examining the impact of the patent gap on post-displacement performance, I also consider some additional factors that may enhance or detract from the impact of the patent gap itself. The first is whether an inventor moves to a new firm in the same technology area as the previous firm from which they were displaced (hypothesis 4). An inventor's post-displacement position is considered similar to the previous position if at least fifty percent of her patents are in the same technology areas as the patents she produced for the declining firm. The second factor is geographic mobility (hypothesis 5). The predicted impact of this factor is more ambiguous: on the one hand, being willing to move may open up significantly more employment opportunities than an inventor may have had locally, improving the match of the new position. On the other hand, moving may distance an inventor from her existing collaboration network, and any regional firm differences may prolong the adjustment time.

Table 2.6: Average Treatment Effect on the Treated

Dependent Variable	Treatment Effect: Less than 1 Year	Between 1 and 2 Years	Between 2 and 3 Years	Less than 1 Year, Same Field	Less than 1 Year, Move
Technological Diversity	0.061***	0.005	0.008	0.057***	0.008
	(0.013)	(0.012)	(0.014)	(0.013)	(0.022)
Productivity	0.351***	-0.005	0.072*	0.575***	-0.077
	(0.031)	(0.037)	(0.037)	(0.067)	(0.133)
Average Citations	-1.398***	-2.119***	0.008	-1.670**	-0.341
	(0.509)	(0.696)	(0.844)	(0.770)	(1.456)
Co-Inventors	3.666***	-0.493	0.819**	7.207***	-3.769
	(0.480)	(0.394)	(0.395)	(1.336)	(2.638)
Treated	5612	3159	2300	3083	1402
Control	13610	9850	7550	14591	16272
Observations	17674	13610	9850	17674	17674

Note: The table presents results for each specification of the PSM-weighted regression. Note that not all inventors in the "treatment" group are able to be matched to an inventor in the control group, which accounts for why the treated numbers do not perfectly match the values in Table 2.1. A positive coefficient indicates that the treatment is associated, on average, with an increase in the outcome variable. Standard errors are included in parentheses.

Significance Levels: * < 0.1, ** < 0.05, *** < 0.01

The results suggest that, even when matching by and controlling for pre-displacement characteristics, the total duration of post-displacement patenting, and other important factors, the impact of the patent gap significantly influences future patenting outcomes. The value of entropy, which is a measure of technological diversity, is 0.758, on average, across the sample, with a standard deviation of 0.626. Patenting again after one year or less leads to an increase of 0.061, on average, compared with inventors with larger patenting gaps. The effect on productivity is similar: inventors who patent again in less than one year experience large gains in productivity (about 0.351 patents per year). On average, inventors across the whole sample produce 1.122 patents per year, which suggests that this value represents a relatively substantial increase. Surprisingly, patenting again in a year or less significantly decreases the number of citations per patent, by approximately 1.398. The mean citations for the whole sample are 11.01. Finally, since relational capital may enhance an inventor's productivity further, I consider the impact of the patent gap on total co-inventors after displacement. Patenting again within a year or less significantly increases co-inventors, by around 3.666 on average. Because the mean for the data is 5.07 co-inventors, this is a relatively large increase.

The impacts of patenting again sooner appear to decline after more than one year away from patenting. The increase in technological diversity is lower and insignificant in the 2- and 3-year groups, compared with inventors who took longer to patent again. This confirms hypothesis one: inventors who take longer to patent again produce less diverse technologies over time. The effect on co-inventors appears to be similar, directly confirming hypothesis 2: a longer time away from patenting has a significant negative impact on co-inventors. Interestingly, inventors who patent again in 2-3 years experience a slight increase in co-inventors over those who return to patenting within 1-2 years. The coefficient on productivity declines or becomes insignificant for inventors who take more than one year to patent again, also confirming hypothesis 6: a longer gap in patenting has a significant negative impact on overall patenting productivity, compared with those who patent again in less than one year.

Patenting again in the same technological field also appears to substantially enhance the performance gains from patenting again more quickly. Productivity and relational capital increase for inventors in this category, relative to the matched sample. As predicted, it may be likely that inventors who are able to work in the same field have a much quicker transition to the new firm environment, and are able to retain more of their accumulated human and relational capital (Poletaev and Robinson, 2008; Nedelkoska and Neffke, 2011). This confirms hypothesis 4: transitioning into a new technological area has significant negative consequences for inventor performance. Interestingly, the gains from patenting again more quickly are significantly reduced if an inventor moves to a new city. When an inventor moves, there may also be regional variation in some of the norms and routines practiced by the new firm, increasing the time it takes for an inventor to adapt to a new firm environment. She also leaves behind geographically proximate connections. This confirms hypothesis 5, suggesting that moving to a new city has a significant negative impact on inventor performance post displacement, and highlights the role that geography-specific human capital plays in influencing inventor performance.

The only variable that appears to behave contrary to my initial predictions is citations. A potential concern for this result is that, in general, average citations per patent have increased over time. This time trend may be driving the increase. The original model controls for the last year that an inventor patented for a declining firm. To test this new hypothesis, the models are re-run, this time controlling instead for the first year that an inventor patents again, in order to ensure that a yearly time-trend cannot impact the results (see Table 2.7). Run this way, the results indicate that the patent gap has no significant effect on citations. This suggests that the time trend for citations, rather than the patent gap itself, was likely driving the initial result.

Table 2.7: The Patent Gap and Average Citations, Matched by Patenting Start Year

Patent Gap	Average Citations
Less Than 1 Year	-0.301 (0.510)
Between 1 and 2 Years	-0.751 (0.578)
Between 2 and 3 Years	-0.206 (0.706)

Note: The table reproduces the results from Table 2.5, row 4 (average citations) using patenting start year rather than final year patenting to match treatment and control inventors. A positive coefficient indicates that the treatment is associated, on average, with an increase in the average citations per patent post displacement. Standard errors are included in parentheses.
Significance Levels: * < 0.1, ** < 0.05, *** < 0.01

Finally, I test the robustness of these results using a series of additional model specifications. First, I matched inventors based on their productivity rather than their total patents. It is possible, therefore, for two inventors to have relatively similar patenting productivity, but vastly different patenting output. For example, one inventor may only produce one patent in one year (a "casual" inventor), while the other may have produced ten over ten years (a "career" inventor); the second inventor may place much greater importance on patenting than the first, reducing the usefulness of the comparison. If inventors with a gap of one year or less are typically career inventors, but they are matched with more casual inventors, this may account for the positive results. To test this, I run the model again, using only inventors who produce more total patents than average. These "career inventors" generated, on average, 14 patents while working for a declining firm. Results of this regression are presented in Table 2.8, Column A. The sign, significance, and coefficient values produced by these models are very similar to the original results, suggesting that this is likely not a problem for the validity of the original matching model.

The firm that an inventor patents again for may also affect the results of the models: for example, if inventors who have a longer transition time are generally patenting for smaller firms with fewer resources or funding for R&D activities, this may account for the positive effects of a gap of one year or less. To control for this, I re-run the original model, and include the size of an inventor's new firm as an additional matching criterion. Although this does not directly control for a firm's R&D budget, smaller firms likely have fewer resources than larger firms, allowing me to at least partially control for this issue. The results, presented in Column B, are in line with the results of the original model, suggesting that firm size differences between the treatment groups is likely not a strong driver of the results. Finally, it is possible that the results of the Move model are impacted by the type of city that an inventor moves to: for example, if displaced inventors are forced to move from high productivity to low productivity cities because there are no local job opportunities that match their skills and abilities, this could account for the negative impacts of moving on inventor performance. To test this, the matching model is again re-run, using the average patenting output per year of the inventor's location (CBSA) post displacement as an additional matching criterion. Again, the resulting coefficients are similar to the original models, suggesting that the size or patenting productivity of a destination city does not explain the effect of mobility on performance.

Table 2.8: Additional Robustness Checks

Dependent Variable	A) Treatment: Less Than One Year (Career Inventors)	B) Treatment: Less Than One Year (Matched by Firm Size)	C) Treatment: Move (Matched by City Productivity)
Technological Diversity	0.048***	0.071***	0.036*
	(0.016)	(0.013)	(0.021)
Productivity	0.332***	0.328***	-0.067
	(0.060)	(0.031)	(0.119)
Average Citations	0.775	-1.125**	-0.552
	(1.101)	(0.512)	(1.370)
Co-Inventors	3.318***	3.265***	-2.255
	0.640	(0.457)	(2.227)
Treated	1569	4657	1404
Control	2709	12976	15032
Observations	4278	17,633	16436

Significance Levels: * < 0.1, ** < 0.05, *** < 0.01

VI. Conclusion

Any significant disruption from work may have negative and pervasive impacts on workers. In the case of inventors, job loss and time away from patenting (the “patent gap”) may lead to decreased future performance for several reasons. Finding re-employment often means transitioning into an unfamiliar firm environment, and adapting to new routines and operating procedures (Grant, 1996; Nelson and Winter, 1982). Inventors are also typically displaced from existing collaboration networks, and must learn to work as a part of new teams of invention (Paruchuri et al, 2006; Frank, 1985). Finally, a patenting gap, or transitioning into a new industry or technology area may cause the inventor to lose valuable industry-specific skills, while forcing her to learn new skills and competencies (Poletaev and Robinson, 2008; Nedelkoska and Neffke, 2011). While prior research has focused on the impacts of displacement on workers in general, as well as the impacts of disruptions like mergers and acquisitions on inventors, this study is among the first to consider inventor performance in response to firm decline and job loss.

The first part of this chapter analyzed the inventor-level characteristics that determine the length of the “patent gap”. Based on data from my case study, the gap period likely constitutes a period of learning or adaptation in which an inventor acclimates to her new patenting position. A shorter gap, therefore, likely indicates a better match between the inventor and her new organizational environment. Inventor networks play an important role: both the quality of network connections, as well as the total number of local and more geographically distant ties significantly reduce the size of the patent gap. Co-inventor networks may be an important source of information for displaced inventors as they search for re-employment. Inventors who are more productive, and who produce a greater diversity of technologies, particularly in growing technology areas, tend to patent again more quickly. While productivity is likely a valuable characteristic for many firms, producing a diverse technology portfolio may enable an inventor to transition into a wider range of jobs and industries after displacement, which may be equally valuable. Inventors may begin patenting again much more quickly when they are able to find re-employment in a technology field that is very similar to their previous patenting field. Transitioning into distant technology areas likely requires considerable on-the-job training, or the pursuit of a new degree altogether, delaying the inventor’s shift into a new patenting role.

Finally, the region where an inventor lives may also influence the patent gap: inventors who live in cities with more patenting firms (assignees) tend to patent again more quickly, and those who move to new destinations also have a reduced patent gap. As Figure 2.1 illustrates, the length of the patenting gap for inventors in the sample varies considerably by CBSA, and larger cities tend to have a smaller median patent gap, on average, than smaller cities. It may, therefore, take smaller cities a longer period of time to recover from the loss of a major firm, if they experience the negative impacts of the patent gap more acutely. The loss of a major firm likely already constitutes a major negative shock to smaller region's innovative capabilities. If a large number of inventors are displaced at once and many are unable to find comparable re-employment opportunities, the effectiveness and productive capacity of regional human capital may never recover from the shock. Because innovation, human capital, and new economic opportunities tend to be concentrated in larger US regions (Balland et al., 2018), inventors' difficulty finding new patenting jobs in smaller US cities may further contribute to the existing divergence between smaller and larger regional economies. Understanding and quantifying the aggregate impacts of the patent gap on regional economies is a fruitful area for future research.

Propensity-score weighted regression revealed that the length of the patent gap significantly influences the future performance of inventors. While inventors who patent again in a year or less experience significant gains to productivity, technological diversity, and co-inventor connections over time, those gains appear to decline if an inventor takes additional years to patent again. Additionally, patenting again in the same technological field increases the gains an inventor already experiences from patenting again more quickly. Inventors are likely better positioned to produce more patents in a technology field that is similar to their previous work, as doing so requires little additional training. If an inventor moves into a more distant technology area, patenting quality may be fairly low initially even if the inventor experiences a shorter patent gap, as the inventor accumulates new knowledge and expertise over time. This may be particularly the case for inventors who choose to learn on the job, rather than seeking out more formal re-training (e.g. university degree or training program). Patents produced as a result of re-training or experiential learning may, in general, be less impactful than those produced using knowledge obtained from an academic degree because of the nature and depth of the learning process (Esposito and van Der Wouden, 2021).

At the same time, moving to a new city reduces or even cancels out the effects of patenting again more quickly. While changing locations may enable an inventor to patent again in a shorter period of time, doing so may be detrimental to her future performance. Again, this may be a result of adapting to the local business culture, rebuilding networks and relational capital, and other parts of the transitional process that may pose significant challenges to the inventor post displacement. Because regions are a nexus of norms and practices, institutions, and other untraded interdependences, moving to a new city constitutes a loss of some accumulated geography-specific human capital. These results highlight the idea that regional mobility may play an important role in inventor performance outcomes. Clearly, job separation, and the patent gap in particular, has a significant impact on inventors' performance as they transition to new firms.

There are clear limitations to this analysis. As discussed earlier, inventors who never patent again cannot be considered by this analysis, although their performance may also be significantly impacted by displacement or job separation. It would be interesting to know how switching to a non-patenting occupation impacts the length of an inventor's time to re-employment, but that is outside the scope of this analysis. Further, these results may not be representative of all firms that decline, although the sample of declining firms is fairly large. Finally, this chapter focuses on the impacts of the patent gap on individual inventors, and their corresponding effects at other scales are merely inferred based on the geography of the patent gap; additional research should seek to better quantify these impacts at firm and regional levels.

Sudden shocks like the closure of a major firm or an unexpected recession can be devastating for regions, and these impacts may be more acute if the resulting job loss has lasting negative impacts on processes of regional innovation and learning and the production of new technologies. From a policy perspective, aiding displaced inventors in the employment search may be critical to firm-level or regional innovation outcomes. Because the length of the patent gap may directly impact an inventor's retention of skills and relational capital, providing more resources to displaced inventors to improve their employment search may somewhat mitigate the negative effects of displacement on inventive capacity. In cases where there are few regional employment opportunities that match inventors' skill requirements, encouraging entrepreneurship and the formation of new firms may help to offset this limitation while encouraging inventors to continue to deploy their existing skills in productive ways (this strategy is further discussed in Chapter 3).

These results also suggest that "brain drain" or the out-migration of inventors following displacement may be detrimental not only to cities that are losing valuable human capital, but to the performance of the mobile inventors themselves. Encouraging workers to stay following job loss may, therefore, be beneficial for the region, local firms, and the individual inventor. Finally, these results raise important considerations for firms: when a firm hires an inventor from another company, maximizing the inventor's performance is in the best interest of the firm. Providing resources and support to help the new hire to adjust quickly to the new environment may be critical to their future performance. Additionally, these results suggest that hiring talented workers from geographically distant places may not be as advantageous as often thought, as transplanted inventors (particularly those from struggling firms) may experience reduced performance as they adapt to their new region alongside their new firm and occupational context.

This study broadly highlights the idea that, while re-employment itself is an important outcome after a mass layoff, the time that it takes a worker to adjust after a career disruption is also an important issue from an economic and regional innovation perspective, and should be a consideration for policy makers, firms, and regional economies.

VII. References

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Chapter 3: Firm Decline, Labor Mobility, and Regional Resilience: A Case Study of Innovation in Rochester, NY

A great deal of research in economic geography and related fields has focused on the emergence of highly innovative industrial clusters like Silicon Valley. Localized clusters of firms are a desirable economic structure, as they facilitate knowledge spillovers, they promote the formation of buyer-supplier networks and interfirm collaboration, and they enable the centralization of industry resources, knowledge, and capabilities (e.g. Porter, 1998; Iammarino and McCann, 2006; Malmberg and Maskell, 2002). Recently, the financial crisis, the Covid-19 pandemic, and other global economic disruptions have illustrated a need for more research that examines not only how successful clusters emerge, but how they can adapt or remain resilient in the face of major economic shocks. In this chapter, I explore the role that labor mobility and the creation of inter-firm networks play in maintaining competitive advantage in a regional cluster of firms facing significant negative pressures.

The mobility of skilled workers across firms is a powerful mechanism for knowledge sharing and the formation of local linkages (Saxenian, 1994; Almeida and Kogut, 1999; Breschi and Lissoni, 2006). When workers move from one firm to the next, they take their skills, capabilities, and relational capital with them. This provides hiring firms with valuable access to new ideas and expertise which can enhance their existing knowledge base and open up new technological possibilities (Audretsch et al., 2021; Eriksson and Lengyel, 2019). I argue that labor mobility not only enhances the innovative capabilities of a regional economy, but can also help a cluster or region to overcome technological lock-in and decay, laying the foundations for sustainable growth and re-development. I illustrate this using Rochester, NY as a case study.

Rochester was formerly a mid-sized company town dominated by three major optics and imaging firms, Eastman Kodak Company, Xerox Corporation, and Bausch and Lomb (referred to as KXB in the text). When the three firms began to decline in the late 1990s, Rochester's optics cluster looked as though it would never recover from the magnitude of the employment loss. However, the region has experienced considerable growth in recent years, and has regained its position as a highly innovative regional economy (particularly relative to its size). Using United States Patent and Trademark Office (USPTO) data to trace the mobility of inventors across firms in Rochester and methods from social network analysis, I show that the decline of the big three companies "seeded" the development of a robust and diverse cluster of small and medium-sized firms in optics, imaging, and related sectors and enhanced their innovative capacity. Displaced workers contributed their skills, experience, and connections to newer, smaller ventures in the region, helping to create a dense network of interfirm linkages and knowledge diffusion that formed the foundation for Rochester's re-invention.

This case study contributes to literature on regional resilience in two major ways: first, drawing on an evolutionary perspective of resilience, it illustrates the potential for regions to function as complex adaptive systems. Strikingly, the apparent "death" or decline of a regional cluster at one moment in time can serve as the engine of that region's resilience in another. Secondly, it highlights the role that labor mobility and network evolution play in contributing to regional resilience outcomes, particularly from an innovation perspective. The chapter proceeds as follows: section II connects literature on labor mobility and regional network formation to work on regional economic resilience. Section III provides an overview of the case study and a timeline of Rochester's recent economic history. Section IV discusses the data and methods used in two parts: focusing on inventors from Eastman Kodak, the first section uses mixed methods to characterize inventors who stayed in the region to patent for new firms. The second presents a broader analysis using patent data to analyze the impacts of inventor mobility networks on regional processes of innovation. Finally, section V presents the results and conclusions of the research.

I. Literature Review

Regional Resilience

At its simplest, regional resilience is the ability of an industrial cluster, an integrated regional economy, to successfully recover from a shock to its economy (Hill, Wial, and Wolman, 2008). More precisely, it is the ability of the workers, firms, organizations, and institutions in a region to work together to overcome significant economic disruption. In this chapter, I conceptualize resilience from an evolutionary perspective: rather than conceive of resilience as a return to a previous state or equilibrium, this view recognizes resilience as an ongoing process of regional adaptation to economic crisis (Simmie and Martin, 2010; Christopherson et al., 2010; Pike et al., 2010). Thus, resilience can be seen as a region's ability to "bounce forward" in response to a shock, rather than "bounce back" to a former state (Martin and Sunley, 2015). A region, in this view, functions as a complex system of economic agents (workers, firms, and organizations) who reconfigure and adapt their industrial, technological, network and institutional structures in response to constant economic change and the dynamics of capitalist competition (Balland, Rigby, and Boschma, 2015; Swanstrom, 2008; Martin and Sunley, 2007). A region's adaptive capacity may be contingent upon its historical evolution, as its pre-existing skills, resources, technologies, network structures, and institutions shape its new evolutionary possibilities.

Networks are an important component of regional resilience. Not only do regions possess particular endowments of resources, competences, and organizations, but these features are connected through complex webs of social interaction (Boschma, 2015; Lawson, 1999). These connections may take the form of formal or contractual relationships between firms and organizations, linkages between buyer and supplier firms within an industry, more informal collaborative relationships between firms and workers, networks of labor mobility across firms, and many more possible networked forms of interaction. Networks may be a critical source of new information, ideas, and resources for struggling firms and industries, and may thus contribute to their adaptive capabilities. The structure of networks can both enhance and impede regional adaptation. For example, when firms and workers are loosely connected, a downturn in one industry is unlikely to impact other industries in the region; at the same time, this lack of cohesion may limit regional actors' ability to work together to develop the region's adaptive capacity (Crespo et al., 2014). On the other hand, tightly-knit networks of similar firms and workers may become too insular or inward-thinking to develop the evolutionary capacity to "bounce forward" or chart a new growth path, thus becoming "locked-in" to evolutionary pathways that have become stagnant or unproductive (Grabher, 1993; Boschma and Frenken, 2010). Finally, networks can exist across multiple spatial scales: regions often possess both internal networks as well as external linkages or pipelines to other locations, whether through formal relationships, networks of firm subsidiaries, or other interregional channels (Bathelt et al., 2004; Esposito and Rigby, 2019). These pipelines can potentially help regions to avoid economic or technological lock-in by expanding the local knowledge base and providing access to economically valuable ideas and technologies. This research builds on this network-based perspective by focusing specifically on labor mobility networks between firms, and the role that their emergence and structure plays in enhancing regional resilience.

Networks and Labor Mobility

In recent decades, labor mobility networks between firms have become more prominent than ever. Much of this is a result of a noticeable shift in the way that firms conduct research and development. While firms throughout much of the 20^{th} century typically conducted R&D internally, in what has been termed the "closed innovation" model, modern firm boundaries are increasingly open and more porous in terms of knowledge flow (Chesborough, 2003; Dahlander and Gann, 2010). Companies often commercialize both their own internal ideas as well as ideas sourced from outside the firm, and building and maintaining channels and connections external to the firm is key to generating value. Under this model of open innovation, the ability of firms to source and exploit external knowledge may be a critical determinant of their innovative performance (Cohen and Levinthal,1990; Laursen and Salter, 2006). External knowledge can be sourced in a number of ways: firms can license technologies from other firms (Teece, 1986); they can acquire other firms (Ahuja and Katila, 2001); and they can hire workers from competing firms (Song, Almeida, and Wu, 2003). This "learning by hiring" strategy gives rise to complex linkages between firms that facilitate knowledge spillovers and other potentially positive externalities.

One reason that sourcing external knowledge has become so important is that the returns to internal R&D have eroded in recent years (Laursen and Salter, 2006). There are two main explanations for this: first, building on the knowledge-based view of the firm, the ability for firms and organizations to remain competitive is directly tied to their ability to continually innovate and produce new ideas (Grant, 1996). Literature in evolutionary economics finds that a firm's ability to produce novel ideas is influenced by its access to technological variety and its capacity to envision and create new combinations of technologies (Nelson and Winter, 1982; Levinthal and March, 1993). In this environment, firms often must search beyond their organizational boundaries to gain access to critical knowledge sources, especially when their competitors are engaged in a similar search process. Second, knowledge workers are more mobile across firms than ever before, making it difficult for firms to prevent their ideas and knowledge from spilling over into other firms (Chesbrough, 2003; Dahl and Sorenson, 2009; Wright and Ellis, 2018). Advancements in communication technologies have also hastened the spread and diffusion of ideas around the world, making the continual search for new ideas even more imperative than ever as firms compete to retain their comparative advantages before their valuable, tacit knowledge can be codified (Maskell and Malberg, 1999).

A number of researchers have analyzed the movement of workers across firms, and the regional networks of inter-firm mobility that they create. Almeida and Kogut (1999) find direct evidence that the flow of knowledge across firms is embedded within these mobility networks. Breschi and Lissoni (2006) find that controlling for networks of inventor mobility explains regional patterns of knowledge spillovers, suggesting that social networks are a more important determinant of knowledge sharing than geographic proximity alone. The mobility of workers across firms may enhance firm performance, as workers contribute new knowledge and expertise to the firm's internal knowledge base (Audretsch et al., 2021; Hoisl, 2009; Eriksson and Lengyel, 2019). However, in an environment where labor mobility is high, losing key workers may have considerable adverse impacts on the source firm if valuable skills and capabilities are lost

(Campbell et al., 2011). Thus, mobility networks have become a crucial component of firms' performance and innovative capacity.

Putting it All Together

Importantly, a culture of open innovation and labor mobility may enhance the resilience of regions or industrial clusters. In her famous work on the Silicon Valley, California and Boston Route 128 semiconductor industries, Saxenian (1996a, 1996b) argues that Silicon Valley's open, network-based industrial system encouraged the diffusion of technological and market intelligence, creating a culture of continual innovation. This system enabled Silicon Valley to adapt to a major downturn in semiconductors in the 1980s, while Route 128's more rigid, hierarchical, and relatively closed system prevented it from regaining its dominance in the computer industry. A more open, networked industrial structure may improve resilience through several mechanisms: first, in industrial clusters or regions where knowledge spillovers are high, the ability to continually produce new combinations of ideas may help firms to identify and develop new growth paths when previous technologies or opportunities have been exhausted. Access to valuable external knowledge may, therefore, help firms to build and maintain competitive advantage over time, even in the face of a downturn or external shock.

Second, high rates of labor mobility may also be highly beneficial to workers, who face considerably lower career risk when they can easily find alternate employment options. Job loss may be less disruptive to workers' lives and their social and professional ties when inter-firm mobility is already common (Casper, 2007). Finally, high levels of mobility may even encourage entrepreneurship: because entrepreneurs can go to work for other regional firms if a start-up fails, labor mobility can offset the risk of starting a new venture. Thus, regions with dynamic labor mobility networks may experience high rates of new firm creation, even as other firms fail

(Ostergaard and Park, 2013). Laid off workers may even be a key source of entrepreneurship and knowledge diffusion in a region in the aftermath of a major firm closure. The development of labor mobility networks is, therefore, one way that regions can enhance their adaptive capacities in the face of an industry or region-wide shock. A key question for the literature on labor mobility networks and regional resilience, however, is network formation: why do these networked structures form in some regions, but not others? Using Rochester, NY as a case study, I argue in this chapter that major firm decline may be one mechanism of network formation (Casper, 2007).

II. Case Study

For decades, the regional economy of Rochester, NY was dominated by three major anchor firms: Eastman Kodak Company (founded in 1892), Xerox Corporation (founded 1906), and Bausch and Lomb (founded 1853). The success of the three firms led to the development of a vibrant and highly specialized economic base that was largely fueled by continued growth in the optics, imaging, and chemicals sectors. At its peak, Kodak was the largest employer by far, with 62,000 local employees in the mid-1980s. Local universities, including the University of Rochester and the Rochester Institute of Technology, grew alongside these major firms, and contributed to the growth of a large and highly skilled local labor force. However, the decline of all three firms during the second half of the 20th century seemingly reversed the economic fortune of the city: massive layoffs reduced the three major employers, which once employed approximately 60% of the local labor force, to only 6% of the regional employment base by 2012 (Applebome, 2012). Layoffs began in the late 1990s and continued into the 21st century. This represented a massive loss of jobs and income for the Rochester community.

However, Rochester's development has not been as bleak as many believed it would be. Unlike other former company towns, Rochester is a story of relative success: while the local population declined after 1999, it has grown steadily in recent years, and has already surpassed its peak 1998 population level (Figure 3.1). While employment in Rochester plummeted after 1998, employment growth has rebounded considerably since 2010. As Figure 3.2 illustrates, employment growth has occurred alongside strong growth in small and medium sized firms, particularly after 2010 (more details on the structure of Rochester's economy are available in Appendix C). Rochester has also remained highly innovative for its size, with patent growth accelerating after 2008 and reaching peak 1998 levels by 2014, as illustrated by Figure 3.3A. Figure 3.3B compares Monroe County (Rochester) to the other largest patenting counties in NYS. Only New York and Westchester counties produce more patents than Rochester, and both are part of the New York City metropolitan area. Rochester's steep decline and recent growth appears particularly impressive next to these large counties. Rochester, by contrast, is in the ninth largest county by population, and similarly sized counties like Erie (Buffalo) and Onondaga (Syracuse) have experienced minimal or no growth in patenting in recent years. Rochester's "knowledge space" is shown in Figure 3.4: nodes represent USPTO patent classes, node sizes represent the number of patents in each class (divided by 100 for visual scale), and the position of nodes indicate the relatedness of technologies to each other (a more detailed explanation is available in the Appendix, and in Kogler, Rigby and Tucker, 2013). The knowledge space is shown in the 1990s, when patenting by KXB was at its peak, compared with the 2000s, when all three firms began to decline. In the 1990s, Rochester had a relatively specialized knowledge space, with a strong technological expertise in optics and chemistry. Technologically, Rochester has remained a strong producer of optics, imaging, and related technologies, which make up the dense core of the knowledge space in both time periods. Rochester has also maintained its expertise in chemicals; optics and chemicals are highlighted in red to visualize their positions in the knowledge space in both time periods. In the second period, Rochester-based firms appear to have diversified into more distant technology areas, including computer hardware and software and communication technologies. Despite its small size and isolated location in Upstate NY, Rochester has adapted to the loss of its largest firms and experienced considerable growth, diversification, and revitalization (relative to other Upstate NY and rust belt cities) in recent years. What factors contributed to the resilience of Rochester's optics cluster, and broader technology growth in the region? Although many factors contributed to the region's success, in the following analysis I focus on the role that labor mobility played in creating the foundation for redevelopment and innovative growth.

Figure 3.1: Population and Employment in Monroe County, NY, 1990-2019

Source: Census County Business Patterns (2021)

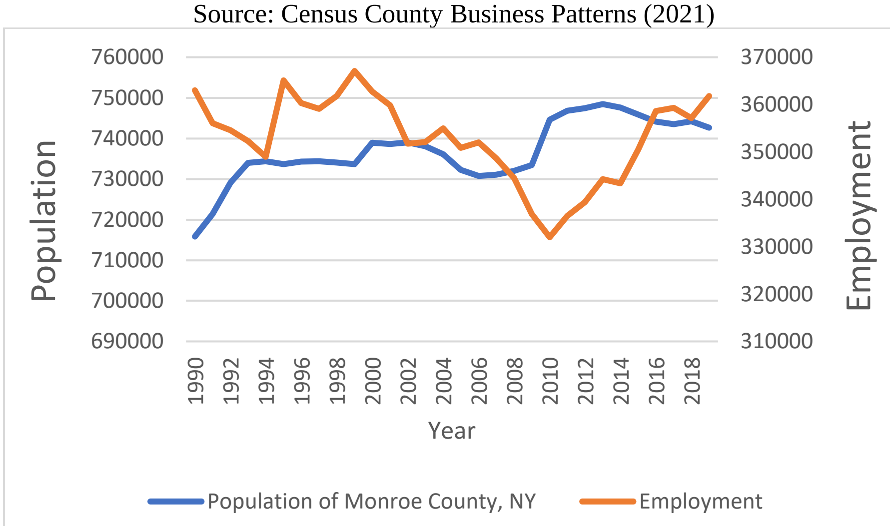


Figure 3.2: Number of Firms in Rochester, NY by Size, 1990-2019

Source: Census County Business Patterns (2021)

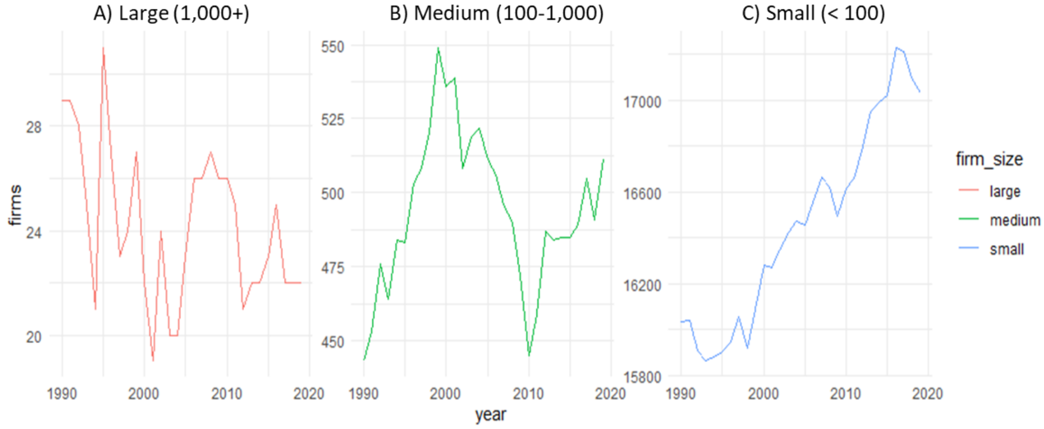


Figure 3.3A: Patents Produced in Rochester, NY, 1976-2014

Source: USPTO Patents View (2021)

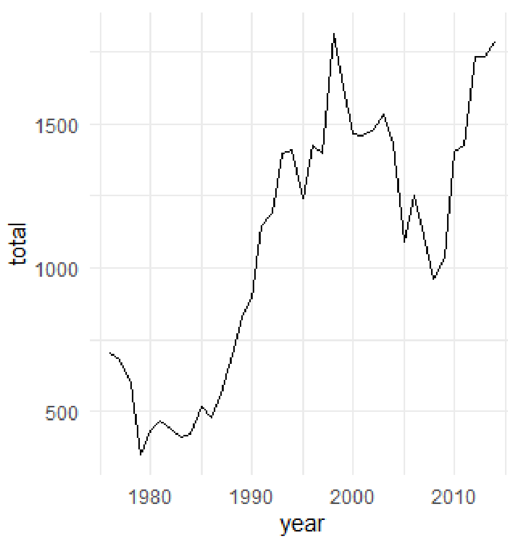


Figure 3.3B: Patents Produced in Largest Patenting NY Counties, 1976-2014

Source: USPTO PatentsView

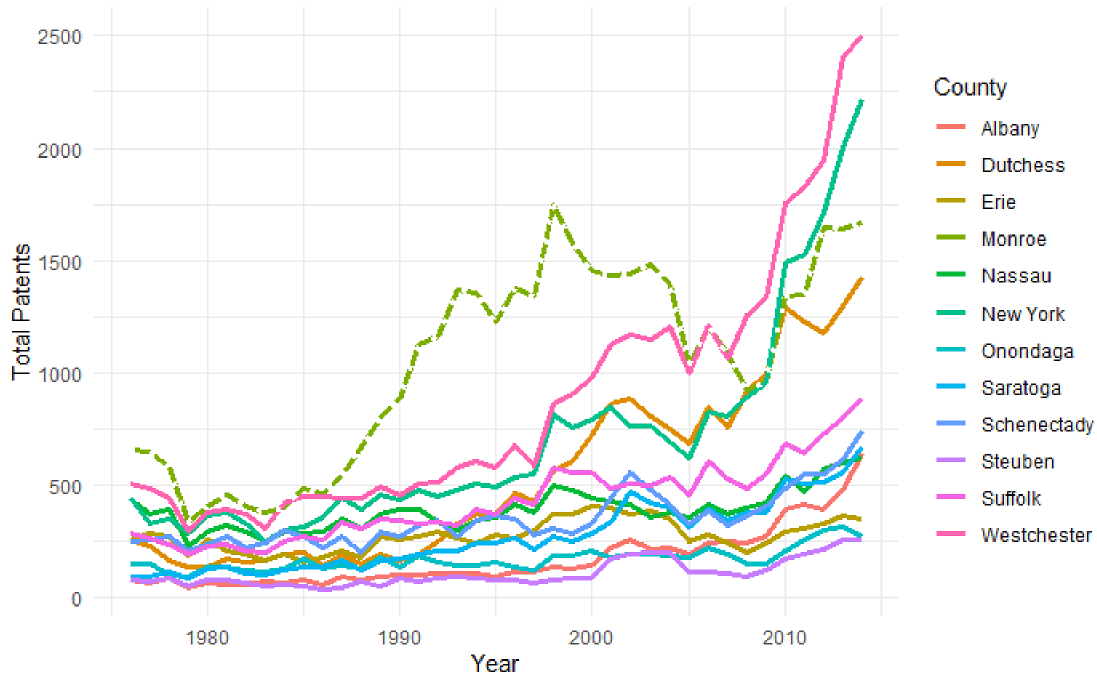
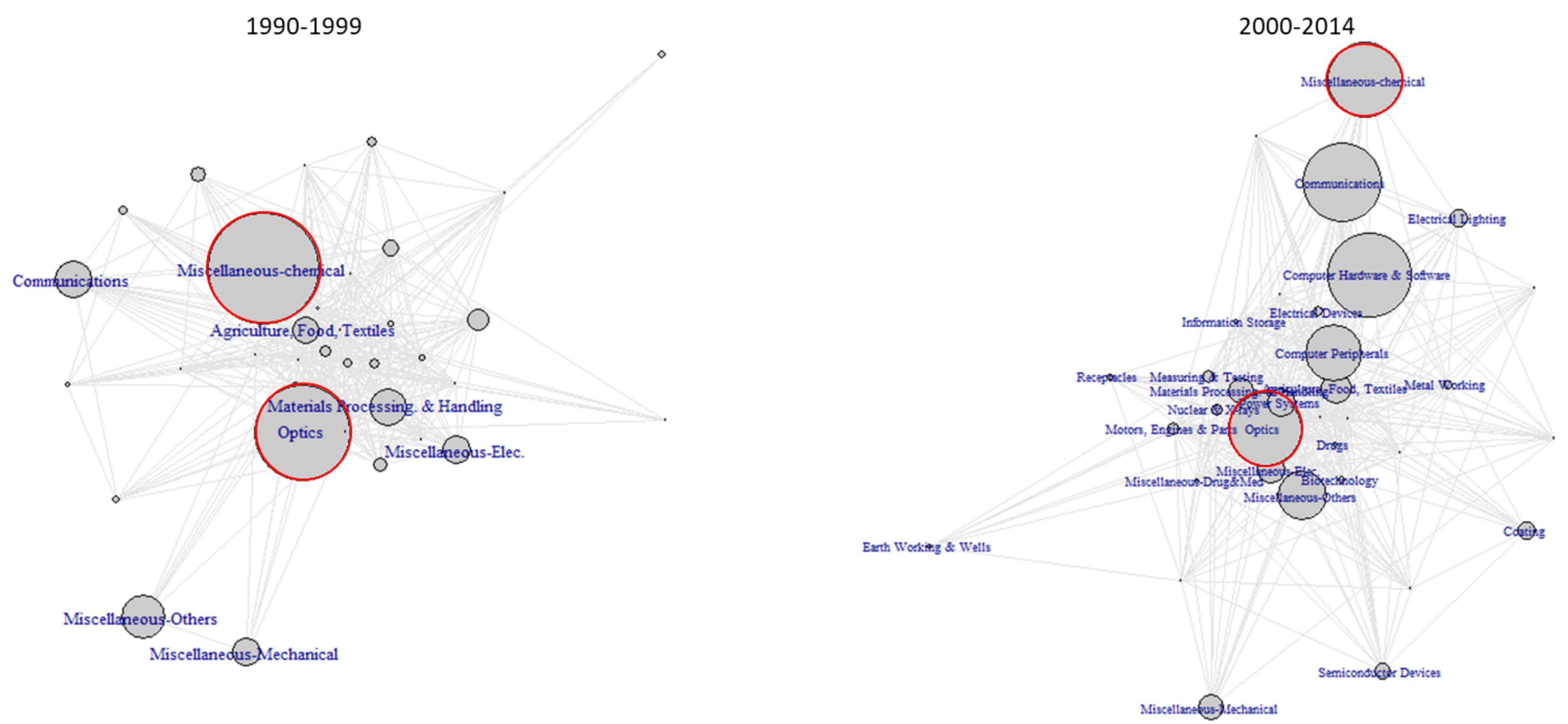


Figure 3.4: Knowledge Space of Rochester, NY by Time Period

Source: USPTO (2021)



III. Data and Methods: Mixed Methods Research

Because I wanted this research to be reflective of the lived experiences of people in Rochester, quantitative analysis was informed and supplemented by 31 interviews with former Eastman Kodak employees. Interviewees were identified through large online Facebook and LinkedIn groups of former Kodak employees, and represent a relatively diverse sample of workers from different areas of the company (e.g. engineering, manufacturing, information technology, finance, management, etc.). Interview questions and topics were open ended, allowing participants to discuss any aspect of their own career transition or the impact of Kodak's decline on the Rochester region. The purpose of the interviews was to identify any emergent patterns or themes prior to conducting quantitative analysis; quotes and general findings from the interviews will be primarily used in the discussion section to provide additional context to empirical results. For reference, a list of anonymized interview participants can be found in Appendix C.

Because the focus of this research is on the development and evolution of Rochester's high-tech industries after the decline of Eastman Kodak and other major firms, empirical work will broadly examine the mobility of local knowledge workers. To begin, I study knowledge workers themselves and their mobility decisions, with a focus on former employees of Eastman Kodak. I chose to examine one firm as a case study for two reasons: first, Kodak was the largest firm by far, and its former workforce represents a large percentage of displaced workers in Rochester over the years. Second, focusing on workers from one firm enabled me to better target my research efforts. Survey data were collected for this analysis in three ways. First, a questionnaire survey was circulated in Kodak alumni groups on both Facebook and LinkedIn to reach a wide audience. Second, because many former Kodak employees are not members of alumni groups, and to ensure a high response rate, the survey was sent to former Kodak employees directly via LinkedIn. Third, taking a snowball sampling approach, survey takers were also asked to circulate the survey amongst people that they knew from Kodak. At this time, 174 former Kodakers have responded to the survey (at the time of writing), 71 of whom formerly patented for the company. These inventors are the focus of the following analysis (the broader survey will be used for future work). The survey was structured in three parts: the first part asked respondents general questions about their demographics (age, gender, education) and their job at Kodak. The second section asked about their experience finding re-employment after leaving Kodak, including questions about their current occupation and employer, whether they moved out of the Rochester region, and their reasons for staying or moving after separating from Eastman Kodak. The final section focused more specifically on patenting activity, asking inventors whether they patented again after leaving Kodak, what occupations they transitioned into if they discontinued patenting, and what challenges and barriers they faced to patenting again for their new firm or organization. A copy of the survey questions is available in the Appendix B of this dissertation. It is important to note that the survey sample is not intended to be representative of all of Kodak's employees; instead, the goal is to provide an illustrative snapshot of inventors from Eastman Kodak to better contextualize the conditions and considerations that impacted the mobility of inventors after leaving their jobs.

Table 3.1 presents descriptive statistics for the inventors in the sample. Column A shows mean statistics for the entire sample, while columns B and C present the minimum and maximum values of each variable, respectively. The average age of respondents was about 62, and 79% of the sample was male. Inventors spent an average of 23 years working for Eastman Kodak, and began working for the company in 1985. Inventors at Kodak were generally highly educated: 72% of respondents had a Master's or PhD, while 24% had a Bachelor's degree. Only 3% of respondents had an Associate's degree or high school education. 47% of respondents left Kodak voluntarily, while the remaining 53% were laid off by the company. After leaving Kodak, 41% of inventors in the sample moved to a new city, while 44% of inventors produced at least one additional patent in their new job. Respondents were asked to rank the similarity of their current job to their work at Kodak, with 1 being least similar and 5 being most similar. On average, most reported working in a moderately similar job to their role at Kodak, with an average score of 3.4 out of 5. The largest concentration of inventors reported similarity scores of 4 or 5, indicating that the majority were able to find re-employment in very similar occupations. I also compiled data on the number of patents each inventor produced while working for Kodak; on average, each inventor produced 28 patents, although the range of patents is quite large, with some inventors producing as many as 206 patents at Kodak, and some producing as few as 1.

Table 3.1: Survey Descriptive Statistics

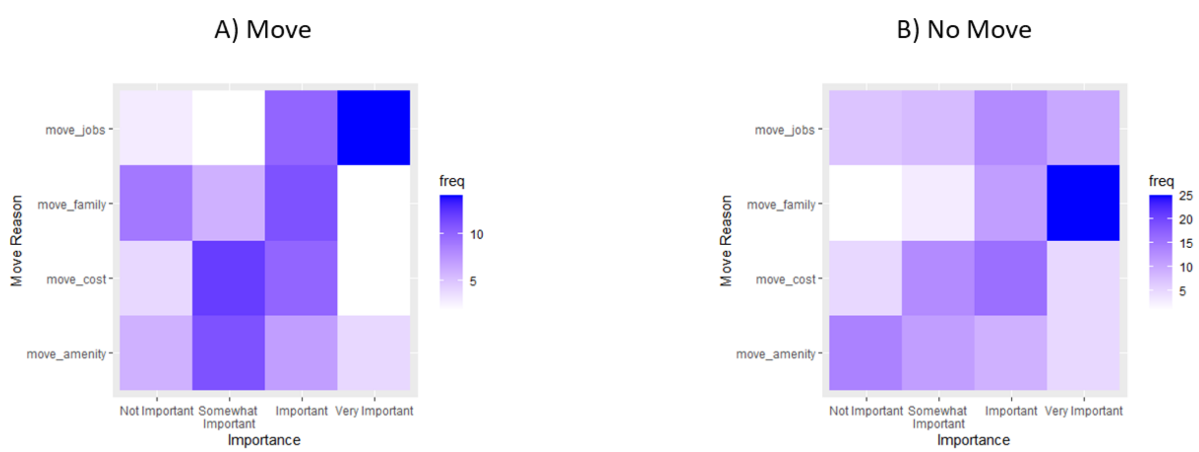
	A) All, Mean	B) All , Min	C) All, Max	D) No Move, Mean	E) Move, Mean	F) Patent Again, Mean	G) Stop Patenting, Mean
Age	61.691	42	77	63.250	59.464	60.310	62.718
Gender (Male)	0.789	0	1	0.810	0.759	0.774	0.800
Years at Kodak	22.605	5	45	24.474	19.804	20.533	24.160
Start Year	1985.129	1962	2001	1984.095	1986.679	1987.500	1983.350
Patent Again?	0.437	0	1	0.429	0.448	1	0
Move?	0.408	0	1	0.000	1.000	0.419	0.400
Voluntary Separation?	0.465	0	1	0.333	0.655	0.548	0.400
Job Similarity	3.379	1	5	3.368	3.393	3.793	3.054
Master's or PhD	0.718	0	1	0.690	0.758	0.871	0.600
Bachelor's Degree	0.239	0	1	0.238	0.241	0.097	0.350
Associates or Technical Degree	0.028	0	1	0.048	0.000	0.032	0.025
High School or GED	0.014	0	1	0.024	0.000	0	0.025
Average Patents at Kodak	28.12	1	206	37.081	9.722	44.333	12.5

Although there were seemingly few economic alternatives after the decline of Rochester's largest firms, a majority of inventors chose to stay in the region. What factors influenced this decision? Characteristics of movers and non-movers are presented in columns D and E of Table 3.1. All respondents were asked to rank the factors that were most influential in their decision to stay or leave, with possible responses ranging from "not important" to "very important". The factors for consideration included friends and family, job opportunities, the cost of living and taxes, and amenities and climate, and respondents were also able to fill in their own responses using an "other" category. Figure 3.5 illustrates inventors' responses using a heat map diagram: the reasons or factors are listed on the y-axis while the importance score is listed on the x-axis. The intensity of color indicates the number of inventors who selected each importance score for each factor. Separate heat maps are shown for inventors who moved out of Rochester and those who chose to stay in the area. The results of this analysis are striking: inventors who chose to move were more likely to rank job opportunities as their most important reason for moving. The cost of living was also rated somewhat important or important by movers, while amenities and family did not appear to factor into the decision for most people. Compared to movers, those who stayed in Rochester chose to do so almost exclusively because of friends and family. The dramatic contrast between the two groups suggests that inventors in each category prioritized very different factors when determining whether to move or stay in the region. Social ties were particularly strong amongst the majority of inventors who found re-employment in Rochester. Interviewees further confirmed this finding, with many attributing family (especially young children), friends, and a commitment to the local community as their motivation for remaining in town (Interviews 8, 9, 15, & 16, 2021). Interviewees who moved reported that higher paying jobs, lower property taxes, and warmer weather were often important considerations in their decision.

Those who stayed went on to work for a diverse range of companies in the Rochester area, including Kodak spin-offs and firms that purchased Kodak's former business units, including Carestream Health, Kodak Alaris, and L3 Harris, local optics and imaging firms including Orthoclinical Diagnostics, Circle Optics, Lumetrics Inc., and Corning Inc., and local universities (primarily the Rochester Institute of Technology). Several inventors who stayed were also involved in the founding of local start-ups: seven respondents reported starting businesses in the area. Interestingly, a number of founders reported starting a business that was very similar to their work at Kodak, while others pivoted into completely different industries or occupations through their entrepreneurship. Finally, inventors who produced a larger number of patents appeared to be more likely to stay in Rochester; it may be the case that more productive inventors simply had an easier time finding suitable employment opportunities locally. Additionally, respondents' answers highlight the importance of professional networks in identifying employment opportunities. Of those who stayed in Rochester, 32% reported that professional connections from Kodak were most helpful, and 32% reported that professional connections outside of Kodak were the most helpful. By contrast, only 15% of people reported that a job board or social media website like LinkedIn was the most helpful, and 17% reported that connections with friends and family were most helpful in their job search.

These results highlight the diversity of strategies that help workers get back to work in the face of job separation: the Rochester regional economy was able to absorb displaced workers through employment in small and medium sized firms, through spin-offs and other firms that took advantage of Kodak's technological expertise in Rochester, and through entrepreneurship and start-ups. Job seekers relied on connections from a variety of sources in order to gain access to information about job opportunities; inventors' called upon both personal and professional connections to successfully transition into re-employment. There is no "typical case" or story among the sample; local people utilized their own unique skills, expertise, technical knowledge, networks, and creativity to transition into re-employment and to re-deploy the skills that they gained at Kodak in new, productive ways. This aspect of the re-employment process was further supported by the interviews; interviewees consistently reported that the key to finding a new job, particularly in Rochester, was a willingness to be flexible and take risks on the job market (Interviews 11, 20, & 24, 2021). While Kodak's former workforce was extremely talented and well-trained, finding a new job often meant being able to repackage existing skills and experience to fit new industries and opportunities. For many inventors, that often meant transitioning into non-patenting positions or changing occupations entirely.

Figure 3.5: Inventors' Reasons for Mobility



Finally, I compare inventors who patented again with those who did not. Although subsequent analysis will focus on repeat inventors and their mobility across Rochester firms, it is important to know who is included in this sample and who is not. Columns F and G of Table 3.1

present mean characteristics for inventors who patented again and those who did not, respectively. Those who proceeded to patent again were slightly younger and worked for Kodak for, on average, four fewer years than those who did not. They were also more likely to move to a new city and to leave Kodak voluntarily, and they were much more likely to have a Master's or PhD. Those who patented again also reported higher job similarity, on average, compared with those who did not. Inventors who never patented again typically reported being unable to find patenting positions in their field and switching occupations voluntarily. A few reported not prioritizing patenting in their job search or working in a research area that did not commonly patent, while some reported working for new companies in R&D roles where there were either few resources for patenting or where trade secrets were prioritized over patenting. 28% of inventors who never patented again worked in engineering or R&D roles that did not patent, while 40% went on to work in management or leadership roles. A few switched occupations altogether, with some moving into sales or marketing roles, and some teaching, advising, or consulting. Inventors who never patented again were also more likely to report lower pay after leaving Kodak; 60% of inventors in this category were paid less at their new jobs, compared with 35% of those who reported patenting again. Although it is impossible to know, this pay differential may be due to occupational switching and the quality of the occupational match, skill mismatch in the new occupation, wage premiums due to experience or education, and any number of other explanations. In general, inventors who patented again are likely to be younger, highly educated, and more likely to have left Kodak for a new job voluntarily (rather than as a result of a layoff or downsizing event).

IV. Data and Methods: Patent Data Analysis

In order to construct networks of labor mobility between firms, we need detailed employment histories for each worker. No publicly accessible data provides this information with such a fine grain of detail, and data from the Census, such as the Longitudinal Employer-Household Dynamics (LEHD) survey, is only available in limited years (Census, 2019). Because I am interested in studying the impact of labor mobility on firm performance (namely, a firm's ability to produce new ideas) and innovation, I use United States Patent and Trademark Office (USPTO) data from the PatentsView database to model labor mobility as the movement of inventors across firms. Using patent records, I am able to identify inventors, the firms that they work for, their location, and the years in which they are actively patenting. When an inventor leaves a firm, new employers are identified by tracing their patenting activity in subsequent years. Assignee information on patents allows me to construct firm-level variables, including variables that capture the number of patents produced by a firm and the kinds of technologies it specializes in. While survey data enabled me to obtain detailed background information on 70 former Kodak inventors, patent data allows me to study the movement of all inventors in the Rochester region[6].

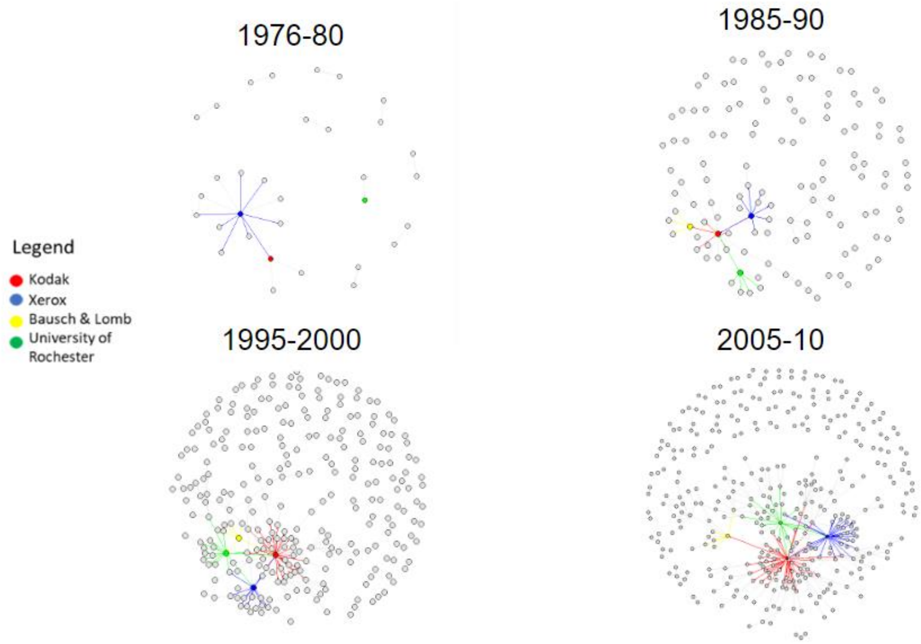
While patents are one of the most comprehensive and accessible data sources on innovation and inventors, there are clear limitations to using patent data that must be acknowledged. Not every firm patents. Patenting requires that inventors describe the production of a new technology in detail; therefore, secrecy is an important opportunity cost of engaging in the patenting process (Hall et al. 2001). Producing new inventions and patenting them requires

[6] Note that PatentsView uses disambiguation algorithms that link individual inventors to a unique Inventor ID. This enables me to trace inventors over time.

access to significant capital and funding, and is typically more easily accessible to larger, more established firms (Lamoreaux and Sokoloff, 2005). Some industries place more competitive value on patents than others (Shackelford and Jankowski, 2021; Sukhatme and Cramer, 2019). Finally, patent data can only tell us about some aspects of the firm's innovative process; data on, for example, R&D spending or hiring is typically not publicly available.

The final dataset contains patents produced by firms in Rochester between the years 1984-2014. This is a critical timeframe for Rochester's economy: the mid-1980s were Kodak, Xerox, and Bausch and Lomb's most successful years, while all companies downsized considerably between 1998 and 2010. This time period, therefore, allows me to capture the formation and evolution of the labor (or in this case, inventor) mobility network across firms. The network is constructed as follows: Rochester-based firms that produce patents constitute the nodes in the network. When an inventor patents for a local firm at one time, t, and patents again for a different local firm at a later time, t + x, a directed edge is drawn from the previous firm to the new firm in the network. The network is shown in Figure 3.6 in five-year time periods from 1976 to 2014 (1976 is included here for reference); edges are colored for the largest actors in the network, which include Eastman Kodak, Xerox, Bausch and Lomb, and the University of Rochester.

Figure 3.6: Inventor Mobility Network in Rochester, NY, 1976-2014



The network diagram reveals several illustrative patterns: there was very little firm mobility prior to 1995. After this time, firm mobility accelerated, driven largely by out-mobility from Kodak, Xerox, and the University of Rochester (the red, blue, and green edges, respectively). This is likely driven, on one hand, by inventors leaving or being laid off from the three major companies and, on the other, inventors from the University of Rochester graduating and entering the local labor force. Further, a clear structure began to form in the network by 2005, with the development of a large, main component anchored by the four largest actors, and a periphery of loosely connected or isolated firms. Table 3.2 presents some basic network statistics, illustrating the dynamism of the network over time. Tie density measures the total number of ties in the network, divided by the total number of possible ties. Transitivity is a measure of clustering in a graph; formally, if nodes *i* and *j* are connected, nodes *j* and *h* are connected, and nodes *i* and *h* are connected, then the relationship is transitive. Degree measures the total number of firms that each firm is connected to. Average degree and transitivity of all ties increases across the time period, and both the number and percentage of Rochester firms in the main component increases considerably over time.

As the descriptive network statistics illustrate, the network becomes both more cohesive and more complex over time. While only about 50 percent of firms are connected to the main network component between 1976 and 1984, more than 70 percent of firms are connected by 2014, and the main component grew by more than 1,500 percent across the study period. While the density of ties declines over time, likely due to the rapidly increasing size of the network, transitivity increases slightly, particularly between 1985 and 2014. While firms in the network prior to 1984 were, on average, hiring 1.8 workers from other firms over a ten-year period, the average degree centrality in the network increased to 5 by 2014, indicating that most firms had hired an average of 5 inventors from other firms. Finally, the increasing mean distance from each firm to every other firm in the network further illustrates the changing size and connectivity of the network over time.

Table 3.2: Select Network Statistics by Ten-Year Time Periods

Year	**Tie Density**	**Density (Component)**	**Transitivity**	**Transitivity (Component)**	**Average Degree**	**Mean Distance**	**Size of Main Component**	**% Firms in Main Component**
1976-84	0.014	0.040	0.047	0.048	1.848	2.260	33	50%
1985-94	0.004	0.009	0.027	0.024	2.27	3.04	157	61.6%
1995-04	0.003	0.006	0.052	0.049	5.00	3.77	355	66.6%
2005-14	0.003	0.006	0.056	0.056	5.09	4.53	537	71.6%

To what extent is the emergence and growth of the densely-connected core of the mobility network driven by inventors leaving Kodak, Xerox, and Bausch and Lomb? In other words, to what extent do these firms act as “bridges” in the network, connecting other firms in the main component? I can measure this formally using betweenness centrality; to do this, I first calculate the shortest path length between all firms. Betweenness centrality is then calculated as a count of the number of shortest paths between two firms that pass through a focal firm (this firm is positioned between the other two, functioning as a “bridge”). Betweenness centrality for the largest firms in the network is shown in Table 3.3 below. Eastman Kodak and Xerox have high betweenness centrality early on, but Kodak and the University of Rochester have significantly higher betweenness centrality than any other firm or organization by the end of the time period. This suggests that these organizations are highly central to the network and the flow of inventors (and information) between firms. Next, I consider the impact of this network structure on the performance of firms in the network using difference-in-differences regression.

Table 3.3: Betweenness Centrality of Major Firms in the Network, 1976-2014

Year	**Eastman Kodak**	**Xerox Company**	**Bausch & Lomb**	**University of Rochester**	**Mean Betweenness**
1976-84	18	187.3	0	3	5.08
1985-94	3376	1725.17	318	1170.17	36.62
1995-04	16,536.69	7,302.28	3,582.26	6,793.28	116.67
2005-14	41,070.75	15,264.92	8,369.06	33,949.19	315.77

To assess the impact of inventor mobility on local firms, I test the relationship between firm performance and a firm’s entry into the large, central component in the labor mobility network. Data are structured in a panel format, with observations for each firm measured across the years 1984-2014. Because not all firms patent, and some industries rely on patenting more than others, I only include firms that produce at least ten patents across the time period. This excludes several small firms that only patent once or twice; it would be challenging to determine the impact of main component membership on firms with so few data points. The final data set contains observations for 172 firms over 31 years, for a total of 5,332 observations. To avoid biasing the results towards KXB and their performance over time, they have been removed from the dataset.

Performance is measured using the total patenting output of a firm as well as firm survival, which is measured as a dummy variable that takes a 1 if a firm closes in a given year (and for all years afterwards) and a zero while the firm is in operation. 34 firms in the dataset, or about 20 percent of the sample, close between 1984 and 2014. Following earlier work by Owen-Smith and Powell (2004), the primary independent variable of interest, main component membership, takes a 1 when a firm becomes connected to the main component of the network, and for all subsequent years in the which the firm remains connected to the main component. A firm must join the network by hiring an inventor from another firm; firms that enter the main component only by losing inventors are not considered members of the main component. Because a firm likely continues to benefit from main component membership even after exiting the main component (the firm may retain the workers it hired, some of its connections, access to knowledge, etc.), but the benefits it accrues likely decline with each additional year outside of the component, this variable also takes a 1 for the five years following main component exit. Somewhat obviously, membership in the main component is also severed if a firm closes.

I also include several additional independent variables in the model to control for other firm characteristics that may impact patenting output. Because older, more established firms likely patent more than smaller, younger firms, I control for the age of the firm. Because the size of a firm is not typically public information, I proxy for the size of a firm's innovative workforce by calculating the number of unique inventors who patent for the firm between 1984 and 2014. Firms that hire more inventors are likely larger firms, and they also likely invest more in R&D spending; this variable may, therefore, proxy for other indicators for which we do not have data.

In addition, while main component membership may be one way that firms gain access to new knowledge, hiring inventors from outside Rochester may also provide firms with valuable external knowledge. Firms that hire local inventors may also hire non-local inventors, and the positive effect of non-local hiring may bias the results of the analysis. To control for this, I include a variable, *Percent Outside Inventors,* which measures the percentage of total inventors hired by a firm who moved from a city outside Rochester[7]. Additionally, data on the year a firm was founded and the year a firm closed were obtained by hand, using public company profiles that are available from business analytics companies Bloomberg and Dun and Bradstreet.

The relatedness of a firm's technologies to other firms in the region may also enhance its patenting output: Kogler, Rigby, and Tucker (2013) broadly find that high levels of relatedness within a city are associated with faster rates of patenting. This is because producing related technologies likely results in efficiency gains for firms in the region, who benefit from centralized resources and human capital, specialized knowledge spillovers, and other agglomeration-induced advantages. In Rochester, firms that produce optics and imaging technologies in the core of the region's knowledge space likely benefit the most from regional specialization. I measure relatedness in each year by creating a firm-technology class matrix; cells in the matrix represent the count of the number of patents that a Rochester-based firm produced in a given technology class. I then perform a one-mode projection to create a network where firms are nodes, and a tie between two firms signifies that the firms patent in the same technology class. Firms that are closer in the network are more related to one another. Average relatedness is a standardized measure of the frequency with which two USPC classes appear in

[7] This percentage variable was chosen because a count of total outside inventor would be highly correlated with the firm size variable – controlling for outside inventors as a percentage of total inventors allows me to include both variables in the model without significant multicollinearity.

the same firm in a given year; higher relatedness values indicate that a firm is more related to other firms within the local network. More details on the implementation of this method can be found in Balland (2017) and Steijn (2017).

I also control for the range of technologies produced by a firm and relative demand for those technologies at the national level. While larger firms with more diversified technology portfolios may have more opportunities and resources to produce patents, firms that specialize in technologies in high demand may have a greater incentive to patent their ideas to keep up with industry competition. *Technological diversity* uses the classes on a firm's patents to calculate the entropy of the technologies being produced; if a firm produces technologies that are spread out across many patent classes, that firm's patent portfolio is more diverse, and the entropy value is higher. Shannon entropy for each firm, f, is calculated as follows:

$$\text{Entropy}_f = -\sum_{fj}(p_{fj} \log (p_{fj})) \tag{1}$$

where p is the proportion of patents in each technology class, j, that the firm produced in Rochester (Guevara et al., 2016). Similar entropy measures have been used in other research in economic geography (e.g. Frenken et al., 2010). *Technology growth* examines a firm's technologies in relation to aggregate technological demand: using all USPTO patents, the average growth in a technology class in each year is computed. Using the set of all technologies produced by the firm, the weighted average technology class growth is calculated.

Although I am primarily interested in whether membership in the network impacts performance, I also include two measures of network centrality in the model to assess whether more central positions enhance the positive effects of main component membership. Again, following Owen-Smith and Powell (2004), network membership may confer benefits to firms in two ways: first, network membership itself may provide a diffuse channel for information spillovers between firms, as inventors move from one firm to another. Second, direct ties and ties to well-connected nodes may provide "proprietary pathways for directed information and resource transfer" between firms. To test this, *Degree centrality* measures the total number of other firms that a firm is connected to within the firm-mobility network by hiring inventors. This is an aggregate count of the firm's in-degree in the network. Because firms likely benefit by hiring inventors from another firm, but do not benefit when an inventor from their firm is hired away, firms' out-degree is not included in the analysis. *Eigenvector centrality* measures how connected a firm is to other well-connected firms in the network. Higher eigenvector centrality indicates that a firm's connections are also well connected.

Finally, I include industry and year fixed effects in the model. Although industry classifications are not available for patent data, I proxy for industries using a USPC to NAICS code crosswalk developed by Zolas et al. (2019). This approximates the probability that a USPC code matches with a particular NAICS industry; using these values, I calculate the aggregate probability that each firm matches with each NAICS industry based on its patenting activity, and assign each firm to the NAICS code with the highest probability match. Because some industries value patenting more than others, controlling for inter-industry differences is key (Shackelford and Jankowski, 2021; Sukhatme and Cramer, 2019). Although selecting industries in this way is somewhat crude (especially because the crosswalk frequently indicates that a firm could belong to multiple industries with differing probabilities based on its patenting activity), firms that are classified within the same industry should share enough similarities in patenting activity to add useful information to the analysis.

Using these variables, I estimate the following two equations for each firm, f, in year, t, and industry, i, using negative binomial regression to model patent counts and a linear probability model to assess a firm's probability of closing. The regression equations are as follows:

$$\text{Patenting}_{ft} = \beta_0 + \beta_1\text{main\_membership}_{fti} + \beta_2\text{controls}_{fti} + \gamma_t + \alpha_i + \varepsilon_{ft} \quad (2)$$

$$\text{Firm Exit}_{ft} = \beta_0 + \beta_1\text{main\_membership}_{fti} + \beta_2\text{controls}_{fti} + \gamma_t + \alpha_i + \varepsilon_{ft} \quad (3)$$

where γ_t is a year fixed effect, α_i is an industry fixed effect for each firm, and ε_{ft} is an error term. Table 3.4 provides summary statistics for the dataset and Table 3.5 present regression results.

Table 3.4: Summary Statistics

Variable	Full Model	Control: No Membership	Treatment: Post Membership
Patents Per Year	1.44	0.57	5.88
	(5.70)	(2.44)	(11.98)
Firm Age	54.96	53.31	68.39
	(50.78)	(48.93)	(57.46)
Degree Centrality	0.16	0.05	0.73
	(0.63)	(0.25)	(1.30)
Eigen Centrality	0.01	0.001	0.05
	(0.08)	(0.03)	(0.17)
Technology Growth	0.33	0.28	0.59
	(4.36)	(4.23)	(4.99)
Average Relatedness	0.35	0.29	0.67
	(1.29)	(1.27)	(1.37)
Technology Diversity	0.27	0.17	0.81
	(0.59)	(0.43)	(0.90)
Firm Size	10.95	5.44	38.85
	(31.26)	(16.12)	(60.63)
Percent Outside Inventors	0.08	0.07	0.13
	(0.20)	(0.20)	(0.18)

Values represent means across all years, standard errors are presented in parentheses.

Table 3.4 presents summary statistics for the full data, for firms that are not in the main component or who have not yet joined, and for firms after they have joined the main component. The difference between the two groups is striking: after joining the main component, firms produce significantly more patents, they employ more inventors and a higher percentage of non-local inventors, and they have higher centrality within the inventor mobility network. Firms that join the main component also produce technologies that are in fast-growing technology areas, that are more diverse across technology classes, and that are more related to Rochester's knowledge core. These results, however, may be misleading: firms likely produce more patents, hire more inventors, and expand their technology portfolios as they become more established over time. If firms tend to join the main component later in their life cycle, this pattern may, therefore, only capture a timing-effect rather than the true influence of main component membership. Employing a difference-in-differences design in the regression model and lagging the independent control variables in the model will both serve to control for this issue to some extent. It is important to note, in addition, that patenting in the United States has increased more generally in the last two decades. This may also account for an increase in patenting activity after firms join the main component of the network. Therefore, including year fixed effects in the model is key to the model specification. I next turn to more formal regression to further examine this relationship with appropriate controls.

Table 3.5: Final Regression Results

Dependent Variable	Total Patents			Firm Exit
Variables	(1) Main Component Membership	(2) Former Kodak/Xerox Mobility	(3) Long Term Effects of Membership	(3) Main Component Membership
Intercept	-19.92 (2464.67)	-20.00 (2566.37)	-19.89 (2426.55)	-0.11*** (0.04)
Main Component Membership	0.51*** (0.06)	0.44*** (0.08)	0.68*** (0.07)	-0.16*** (0.01)
Main Component (Long Term)	--	--	0.31*** (0.07)	
Kodak/Xerox Mobility	--	0.55*** (0.07)	--	--
Firm age	-0.001** (0.0005)	-0.001** (0.0005)	-0.001* (0.0004)	0.0004*** (0.0001)
Degree Centrality	0.21*** (0.03)	0.20*** (0.03)	0.18*** (0.03)	0.02** (0.01)
Eigenvector Centrality	0.17 (0.17)	0.16 (0.17)	0.02 (0.17)	0.22*** (0.06)
Technology Growth	0.008** (0.004)	0.008** (0.004)	0.009** (0.003)	0.001 (0.001)
Average Relatedness	0.15*** (0.01)	0.15*** (0.01)	0.15*** (0.01)	-0.007** (0.003)
Tech Diversity	1.77*** (0.03)	1.77*** (0.03)	1.76*** (0.03)	-0.05*** (0.01)
Firm Size (Inventor Count)	0.001 (0.001)	0.001** (0.001)	0.002*** (0.001)	0.001*** (0.0001)
Percent Outside Inventors	0.87*** (0.11)	0.87*** (0.11)	0.85*** (0.11)	-0.04*** (0.02)
Year Fixed Effects?	Yes	Yes	Yes	Yes
Industry Fixed Effects?	Yes	Yes	Yes	Yes
R2	0.34	0.34	0.35	0.19
Observations	5,332	5,332	5,332	5,332

Results of the regressions are presented above in Table 3.5. Regression 1 tests the impact of main component membership on the number of patents a firm produces in a year. When a firm becomes connected to the main component of the network in one year, it is associated with a statistically significant increase of 0.51 patents the following year, holding all else constant. Other factors also influence patenting: as expected, firms whose technologies are more closely related to other firms in Rochester, firms which produce more diverse technologies, and firms which patent in fast-growing technology classes produce more patents per year. Additionally, firms which employ both more inventors and a higher percentage of non-local inventors also tend to produce more patents per year. Network centrality, specifically degree centrality, also has a positive and statistically significant effect on patenting, suggesting that more hiring inventors from local firms enhances a firm's patenting activity. Eigenvector centrality, or the level of influence of nodes in the network, does not have a statistically significant effect.

Is this increase the result of membership in the main component, or do the benefits of main component membership generally accrue to firms that directly hire former Kodak, Xerox, or Bausch and Lomb inventors? As a robustness test, I examine this by splitting the main component membership variable into two: Direct Mobility takes a 1 if a firm hires a former inventor from one of the three big firms, while the main component membership variable, in this case, only takes a 1 for firms that are connected to the main component but who have not hired a former inventor from one of the big firms. I find that the positive effect on patenting is slightly larger for direct mobility: firms that employ inventors from one of the three big firms experience an increase of 0.55 patents per year. By contrast, firms that are indirectly connected to the three big firms, but who are members of the larger main component, experience an increase of 0.44 patents per year. This generally suggests that membership in the main component, whether through a direct or indirect connection to KXB, is associated with a positive increase in patenting, compared with firms that are not connected to the main component.

Finally, do the benefits of main component membership impact patenting within the first few years, or are there long-term positive effects of membership? To test this, I split the main component measure into short-term and long-term variables: Membership (short term) takes a 1 within the first five years of joining the main component, and a zero otherwise. Membership (long term) takes a 1 after the first five years of membership, and a 0 otherwise. Results of regression using these variables are presented in column 3. In the first five years, main component membership is associated with a positive increase in patenting of 0.68 patents per year, while long-term membership is associated with a more modest increase of 0.31 patents per year. This suggests that firms typically exploit the benefits of joining the firm mobility network (through hiring inventors from other firms) within the first five years, although there are long-term benefits to main component membership as well.

Regression 4 examines the impact of main component membership on firm exit. The main component variable has the strongest negative effect on the probability of a firm closing: joining the main component of the firm mobility network is associated with a 16 percent reduction in the probability of firm closure. It may be that firms that hire workers away from other firms gain access to skills, ideas, or connections that enhance their innovative capacity and improve their chances of survival. Firms that are older and larger are more likely to close than smaller, younger firms. Firms that produce more diverse technologies, as well as firms whose technologies are closer to the center of Rochester's knowledge core, are also less likely to close than more specialized firms. Hiring more inventors from outside of Rochester also improves a firm's chances of survival. Importantly, there may be a simultaneity bias in this model that must be acknowledged: while, on the one hand, hiring inventors from other firms may enhance firm survival, firms that were already in decline may not have the resources to do so. It may be the case, then, that joining the main component does not decrease the probability of firm exit, but that approaching firm exit decreases the probability of hiring new inventors. More work is needed to better tease apart the causality of this effect.

V. Discussion and Concluding Remarks

While the bankruptcy or decline of a major firm is often devastating for workers and the local economy, in some cases it can also create new economic opportunities. When a city's firms are seemingly locked into a stagnant or unproductive economic trajectory or a period of what Martin and Sunley (2015) call "adaptive inertia", whether as a result of technological change, the maturity of an industry and its technologies, or increasing competitive pressures, a major shock or tipping point in the existing system may open up new evolutionary and adaptive possibilities for the region (Grabher, 1993; Boschma and Frenken, 2010). In this chapter, using the decline of three major firms in Rochester, NY as an illustrative case study, this research pursued three main lines of inquiry: first, using survey data on former Kodak inventors, this work assessed the mobility decisions of Kodak's former inventors, and their reasons for staying or moving out of the Rochester region. Second, using USPTO patent data, I provide a detailed descriptive analysis of the movement of inventors out of Kodak, Xerox, and Bausch and Lomb (KXB) and the formation of dense networks of labor mobility between Rochester firms that formed as a result of KXB's decline. Finally, using a difference-in-differences research design and negative binomial regression, I provide a preliminary look at the impacts of network formation on the innovative performance of firms in Rochester. To my knowledge, this work is among the first to connect firm decline, network formation, and regional technological resilience in this way.

Kodak's decline and eventual bankruptcy displaced thousands of local workers in Rochester. Based on a survey with 71 of Kodak's former inventors, I find that many workers preferred to stay in the local area following job separation. This decision was motivated primarily by ties to friends and family, as well as a sense of connection to the Rochester community more broadly. For many, social ties were a much more important consideration than job opportunities and pay expectations, the cost of living, and access to local amenities or agreeable weather. A desire to stay in town, therefore, led to the development of a large pool of highly skilled labor which enhanced the talent and human capital available to the region's many small and emerging firms. However, many inventors also reported being unable to find new career opportunities that involved the production of patents, forcing them to switch occupations or re-deploy their skills in new ways in order to find re-employment locally. On a broader scale, while the decline of Rochester's major firms may have freed up valuable human capital that could be utilized by other regional companies, some skills and technological expertise were also undoubtedly lost along the way, as some inventors transitioned into non-patenting roles and others moved away to seek employment opportunities elsewhere.

Focusing on the inventors from KXB who stayed in the region and continued patenting, I find compelling evidence that their movement across firms was a primary driver of the formation of dense networks of labor mobility, particularly after 1998. Kodak and Xerox, in particular, play a key bridging role in the formation of a large giant component in the labor mobility network, which becomes both more complex and more cohesive over time. The University of Rochester also plays an important role in network formation, as former students and researchers frequently move from academic to industry roles within the community. Using regression analysis, I formally test whether membership in the main component enhances the innovative output of firms. Being connected to the giant component in the network by either a) hiring someone directly from Kodak, Xerox, or Bausch and Lomb or b) hiring an inventor from a firm that is already in the main component both enhances the patenting performance and survival of firms. The number of connections a firm has in the network is also has a positive effect on patenting, suggesting that while membership alone is enough to convey firms with access to innovation-enhancing connections and knowledge spillovers, hiring more inventors from firms in the network also enhances firms' innovative capacities. This indicates that the benefits of labor mobility tend to both accrue diffusely throughout the network, as well as through more formal partnerships or the accumulation of network ties.

These findings directly contribute to previous literature on labor mobility and regional resilience by showing that network creation through firm decline is one factor that enhanced the innovative capacity of the region, thus helping Rochester to remain a hub of innovation in spite of the loss of its major anchor firms. This loss was due, in part, to adaptive inertia: in the case of Kodak, interviewees suggested that a continued investment in film photography, even after the technology was displaced by the emergence of digital photography, was largely the cause of the company's demise. Prior to its' decline, however, Kodak was proactive in investing in research and development in a wide range of products and technology areas; not only did many of these products form the basis of a number of successful spin-off companies, including Kodak Alaris and Carestream Health, but Kodak's former workforce also possessed extremely valuable technological expertise as a result of this continued investment. As one interviewee pointed out, the resources and technologies that were neglected by Kodak's myopic focus on maintaining its economic base at the expense of new ideas were able to "leach" into the community in the form of these spin-off firms, as well as acquisitions of Kodak's former business units and new ventures (Interview 14, 2021). Although I cannot formally test this hypothesis, I posit that one possible mechanism for Rochester's ability to return to previous levels of patenting was that Kodak's demise enabled many of these workers and their skills to diffuse throughout the regional economy, thus providing existing and emerging firms with an injection of new and valuable ideas which could enhance their own innovative processes.

On a broader scale, this shock or turning point shifted Rochester's innovative ecosystem and the local distribution of resources, skills, and expertise from one that was built around three large firms to a larger and more dynamic network of small and medium sized companies. One key element of this dynamic shift, as this chapter highlights, was the formation of a large and diffuse network of labor mobility across firms. This type of networked ecosystem may be particularly beneficial for regional resilience because it first, provides local firms with a diverse source of ideas and competences through both direct hiring and access and proximity to regional knowledge spillovers. In this way, firms can better source external knowledge that can enhance their internal R&D activities. In an era of open innovation, this kind of access is key to effective knowledge production. Second, a larger and more diffuse network of firms may be more robust to future downturns or shocks, as a shock to one firm or industry is unlikely to impact other firms in the network. This case illustrates one way that the decline of an economy's economic base in one time period can form the foundation for its adaptation and recovery in the next, thus enabling it to "bounce forward" to a new evolutionary form, rather than back to its previous configuration (Martin and Sunley, 2015).

There are a number of limitations to this analysis, as well as fruitful areas for future research. This research narrowly focused on regional resilience from an innovation perspective, conceptualizing the ability of the Rochester region to adapt to a major shock as its ability to return to or surpass previous levels of patenting after a significant downturn. I cannot make any inferences about the impact of this increase in innovation on economic indicators like employment growth or GDP, although there is a significant body of research that supports the link between innovation and economic growth. I also cannot say anything about the distributional effects of innovative or technological resilience, and whether the positive benefits of this type of growth are concentrated within firms and the R&D workforce or if there are ripple effects within the wider Rochester community. I have collected survey data and intend to produce future research that focuses on the employment transitions of Kodak's workforce more broadly, but that has not been the focus of this paper. There were undoubtedly other factors that enabled Rochester to absorb the loss of KXB, including the existence of robust healthcare and service sectors, which are not the focus of this research. Finally, there are potential downsides to using a case study like Rochester as the focus of my analysis: although firm decline may be a potential mechanism for network formation, this may be contingent on the type of firm and industry affected, the makeup of the firm's labor force, and the broader regional economy in which the firm is situated. For example, in the case of Rochester, KXB were highly innovative, high-tech firms, and their combined labor force was highly skilled, which enhanced the probability that displaced workers would find re-employment in local firms. The decline of a manufacturing plant might play out very differently. The Rochester region is also considered affordable and "up-and-coming" by its residents (as discussed by interview respondents); a similar economic shock in a more expensive region, or a region that has experienced persistent decline and urban decay, may also play out very differently. Future work should consider whether Rochester's experience is replicable in alternative regions and industries.

Finally, this research illustrates several lessons for policy makers, particularly those in regions that are facing the decline of a major employer. First, the large population of displaced workers were able to find regional re-employment as a result of a number of factors: first, Kodak in particular sold off many of its business units and technologies as it approached bankruptcy, leading to the creation of spin-offs and the emergence of additional firms through the purchase of Kodak's intellectual property. By hiring former Kodak workers and sometimes even adapting Kodak's organizational structure to their new organizations (according to interviewees), these firms were able to exploit existing knowledge, networks, and infrastructures to gain a considerable competitive advantage (Interviews 13, 14, 18, 26, 2021)[8]. Many of Kodak's workers were able to leave Kodak to directly work for one of these firms. Second, several former KXB employees "saw the writing on the wall" and left their firms in order to start new ventures using their technological expertise (Interviews 12, 24, 2021). According to interviewees, Kodak often supported and formed partnerships with these new enterprises, helping them to establish themselves within the regional economy (Interview 23, 2021). These spin-offs and new businesses formed an important component of the regional innovative ecosystem that, as I have argued above, ultimately enhanced the region's adaptive capacity. Finally, Kodak provided free employment counseling to displaced workers along with educational incentives, helping workers who could not find suitable re-employment to transition into new occupations and re-deploy their existing skills (Interviews 5 and 7, 2020). Respondents also discussed utilizing free employment support and networking organizations in the region to aid in the job search process (Interview 31, 2022). This highlights the role that spin-offs, support for entrepreneurship, and re-employment assistance all played in getting displaced workers back to work. Regions experiencing similar shocks should consider developing a similarly multi-pronged approach to regional redevelopment efforts. Finally, the decline or bankruptcy of a major firm may also lead to some degree of human capital loss or brain drain as workers both switch occupations or move to new

[8] It is important to note, however, that spin-offs both benefited and were disadvantaged by keeping Kodak's structure and personnel: while the firms benefited greatly from the skills and expertise of Kodak's workers, some interviewees reported that the deeply ingrained company culture was somewhat inflexible, and made workplace change difficult (e.g. Interview 18, 2021).

regions to find suitable re-employment, and policy makers should prepare for this potential loss of talent as they plan for their economic futures.

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Conclusion

I. Introduction

As the United States and other advanced economies continue to pursue and support growth in high tech industries, the transition into the Knowledge Economy has transformed the landscape of economic development. One key feature of the knowledge economy is the growing importance of knowledge as a source of competitive advantage: organizations are incentivized to continually create and access new ideas as an input into the recombinatory process of knowledge production. Organizations that can both create and commercialize new ideas and technologies gain economic success, while those that cannot keep up with the pace of technological change are often driven from the market through a process of creative destruction. While a large body of literature has focused on how regions can promote the growth of successful high tech industrial clusters, less work has examined the destructive side of the knowledge economy. This dissertation seeks to fill this gap by studying the transitions of both knowledge workers and regional economies in response to the decline of major firms and industries.

Chapters 1 and 2 of the dissertation follow the career trajectories of knowledge workers as they are laid off or displaced from declining firms. More specifically, I use data on US patents to trace inventors who worked for these firms across their subsequent patenting careers to examine how job separation impacts both their mobility decisions and their future patenting performance. Patent data is the most accessible and comprehensive record of innovation that is currently available, and the inventors on patents are typically the scientists, engineers, and researchers who conduct research and development within firms, universities, and other organizations. Although knowledge workers make up a growing share of the labor force, and are a crucial driver of the production of new technologies, limited research has examined their employment transitions in response to involuntary job separation. Chapter 3 of the dissertation expands this analysis to the regional level, using Rochester, NY as a case study to examine the city's transition after the decline of its three largest firms. By incorporating statistical analysis of patent and economic data with survey and interview data collected from inventors who worked for a declining firm, this dissertation combines rigorous empirical methods with the voices and perspectives of knowledge workers themselves to make novel contributions to literatures in Economic Geography (and other disciplines) on inventor mobility and productivity, employment transitions, and regional economic resilience.

II. Executive Summary

In Chapter 1, I focus on inventor mobility across both firms and US regions, using a sample of US inventors who previously worked for major declining firms. All of the firms in the sample either went bankrupt, closed, were acquired, or merged with another company. Less than half of inventors in the sample patent again for new firms; while some inventors continue to patent for the declining firm, many likely switch into non-patenting occupations following job separation. I find that inventors who are more productive, and who possess a more diverse or valuable range of technological expertise, are most likely to patent again for a new firm after separating from their jobs. Networks are also a strong determinant of inventor mobility, as inventors who collaborated with a larger number of co-inventors, and those whose co-inventors are more influential, are also more likely to transition into patenting positions for new firms. Focusing on geographic mobility, I find that inventors are more likely to find new, patenting positions locally when they live in a region that has a large mix of firms that produce both related and unrelated technological variety (Frenken et al., 2007). However, inventors who are both more productive and whose skillsets are more technologically diverse are more likely to move to new cities.

Chapter 2 examined the impact of job separation on inventors' future patenting careers. While some inventors were able to leave a declining firm and return to patenting immediately (in one year or less), many inventors faced a much larger gap in patenting; I hypothesized that experiencing a larger gap or transition time between displacement and patenting again would have a negative effect on future patenting. I find that inventors who patent again in one year or less experience a significant boost in productivity, technological diversity, and total co-inventors over the course of their subsequent careers, compared with inventors who experience a longer gap period. On one hand, a longer gap may indicate that the new job is a poor match for inventors' accumulated skills and expertise, requiring more on-the-job training and work experience in order for the inventor to return to patenting. On the other hand, this gap may be the result of limited patenting resources at the new firm, or the inventor may have placed less emphasis on patenting in their new position; in any case, this gap may lead to the deterioration of industry or firm-specific skills and relational capital which would negatively impact an inventor's future patenting activity. In addition, when there are few local employment opportunities that are a strong match for an inventor's skills, they may consider finding employment in a new technology field or moving to a new city to access more employment opportunities; while patenting for a new firm in the same technology field significantly enhances the positive effects associated with patenting again more quickly, moving to a new city reduces or even cancels out the benefits of a short patenting gap. This suggests that there may also be geography-specific human capital that an inventor loses when they move to an unfamiliar city after losing a job or leaving a declining firm.

Chapter 3 studies the impact of firm decline on regional economic resilience, using Rochester, NY as a case study. Building on the analysis from earlier chapters, I focus on regional resilience from an innovation perspective, investigating the impact of inventor mobility out of declining firms on the innovative performance of other regional patenting firms. After Eastman Kodak, Xerox, and Bausch and Lomb (KXB) laid off thousands of workers simultaneously, Rochester seemed as though it would never recover from the magnitude of the shock. However, I argue that the loss of the region's large anchor firms actually laid the foundation for new growth and development. Although some inventors moved out of Rochester after leaving their jobs at KXB, many stayed and found re-employment in the area in order to stay close to friends, family, and the local community. Those who were able to find new, patenting positions were able to contribute the valuable skills and expertise that they gained from their previous role to their new company, thus enhancing the knowledge base of regional firms. I showed that the movement of displaced inventors across firms spurred the creation of dense networks of regional labor mobility. Membership in the network's main component significantly enhanced the patenting performance of firms; following work by Saxenian (1996) and others, I argue that labor mobility networks provided firms with critical access to both direct technical expertise and more diffuse knowledge spillovers, opening up new technological possibilities that would not have been available otherwise. From a resilience perspective, this major shock shifted Rochester's innovative ecosystem and the local distribution of resources, skills, and expertise from one that was built around three large firms to a larger and more dynamic network of small and medium sized companies, thus contributing to Rochester's ability to re-invent itself and emerge as a highly innovative industrial cluster once again.

III. Contributions of the Research and Policy Recommendations

This work contributes to scholarly research and debates in the following ways. First, it combines literatures on employment transitions and mass layoffs with literature on inventor mobilities by studying the mobility of knowledge workers in response to firm decline. To my knowledge, I am the first to undertake this line of inquiry. Although previous research finds that geographic mobility in general tends to enhance the productivity of inventors (e.g. Hoisl, 2009; van der Wouden and Rigby, 2020; Miguelez, 2019), my work shows that inventors who move in response to a layoff (or to avoid a layoff event) performed similarly or worse than inventors who did not, even though moving enabled them to resume patenting in one year or less. This suggests that inventors who move during periods of firm decline may be significantly different from inventors who move during periods of relative growth, and that the resulting impacts of mobility on inventor performance may play out differently depending on the context of the move. Next, it contributes to debates about the roles that related and unrelated technological and industrial variety play in enhancing a region's ability to adapt to major employment shocks (Frenken et al., 2007; Hane-Weijman et al, 2018). Inventors who separated from a declining firm were more likely to find re-employment locally in regions that had both a higher mix of related and unrelated variety; during periods when the firm was doing relatively well, however, inventors were more likely to move away from these same cities. This further highlights the different incentives faced by inventors who leave their jobs in response to firm decline.

Finally, this dissertation makes a major contribution to literatures on regional economic resilience by first, highlighting the role that the formation of labor mobility networks can play in enhancing a region's adaptive capacity. Second, building on work by Casper (2007), I show that the decline of a major firm (or firms) can serve as the engine of network formation: as KXB's former workforce found re-employment in new firms, their mobility created dense inter-firm linkages which facilitated both direct and indirect knowledge sharing and enhanced the innovative capacity of the region. Third, I provide evidence to support the idea that regions function as complex adaptive systems in which adaptation is an ongoing process. Under this evolutionary model of resilience, agents can use and take advantage of the region's unique mix of resources, capabilities, and linkages to "bounce forward" and chart a new growth path in the face of a major shock. Unlike other definitions of resilience, this perspective recognizes that there is often no singular state or equilibrium to which a region must return after being knocked off of its growth path; instead, resilience plays out in complex and uneven ways across regions, and while some places will be able to absorb the effects of a shock more easily and resume business as usual, other shocks will require regions to reconfigure or reimagine their industrial, technological, network, or institutional structures entirely in order to respond and adapt to economic change (Balland, Rigby, and Boschma, 2015; Swanstrom, 2008; Martin and Sunley, 2007). Rochester serves as an illustrative example of a region that was able to successfully reconfigure those structures in order to transform itself from a specialized company town to a relatively diversified cluster of small and medium sized firms. This highlights the usefulness of an evolutionary model of resilience in understanding Rochester's transition, and in developing policy recommendations for cities undergoing similar processes in the future.

The results of this dissertation research have important implications for regional economies. First, smaller, less technologically diverse regions are likely to experience the largest adverse impacts when a firm declines: not only do these regions have to face the usual consequences of major layoffs (e.g. loss of income and consumer spending, increased pressure on regional services, and other ripple effects), but my research also suggests that brain drain, or the loss of economically valuable skills and technological capabilities, may also be more acute in these regions. Additionally, regional skill loss after the decline of a major firm may occur through three mechanisms: first, as mentioned, some knowledge workers may move away to seek employment elsewhere that is a better match for their skills or pay expectations. Inventors who assign a higher priority to career success over family or geographic attachment are especially likely to move, and these inventors tend to have higher rates of productivity and technological diversity. Geographic mobility, in this case, constitutes a direct loss of valuable skills and technological expertise. Second, some knowledge workers may switch occupations and stop patenting entirely, leaving industry and firm-specific skills unused in their new occupation. Inventors who feel a strong sense of geographic attachment may be more willing to switch occupations in order to avoid moving to a new location, but doing so may render many of their accumulated industry and firm-specific skills redundant. Finally, transitioning to a new patenting position may involve a considerable transition period, during which time existing skills are unused and may even began to decline over time. When they begin a new job, inventors must adapt to their new firm and its particular operating environment, the specificities of their new technological field, and their new co-invention relationships. They may face considerable barriers to patenting again, including a lack of support or resources for research and development in their new position. As a result, some inventors may take much longer to return to patenting than others. For all of these reasons, the decline of a major firm may have long-term implications for the innovative capacity of regions, if the loss of skills is not offset by efforts to attract, retain, and train new talent. Because innovation is an increasingly important source of economic value for regional economies, any loss of human capital in the aftermath of a major shock could undermine a region's redevelopment efforts.

This dissertation also highlights important policy implications for regions that experience economic shocks in the future. First, in the aftermath of the decline of a major firm, workers may initially struggle to find employment that is an adequate match for their skills and expertise. In the case of inventors, a significant number of inventors will likely be unable to find patenting positions that are equivalent to their previous work. In my sample of Eastman Kodak inventors alone, more than fifty percent of inventors never produced another patent after leaving Kodak. While some transitioned into research and development roles that simply did not prioritize patenting, others changed occupations entirely. Workers whose skill sets are more specialized may have a particularly challenging employment transition, especially in the aftermath of an industry or technology-specific shock. Firms and regions should be prepared to provide assistance to displaced workers to help them better transition into new occupations and technology areas, whether through employment assistance and counseling programs, training and educational incentives, and other initiatives aimed at helping workers to re-deploy their skills in productive ways. As Chapter 2 emphasized, finding re-employment that is a strong match for workers' skills, and doing so quickly, is critical not only for knowledge workers themselves but for their performance in their future firm. Because the most skilled and productive workers will face the greatest incentives to move to new cities, efforts to either retain highly skilled individuals or retrain and upskill the existing workforce may also aid in the transitional process.

In addition, the Rochester case study highlights the need for a multifaceted approach to re-development efforts: while the loss of a major employer can have pervasive negative impacts on regional development, it can also open up new opportunities for growth. First, helping workers find re-employment opportunities locally may provide existing firms and organizations with access to valuable external knowledge and expertise while minimizing the disruption to workers' lives. Large firms like Eastman Kodak typically have more funding and resources to train their workforce than smaller firms and start-ups, and major layoffs could free up valuable skills and competencies that emerging companies can take advantage of by hiring displaced workers. Providing re-employment assistance to workers may, therefore, not only help individual workers, but enhance the knowledge and skill base of regional firms and contribute to regional adaptation efforts. In cases where local re-employment opportunities are unrelated to the declining firm, displaced workers likely still have transferable skills that could be valuable to local firms: for example, many former employees of Eastman Kodak were able to use their leadership or managerial skills to transition into new occupations and industries following job separation. Services like employment counseling may help workers to identify and market those skills. In regions where the local economy is too small to fully absorb the employment shock, support for spin-off firms, entrepreneurship, and the creation of start-ups may also provide significant re-employment opportunities in occupational or technological areas that are related to workers' previous job. Even though a technology shock might render the technology or product produced by the declining firm obsolete, there may be related applications of that technology field that are economically valuable and could fuel new growth. While considerable research has both stressed and debated the need to, for example, attract skilled workers to promote regional re-development (e.g. Florida, 2002; Lee et al., 2004; Peck, 2005; Kotkin, 2020), this research compliments externally-focused development perspectives by emphasizing the role that existing regional skills, resources, and expertise can play in enhancing a region's ability to adapt to major shocks. My dissertation adds to a growing body of literature in Economic Geography that has focused on this type of development in recent years: for example, emerging literature on Smart Specialization promotes policies that utilize existing place-based capabilities to help regions diversity into high value-added activities that are related to existing competencies (Balland et al., 2019; McCann and Ortega-Argilés, 2015; Foray, David, and Hall, 2009). As the Rochester case study illustrates, effectively utilizing and re-deploying the assets and capabilities that a region already has in new and creative ways can open up new economic possibilities for regions that have exhausted or are locked into existing growth paths.

IV. Areas for Future Work

Although this research has identified important implications and lessons for policy makers and economic development scholars, it also highlights some fruitful areas for future research. First, Chapter 1 and Chapter 2 only consider the effects of job separation on individual inventors; I can only infer the potential impacts on regional economies. Future research should focus on the impacts of firm decline and other economic shocks on regions, their innovative capacities, and their ability to adapt to the shock more broadly. Can we quantify the impact of firm decline on the geography of innovation on a wider scale? What factors either magnify or mitigate those impacts? While Chapter 3 provided an illustrative case study that showed one city's process of adaptation to firm decline, different cities have diverse endowments of resources, firms, human capital, institutions, and other place-based factors. No two cities will respond in the same way to an economic shock, and strategies that were successful in a city like Rochester may not work in other places. There is considerable space for more research on these topics, using both different case studies and at different scales of analysis.

Additionally, this dissertation is limited to studying employment transitions and regional resilience from the perspective of inventors and innovation. While inventors are an important group of workers, the results of Chapters 1 and 2 may not be generalizable to other segments of the labor force. Workers from many occupations and skill levels contribute to a region's knowledge base and innovative potential, whether they patent or not. Some industries value patents heavily, while others may rely on trade secrets, or simply have fewer resources to produce patents. There is considerable space for future research that expands these analyses to include knowledge workers in non-patenting roles, as well as workers who are not traditionally considered "knowledge workers" more broadly. Second, future research should investigate the link between innovative or technological resilience and economic outcomes more widely. Is an increase or resurgence in patenting a good predictor of increases in other economic indicators, such as employment or regional income levels? Finally, while policies that prioritize development in high tech industries can stimulate considerable regional growth and prosperity, some workers and neighborhoods likely reap more of the benefits of these policies than others: although my dissertation makes policy recommendations, it does not consider, for example, the distributional effects of development policy in the knowledge economy, or the impacts of place-based employment and innovation policies on equity and inequality. Research on these and other issues would greatly improve our understanding of regional resilience and development policy, and help researchers in this field to develop policy recommendations that are sensitive to the needs of workers across the labor force. While my dissertation research is only one piece of a larger research puzzle, it nevertheless constitutes an original contribution to our understanding of the employment transitions of knowledge workers and regional resilience in the knowledge economy.

V. References

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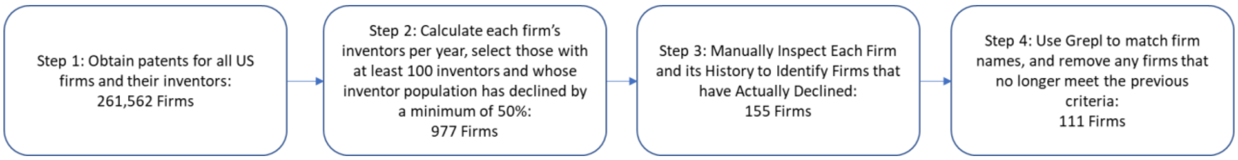
Appendix A

A. Creation of the Dataset

Figure A1: Creation of the Dataset



The process of creating the final dataset proceeded as follows: first, all firms (or assignees, as they are called on patents) with at least 100 inventors were selected. In smaller firms, the number of inventors per year often fluctuates much more, exhibiting patterns of “decline” when that may not be the reality (e.g. if a firm has 2 inventors in one year, and 1 the next, this may not actually be a be a reflection of the firm’s economic health). Then, using the number of inventors in a firm per year, firms that experienced a loss in at least 50% of their inventors after reaching their maximum number of inventors were selected. This was cross-referenced with the number of patents per year; “declining” firms had to also experience a simultaneous decline in patent production.

Many of these firms have lost much more than 50% of their inventors. Fluctuations in the number of inventors may occur for a number of reasons: a firm may actually be experiencing difficulties, and this may be a true reflection of inventor displacement. If a firm is otherwise performing well, but cuts its budget for innovation, this may result in a drop in inventor numbers. Many firms merge or change names over time, and this change may artificially create the appearance of inventor displacement when there has been none. To ensure the data contained only firms that have displaced or laid off inventors, I looked into the history and background of each firm to only retain those that had a) gone bankrupt or shuttered completely (12 firms), b) declined and were acquired by a larger firm (65 firms), c) merged with another firm (22 firms) or d) declined more generally, either laying off workers or restructuring from within while staying open and maintaining ownership (13 firms). Some firms did not have any information online, and those were also removed from the list.

Finally, to ensure that all patents from each firm were included, matching was performed with selected firm names and all other names in the assignee database. The names were stripped of common terms (e.g. “llc”, “corp”) and stop words (“the”, “and”, etc.), and converted to lowercase to improve the quality of the matching, which are common steps in natural language processing. Matching was performed using the “grepl” function in base R. The final set matched all variations of firm names with the original firm name (e.g. General Motors Corporation and General Motors Company would be matched together). This also accounted for cases where the assignee on the patent was misspelled (e.g. General Motors Company and General Motors Compnay). Firms were removed from the dataset at this point, if the previous criteria for decline was no longer met (e.g. if initially the firm experienced a 50% decline in inventors, but once all patents were accounted for the final value was only 30%). This final dataset contains 110 firms and 89,073 inventors. This is not an exhaustive set of all firms in the US that have declined over this time period, but it is sizeable enough to draw conclusions about inventors and their responses to firm decline.

B. Firm List

Below is a list of all of the firms included in the final dataset. Because many of the firms have used multiple variations of the same name on patents, the names listed below may be incomplete. Terms like "inc.", "llc.", and "corp" were removed to improve matching from many of the firm names.

Table A1: Firm List

Allied Chemical Corporation	Jds Uniphase
American Can Company	Kodak
Amoco	Lever Brothers Company
Armstrong Cork	Lsi Logic Corporation
Athena Neurosciences	Lucas Industries
Atheros Communications	Lucent
Atlantic Richfield Company	Mannesmann
Ausimont	Marconi Communications
Bea Systems	Martin Marietta
Berlex Laboratories	Maxtor Corporation
Best Lock Corporation	Mcdonnell Douglas Corporation
Betz Laboratories	Mci Communications Corporation
Breed Automotive	Merrell Dow Pharmaceuticals
British Technology Group	Minolta
Bunker Ramo Corporation	Motorola
Burroughs Corporation	National Research Development Corporation
Cabletron Systems	Nec Corporation
Calsonic Kansei	Neurogen Corporation
Cetus Corporation	Nexpress Solutions
Chartered Semiconductor	Nokia Mobile Phones
Chiron Corporation	Nortel
Chrysler	Oclaro
Cingular Wireless	Outboard Marine Corporation
Compaq	Phillips Petroleum Company
Conexant Systems	Picker International
Cooper Industries	Pioneer Corporation
Corixa Corporation	Polaroid
Credence Systems	Qimonda
Dade Behring	Rca Corporation
Data General	Rhodia
Delco Electronics	Robertshaw Controls Company

Digital Equipment Corporation
Discovision Associates
Dow Chemical
Dresser Industries
Electronic Data Systems
Energy Conversion Devices
Engelhard Corporation
Fmc Technologies
Ford Motor Company
Fort James Corporation
Fuji Photo Film Co
General Foods Corporation
General Motors
Genlyte Thomas Group
Goldstar Co
Gould Inc
Grumman Aerospace Corporation
Gtech Corporation
Hercules Incorporated
Hughes
Human Genome Sciences
Imperial Chemical Industries
International Harvester Company
Iomega Corporation
Rockwell International
Rorer Pharmaceutical Corporation
Sandoz
Sarnoff Corporation
Sperry Rand Corporation
Stauffer Chemical
Sterling
Sterling Winthrop
Storage Technology Corporation
Sun Microsystems
Tandem Computers
Tektronix
Texaco
The Hoover Company
The Mead Corporation
Trw Inc
Union Carbide
Union Oil Company Of California
United States Surgical Corporation
Univation Technologies
Utc Fuel Cells
Vlsi Technology
Westinghouse Electric Corp
Wyeth

Table A2: Dependent Variable Construction

	Did the inventor produce their last patent when the firm was:	
Did the inventor patent for a new firm?	Declining?	Growing?
Yes	New Firm (Decline) = 1 New Firm (Growth) = 0	New Firm (Decline) = 0 New Firm (Growth) = 1
No	New Firm (Decline) = 0 New Firm (Growth) = 0	New Firm (Decline) = 0 New Firm (Growth) = 0
Did the inventor patent again in a new CBSA?		
Yes	Move (Decline) = 1 Move (Growth) = 0	Move (Decline) = 0 Move (Growth) = 1
No	Move (Decline) = 0 Move (Growth) = 0	Move (Decline) = 0 Move (Growth) = 0

This table provides a more detailed explanation for how the primary dependent variables in the analysis were coded.

Appendix B

A. USPC Patent Technological Classification

The following patent classification system was developed and adapted from Hall et al. (2001). More information on the creation of this classification system can be found in their work.

Table B1: USPC Technology Fields Based on Hall et al. (2001)

Category 6	Category 36	USPC Classes
Chemical	Agriculture, Food, Textiles	8,19,71,127,428,504
Chemical	Coating	106,118,401,427
Chemical	Gas	48,96,95
Chemical	Miscellaneous-chemical	23,34,44,102,117,149,156,159,162,196,201,202,203,204,208,210,222,252,260,261,349,366,416,422,423,430,436,494,501,506,512,588,930
Chemical	Organic Compounds	260,987
Chemical	Resins	260
Computers & Communications	Communications	178,333,340,342,343,358,367,370,375,379,385,455,902
Computers & Communications	Computer Hardware & Software	341,380,382,700,701,702,703,704,705,706,707,708,709,710,712,713,714,715,716,717,718,719,725
Computers & Communications	Computer Peripherals	345,347
Computers & Communications	Information Storage	369,365,711,726
Drugs & Medical	Biotechnology	435,800
Drugs & Medical	Drugs	424
Drugs & Medical	Miscellaneous-Drug&Med	351,433,623
Drugs & Medical	Surgery & Medical Instruments	128
Electrical & Electronic	Electrical Devices	174,200,327,329,330,331,332,334,335,336,337,338,219,439
Electrical & Electronic	Electrical Lighting	313,314,315,362,372,445
Electrical & Electronic	Measuring & Testing	73,324,356,374
Electrical & Electronic	Miscellaneous-Elec.	191,200,219,307,346,348,377,381,386,850
Electrical & Electronic	Nuclear & X-rays	250,376,378,976
Electrical & Electronic	Power Systems	60,136,290,310,318,320,322,323,361,363,429
Electrical & Electronic	Semiconductor Devices	257,326,438,505

Mechanical	Materials Processing. & Handling	65,82,83,125,141,142,144,173,209,221,225,226,234,241,242,264,271,407,408,409,414,425,451,493
Mechanical	Metal Working	29,72,75,76,140,147,148,163,164,228,266,270,413,419,420
Mechanical	Miscellaneous-Mechanical	7,16,42,49,51,74,81,86,89,100,124,157,184,193,194,198,212,227,235,239,254,267,291,294,384,400,402,406,411,453,454,470,482,483,492,252,901
Mechanical	Motors, Engines & Parts	91,92,123,185,188,192,251,303,415,417,418,464,474,475,476,477
Mechanical	Optics	352,353,355,359,396,398,399
Mechanical	Transportation	104,105,114,152,180,187,213,238,244,246,258,280,293,295,296,298,301,305,410,440,903
Others	Agriculture, Husbandry, Food	43,47,56,99,111,119,131,426,449,452,460
Others	Amusement Devices	273,446,463,472,473,984
Others	Apparel & Textile	2,12,24,26,28,36,38,57,66,68,69,79,87,112,139,223,450
Others	Earth Working & Wells	37,166,171,172,175,299,405,252
Others	Furniture, House Fixtures	4,5,30,70,132,182,211,256,297,312
Others	Heating	110,122,126,165,237,373,431,432
Others	Miscellaneous-Others	14,15,27,33,40,52,54,59,62,63,84,101,108,109,116,134,135,137,150,160,168,169,177,181,186,190,199,231,236,245,248,249,269,276,278,279,281,283,289,292,300,368,404,412,428,434,441,462,503,968,977
Others	Pipes & Joints	138,277,285,403
Others	Receptacles	53,206,215,217,220,224,229,232,383

B. Survey Questions Used in Chapters 2 and 3

Displacement from Kodak

1. What is your current age?
2. What is your gender?
3. How long did you work for Kodak (in years)?
4. What year did you start working for Kodak?
5. What is your highest level of education?
    a. Some high school
    b. High school
    c. Associates or technical degree
    d. Bachelor's
    e. Master's or PhD
6. What year did you leave Kodak?
7. Did you leave Kodak voluntarily (i.e. you were *not* laid off)?
    a. Yes
    b. No
8. Which job category best describes your work at Kodak (Check all that apply)?
    a. Manager
    b. Engineer
    c. Researcher
    d. Technician
    e. Manufacturing and machine operations
    f. Maintenance
    g. Product Development
    h. Human Resources
    i. Finance
    j. Information Technology
    k. Logistics
    l. Quality Assurance
    m. Marketing or Sales
    n. Other [fill in the blank]
9. Which technical area did you work in?
    a. Software Development
    b. Electronic Development
    c. Mechanical Development
    d. Materials/Chemical Development
    e. Packaging
    f. Not Applicable

Finding Re-employment After Kodak

10. What is your current employment status?
    a. Employed

b. Unemployed and looking for a job
c. Retired
d. In school or training
e. Self-employed (started a business)
f. Underemployed
g. Other [fill in the blank]

11. What company do you currently work for? [fill in the blank]

12. If you have worked for more than one company since leaving Kodak, please list them in chronological order: [fill in the blank]

13. Did you move after you left Kodak?
    a. Yes
    b. No

14. If yes, what city did you move to? (Use City, State format if in US)
    [Fill in the blank]

15. If yes, please select that explanation that best explains your reason for moving:
    a. There were few employment opportunities in Rochester in my field
    b. There were few employment opportunities in Rochester in general
    c. I no longer wanted to live in Rochester
    d. I moved to be closer to friends or family
    e. I moved to take advantage of warmer weather or better amenities in another location
    f. I moved to take advantage of lower taxes or more affordable housing in another city
    g. Other (please explain)

16. If you decided to stay OR move away, what were the most important factors in this decision? (Check all that apply)
    a. Being close to friends and family
    b. Cost of living
    c. Local amenities (e.g. weather)
    d. Job opportunities
    e. Other [Fill in the Blank]

17. How did you find your new job? Rank in order of importance:
    a. Friends and family
    b. Work connections from Kodak
    c. Work connections outside of Kodak
    d. Online job board (e.g. Indeed)
    e. Social Media (e.g. LinkedIn, etc.)
    f. Not Applicable

Re-employment After Kodak

18. What is your current job category (check all that apply)?

a. Manager
b. Engineer
c. Researcher
d. Technician
e. Manufacturing and machine operations
f. Maintenance
g. Product Development
h. Human Resources
i. Finance
j. Information Technology
k. Logistics
l. Quality Assurance
m. Marketing or Sales
n. Other [fill in the blank]

19. What is your current technological area?

a. Software Development
b. Electronic Development
c. Mechanical Development
d. Materials/Chemical Development
e. Packaging
f. Not Applicable
g. Other [fill in the blank]

20. Describe your current pay at your new job (compared to when you left Kodak):

a. More than I was paid at Kodak
b. The same as I was paid at Kodak
c. Less than I was paid at Kodak

21. If you work or worked for another company after Kodak, how similar was the work you did to your Kodak job:

Not Similar 1 2 3 4 5 Extremely Similar

22. If you started a new company after Kodak, how similar is/was your company to the work you did at Kodak?

Not Similar 1 2 3 4 5 Extremely Similar

Optional Patent Survey

If you produced a patent at any time during your career at Kodak, please answer the following questions:

23. Please provide your name, as it appeared on any patents that you may have produced while working for Kodak. If your name has changed since you began patenting, please provide multiple names, separated by a comma (,).

24. Have you produced a patent since you left Kodak? [if No, please proceed to section 2]

a. Yes
b. No

Section 2: Inventors who Did Not Patent Again

25. If you did not produce any patents after leaving Kodak, please select the response that best represents your experience: "After leaving Kodak, I…"

a. Retired
b. Exited the Labor Force
c. Switched into a non-patenting role or occupation

26. If you answered C for question 25, please indicate the job title that you currently hold:

27. Please select the response that best fits why you did not patent again after leaving Kodak:

d. I did not want to produce patents in my new job
e. I was unable to find a patenting job in any city
f. I was unable to find a patenting job in Rochester, and I did not want to move
g. I was offered a non-patenting job that paid more than my previous patenting job
h. I voluntarily changed occupations after leaving Kodak
i. I exited the labor force or retired after leaving Kodak
j. Other (please explain)

28. If you patented again after leaving Kodak, did you face any challenges producing new patents? Check all that apply (if applicable):

- I needed to learn a lot about my new field or technology area
- I needed to gain experience at my new company in order to produce patents
- I needed to get to know my co-workers or research team before I could patent
- My new firm did not have as many resources for producing patents as Kodak did
- Other (fill in the blank)
- NA

C. Cox Proportional Hazards Model Goodness of Fit

Table B2: Cox Proportional Hazards Test Results

	Chisq	df	p
First Year	314.02	1	2.00E-16
Eigenvector	1.242	1	2.65E-01
Degree	13.023	1	3.10E-04
Diversity	63.6	1	1.50E-15
Average Patents	9.799	1	1.75E-03
Outside Inventors	0.933	1	3.34E-01
Weighted Tech Growth	5.494	1	1.91E-02
Ubiquity	3.95	1	4.69E-02
Distance Moved	1035.416	1	2.00E-16
City Size	0.488	1	4.85E-01
Tech Similarity	478.494	1	2.00E-16
Non-Compete Score	6.658	1	9.87E-03
GLOBAL	1596.501	12	2.00E-16

Using the Survival package in R, the proportional hazards assumption was assessed for the original Cox Proportional Hazards model. To do this, the cox.zph function correlates the model's set of scaled Schoenfeld residuals with time, to test for independence between residuals and time. A significant P-value indicates that there is a significant relationship between the residuals and time, and the proportional hazards assumption is therefore violated. Results of this test are shown in table A3. Because several individual variables have P-values <0.01, and the global result is also <0.01, I conclude that the proportional hazards assumption is violated, and a Cox model is not a good fit for this data. See Therneau (2021) for more details on this method.

Appendix C

I. Construction of the Knowledge Space

The knowledge space in Figure 4 was constructed based on methods developed by Kogler, Rigby, and Tucker (2013). First, data was gathered on all Rochester patents and the corresponding USPTO patent classes from 1976-2014 from Patents View. There are 44,877 total patents in this data set. To simplify knowledge space visualization, USPTO patent classes were aggregated into the 36 broad technology categories, as defined by Hall et al. (2001). Then, using the igraph package in R, I construct a patent – technology category network (Csardi and Nepusz, 2006). I performed a bipartite one-mode projection on this network to get a technology category – technology category network; an edge between two nodes signifies that the two technology categories appear on the same patent, and are therefore technologically related. Edges are weighted by the number of times two technology categories co-occur on different patents, while nodes are sized by the total number of patents produced in each category (divided by 100 to scale the visualization for viewing). The resulting network is then visualized in R for the time periods 1990-1999 and 2000-2014. Nodes that are closer together in the network visualization are more similar than nodes that are further apart, while larger nodes represent technology areas in which Rochester inventors have produced more patents.

II. Additional Data on Rochester's Economy

Figure C1: Breakdown of Monroe County Employment by Largest NAICS Categories

Source: Census County Business Patterns

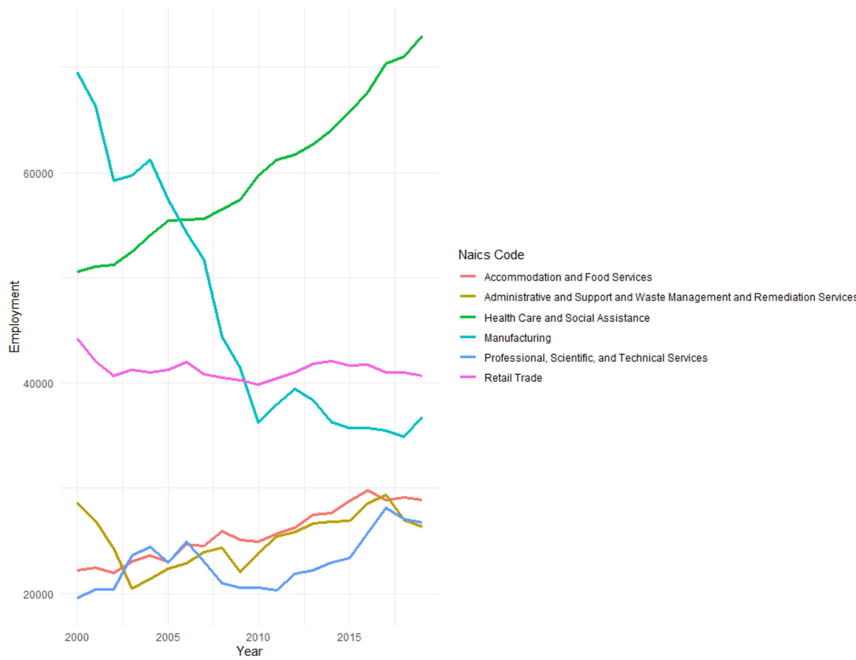
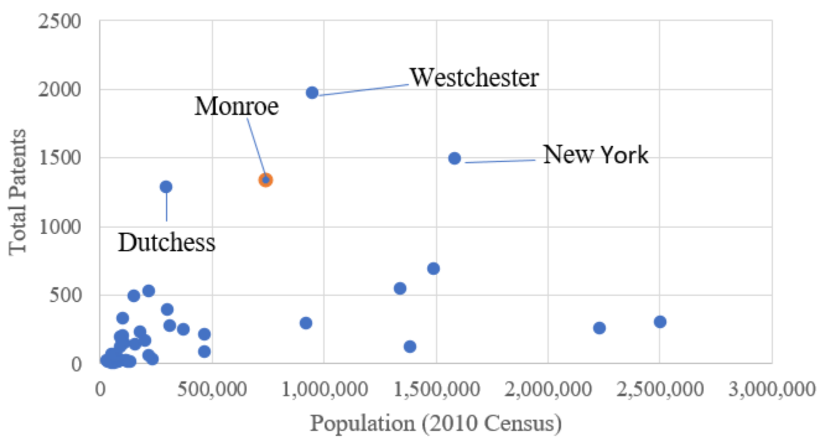


Figure A1 details employment growth in Monroe County by NAICS categories. This provides important context for the larger research study. Inventors and knowledge workers are in the Professional, Scientific, and Technical Services category. This category accounts for nearly 30,000 workers in the region and has grown in recent years (with a modest decline after 2017). My analysis of innovation growth in Rochester cannot tell the full story of Rochester's recovery, however. Much of the employment growth in Rochester has been in the Health Care and Social Assistance category, while manufacturing employment has declined significantly. Many former Kodak employees switched in healthcare or service industry occupations after leaving Kodak, and growth in these sectors has also been instrumental to Rochester's recovery. I hope to focus more on this broader story in future research.

Focusing more on innovation in Upstate NY, figure A2 illustrates the population and patent production in NYS counties in 2010. Most counties are clustered near zero on the graph, and a number of counties with high populations produce relatively few patents. The main outliers that stand out in the graph are Westchester and New York counties, which are both a part of the NY metropolitan area, Monroe County, and Dutchess County, which is the location of the city of Poughkeepsie and the home of IBM. Given that the major patenting firms in Rochester have declined in recent years, I argue that Rochester's recovery and its continued strength in patenting is particularly remarkable.

Figure C2: Patents and Population in NYS Counties, 2010



III. List of Interview Subjects

The following list provides more detail on the dates of each interview, as well as the occupation of each interviewee to illustrate the diversity of perspectives represented by my field work. In order to protect the anonymity of respondents, no additional information is provided.

Table C1: Interview Respondents

Interviewee Number	Interview Date	Role at Kodak
1	2/13/20	Mechanical Engineering
2	2/13/20	Engineering
3	2/13/20	Mechanical Engineer
4	2/13/20	Environmental Testing
5	2/13/20	Chemical Engineer
6	2/13/20	Chemist
7	2/13/20	Quality Engineer
8	2/13/20	Mechanical E
9	10/21/21	Finance
10	10/21/21	Manager
11	10/21/21	Chemist
12	10/22/21	Finance
13	10/22/21	Manufacturing, Manager
14	10/22/21	Manager
15	10/25/21	Chemist
	10/25/21	IT
16	10/25/21	Manager
17	10/25/21	IT
18	10/26/21	Manager, Researcher
19	10/26/21	Technical Support
20	10/27/21	Technical Writer
21	10/31/21	Industrial Engineer
22	11/2/21	Service Engineering, Management
23		Electrical Engineer
24	11/3/21	Research Fellow
25	11/8/21	IT
26	11/8/21	Imaging Scientist
27	4/28/22	Project Manager
28	4/28/22	Chemist
29	4/28/22	Senior Principal Scientist
30	5/3/22	Physicist
31	5/18/22	