OLD WORLD IN THE NEW ECONOMY:
SHAPING METROPOLITAN AMERICA'S INNOVATION LANDSCAPE THROUGH A HALF CENTURY OF PATENTED TRADITIONAL TECHNOLOGIES

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ABSTRACT

This dissertation investigates the restructuring process of regional economic development in US metropolitan areas through detailed analyses of the persistence of traditional technological innovations and their complex interplay with high-tech innovations. The dissertation is structured into three interconnected essays that address key issues: the sustainability of innovation in traditional fields, the impact of regional knowledge structures around traditional fields on high-tech innovation, and the potential for high-tech innovation capabilities to foster innovation in traditional fields.

The first essay examines whether regions historically specialized in traditional technological fields can sustain innovation in these fields amidst stagnant population and economic growth. Contrary to the conventional wisdom that economic and population declines necessarily lead to diminished innovation, the findings reveal the enduring significance of traditional technological innovation for regional economies.

The second essay investigates how diverse knowledge structures surrounding traditional fields can bolster a region's capacity to innovate within high-tech fields. This chapter highlights that, regions with a broader mix of patenting activities across both related and unrelated traditional technological sub-categories tend to exhibit higher innovation growth in high-tech fields, thereby demonstrating a stronger capacity for economic restructuring. Conversely, a high level of specialization in patenting within

specific traditional sub-categories may hinder a region's ability to restructure effectively.

The third essay assesses the potential for robust innovation capabilities in high-tech fields to enhance innovation in traditional fields. This notion challenges the traditional linear perspective of technological progression from traditional to high-tech fields. The results suggest instead a relationship where strong high-tech innovation capabilities stimulate innovation within traditional fields. However, traditional innovation is primarily shaped by path dependency, with the influence of high-tech fields serving a more complementary role.

Overall, this dissertation critiques existing economic development theories that focus predominantly on growth and the prioritization of high-tech industries at the expense of traditional sectors. It provides policy recommendations for regions aiming to leverage their established industrial strengths within a knowledge-driven economy. The research underscores the necessity of integrating industrial policy with prevalent place-based strategies to achieve sustainable economic growth and revitalization, particularly in regions struggling with the effects of de-industrialization and economic transition.

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CHAPTER I

INTRODUCTION

Urban decision-makers and regional scientists have long recognized that innovative industries significantly facilitate a region's economic development in the knowledge era. Most contemporary scholarship regarding innovation-led development centers around a few emerging high-tech industries, such as IT and life sciences, and a few growing regions, such as Silicon Valley and Boston (Mayer, 2011; Saxenian, 1996). By contrast, the decline of traditional industries, especially in regions like the US Rust Belt, is often cited as the root cause of widespread regional decline, notably in population loss (Partridge et al., 2015; Wiechmann & Pallagst, 2012). There is also broad agreement that policymakers in these regions have struggled to shift these de-industrialized economies towards competing with high-tech centers (Bingham & Eberts, 1990; Cooke, 1995; Neumann, 2016).

This perspective stems from mainline economic development theories. For instance, theorists observe the growth and decline of regional economies and conclude that innovation, productivity, and population change tend to reinforce each other, such as what endogenous growth theory has suggested (Krugman, 1991b; Lucas, 1988; Romer, 1986). Agglomeration theory also focuses on the relationship between overall or sector-specific industrial structure and overall or sector-specific innovation growth (Feldman & Audretsch, 1999; Glaeser et al., 1992; Jacobs, 1969). Nevertheless, I suggest that the dynamics among these economic factors are more complex in the process of economic restructuring, in that innovation may be sustained without population growth, new industrial strengths could arise from entirely different older industrial structures, and high-tech industries can drive knowledge creation within traditional industries.

My dissertation employs patented technological innovations as a lens to examine regions and industries that underwent major restructuring over the last half-century, with patent data sourced from the US Patent and Trademark Office (USPTO). Based on the United States Patent Classification (USPC) scheme used by the USPTO, this study identifies Chemical (excluding Drugs), Electrical and Electronics; Mechanical; and Others as traditional (technological) fields, or traditional (technological) categories, while classifying Computers and Communications, along with Drugs and Medical, as high-tech (technological) fields, or high-tech (technological) categories. A region's knowledge structure is evaluated in terms of its diversity, where patenting can show strong specialization in its top technological sub-categories, or a broad range of patenting activity across various technological sub-categories.

This dissertation comprises three interconnected essays, which offer in-depth analyses into the following questions: 1) Can metropolitan regions historically specialized in traditional technological fields sustain significant traditional innovation without notable population growth? 2) What effect does the traditional knowledge structure of metropolitan regions have on their ability to innovate within high-tech fields? 3) Does a metropolitan region's specialization in high-tech fields enhance its capacity to innovate in traditional fields?

While certain regions with distinct advantages – such as substantial economic size, strategic geographic location, and robust connectivity – may navigate industrial restructuring without severe population loss, job reduction, or economic stagnation, the majority of regions and cities are grappling with increasing uncertainties. These economic uncertainties stem from factors like technological advancements, global outsourcing, and the resultant demographic shifts and urban decline. A prominent example is that the widespread and systematic decline of manufacturing and industrial activities has posed significant economic development challenges across various regional economies, particularly in the United States and European Union. This phenomenon has been extensively documented in the urban decline and urban shrinkage literature, highlighting the profound adverse effects of de-industrialization on economic and urban landscapes (Hollander et al., 2009; Martinez-Fernandez et al., 2012; Pallagst et al., 2013).

In the context of the United States, the emergence of "Shrinking Cities" illustrates a significant consequence of de-industrialization, with approximately 80 US cities, primarily in the Midwestern and Northeastern regions, experiencing notable population declines (Ganning & Tighe, 2021). The timeline of de-industrialization usually extends over several decades (Cochrane et al., 2014; Mallach, 2014), drastically altering the geographic and economic fabric of affected regions and influencing the lives of multiple generations of local residents. One potential explanation for this transformation is the deep entrenchment of regional economies, institutions, and local cultures in their former industrial specialization, leading to substantial challenges in adapting to the new demands of a knowledge-based economy (Weaver et al., 2017).

The extensive nature of demographic changes has triggered many secondary effects, including diminished productivity and innovation, increased job losses, shrinking tax bases, rising inequality, urban decay, deterioration of public services, land abandonment, property decay, and even social unrest (Mallach, 2023; Martinez-Fernandez et al., 2012; 2016; Wiechmann & Pallagst, 2012). These developments have posed substantial challenges, especially for those unable to relocate to other cities or secure employment in emerging industries. Cities and regions that were once bustling centers of industry now grapple with the complex task of reinventing their economic identities, often further hindered by outdated infrastructures and skill sets that are incompatible with nascent industries (Taft, 2016). Consequently, it is imperative to address the multifaceted impacts of de-industrialization and to formulate effective strategies for economic recovery and sustainable growth.

Given the complexity of restructuring industrial bases, limited resources and capital, and negative outlook for future economic growth, place-based development strategies are often recommended for these economically lagging regions and cities (Betz & Partridge, 2013; Partridge et al., 2015). These strategies aim to improve the quality of life for residents who remain, embodying a broad spectrum of scholarship on quality of place, downtown revitalization, smart growth, and smart decline (Harrison, 2017; Herrmann et al., 2016; Hollander & Németh, 2011; Neumann, 2016; Schilling & Logan, 2008). Such policies are widely supported and institutionalized by entities like the Appalachian Regional Commission. Additionally, improving the quality of place has become a prevalent strategy for economic development planning in many Rust Belt or shrinking cities. In contrast, industrial policies, particularly those concerning advanced industries, receive less attention in academic research focused on these areas, highlighting a gap in the exploration of comprehensive development approaches for these regions and cities.

This dissertation advocates for a renewed emphasis on industrial policy as a vital, complementary approach for these economically lagging regions and cities. Such an approach may not be universally applicable, particularly in smaller towns and rural areas that lack the essential economic and industrial infrastructure necessary for initiating economic diversification and industrial restructuring. However, it holds significant promise for regions and medium-to-large cities endowed with substantial industrial resources and capabilities. Unlike place-based strategies, which primarily target immediate improvements in living conditions and employment opportunity for current residents, industrial policy aims for a more comprehensive economic revitalization. It seeks to cultivate or attract new industries and workforce talent, thereby offering a sustainable path for economic resilience and revitalization over the long term. Through the adoption of industrial strategies, regions can harness their latent industrial strengths to stimulate innovation and ultimately transform their economic landscape.

The first essay "*Reinforcing the Role of Older Industrial Centers? The Persistence of Traditional Technological Innovation in US Metropolitan Regions*" (Chapter 2) investigates the technological innovation activities in traditional fields in US's metropolitan areas between 1976-2014. Compared to high-tech fields, traditional fields demonstrate less innovative momentum in the knowledge economy era (Hall et al., 2001; Rigby, 2015). The economic challenges of some established industrial centers, such as the US Rust Belt regions, are hence attributed to their less-innovative industrial specializations, along with other reasons such as uncompetitive wages and population loss (Alder et al., 2014). However, I claim that though regions specializing in traditional technological fields may experience economic decline and population loss, they can sustain innovation activities in their traditional specializations. I test the following hypothesis: *regions with higher original patenting levels in traditional technological fields experienced greater patenting levels in those fields from 1976 to 2014*, and investigate the economic factors that have led to those sustained innovation activities.

Mainstream economic development literature, such as endogenous growth theory (Krugman, 1991; Lucas, 1988; Romer, 1986), industry life cycle theory (Hekman, 1980; Norton & Rees, 1979), and the stage theory of economic development (Parr, 1999), tends to suggest that incubating the more innovative high-tech industries is the preferable strategy for economic development. Nevertheless, recent empirical studies reveal that certain Rust Belt regions remain as innovation hotspots of traditional industries, even after their production activities and population declined (Hannigan et al., 2015; Mudambi et al., 2017). The perspective of evolutionary economic geography and industry-based economic development also provides potential explanations for the persistence of significant traditional innovations in these established industrial regions, despite a reduction in production activities (Boschma et al., 2015; Dumais et al., 2002; Klepper, 2002; 2010; 2016; Rigby, 2015). However, the broad applicability of these empirical findings requires further examination. This study also investigates the economic factors that have led to those sustained innovation activities by testing two sub-samples of regions experiencing population loss and slow economic growth during the study period.

The findings first indicate that traditional technological innovation continues to thrive even in regions undergoing population and economic downturns. Nevertheless, the resilience of innovation diminishes as regional populations decrease. Furthermore, the research posits that the existence of large manufacturing establishments and a large overall size of the manufacturing industry may contribute to the lower innovation performance of some Shrinking City regions. Subsequent to these observations, the study offers targeted policy recommendations to tackle the identified challenges and suggests new directions of academic inquiry.

Essay 2 "*Regional Innovation and Transformation: High Tech Innovation Growth and the Knowledge Structure around Traditional Technologies*" (Chapter 3) delves into the mechanism by which cultivating a diverse knowledge base not only enhances innovation growth but also supports the emergence of entirely new industrial capabilities within a region. Significant progress has been made in agglomeration research regarding the relationship between the industrial structure of a region's economy and its innovation growth, including the theory of MAR externalities (Arrow, 1962; Marshall, 1920; Romer, 1986), Jacobian externalities (Feldman & Audretsch, 1999; Glaeser et al., 1992; Jacobs, 1969), and related and unrelated variety (Castaldi et al., 2015; Frenken et al., 2007; Miguelez & Moreno, 2018). However, previous studies have mainly focused on how a region's overall or sector-specific industrial structure impacts its aggregate or sector-specific innovation growth. Fewer studies have explored how preexisting industrial structure is associated with the emergence of new industrial strengths, which could provide valuable insights for regions seeking to reinvent their export base.

This essay instead relates the topic to the processes of economic restructuring, asking *whether a more specialized or diversified knowledge structure within traditional* *technological fields better encourages high-tech innovation growth from 1986 to 2014*. By examining metropolitan areas that were innovating in traditional fields in 1986, this study finds that regions with greater diversity across both related and unrelated traditional technological sub-categories demonstrated higher levels of innovation in high-tech fields, thus exhibiting a stronger capacity to restructure their knowledge base. In contrast, a high degree of specialization in specific traditional technological sub-categories negatively impacts a region's ability to undergo restructuring. The trend remains consistent across multiple time periods from 1986 to 2014.

This study further clarifies the nuances in existing scholarship that propose reasons for how knowledge diversity can lead to innovation within technological fields that significantly diverge from a region's historical specialization. Based on its findings, this study posits, first, that regions with a broad array of traditional technologies – whether related or unrelated – offer more opportunities for high-tech companies to uncover new market needs among local industries. Second, regions marked by greater diversity, often correlating with larger economies and populations, foster economies of scale that better support high-tech start-ups, including those that deviate from their initial technological specializations. Third, while scholars may argue that regions historically focused on specific traditional technological fields have successfully integrated high-tech expertise, this study challenges this view, positing that most of these regions actually exhibit a high degree of related variety rather than a high degree of specialization.

Essay 3 "*High-tech Regions as Innovators of Traditional Technologies: Can High-tech Innovation Capability Foster Traditional Innovation?*" (Chapter 4) examines the potential for high-tech innovation to foster innovation within traditional fields. Given the role of innovation in economic development (Lucas, 1988; Romer, 1986; Solow, 1956), people have imagined technological progress as a linear process moving away from traditional fields and tending toward high-tech fields. Hence, pursuing innovation capacity in the more advanced high-tech fields has been a major direction of economic development. Besides high-tech regions and companies, scholars have also investigated how firms and regions specialized in the traditional fields have started to develop innovation capacity in high-tech fields (Hannigan et al., 2015; Mendonça, 2009; Robertson & Patel, 2007).

However, drawing from Schumpeter's (1942) theory of innovation and entrepreneurship, through the lens of evolutionary economics (Dosi et al., 1988; Nelson & Winter, 1982), to insights from the evolutionary economic geography community (Asheim et al., 2011; Asheim et al., 2017), a long line of theorists has consistently highlighted that technological progress is virtually never linear. Instead, there exists a symbiotic relationship between high-tech fields and non-high-tech fields, with innovations impacting across various economic activities. Despite this, there has been a scarcity of research investigating whether regions with stronger innovation capabilities in high-tech fields also contribute to innovation in traditional fields.

This study aims to address this research gap by testing the hypothesis that *regions with higher patenting levels in high-tech fields had greater patenting levels in traditional fields from 1996 to 2014*, while accounting for the impact of historical traditional specializations and other confounding variables. Additionally, this study replaces general patenting levels in the high-tech and traditional fields with specific technological categories, thereby providing a more detailed view of the hypothesized relationship. The results of this study support the primary hypothesis, and uncovers a positive association between the overall patenting levels in traditional categories and both of the two high-tech categories. This study also finds that among the traditional categories, the Mechanical category seems to have been the least influenced by advancements in overall high-tech innovation. The analysis further indicates that regional innovation, including in the traditional fields, is predominantly influenced by path dependency, with the high-tech fields' impact being more complementary.

The study delves into potential explanations for main findings, linking them with insights from both the current study's results and existing literature. First, innovating in traditional fields increasingly requires similar economic catalysts as does innovating in high-tech fields, such as human capital, research institutions, innovation infrastructure, and global competition (Acs et al., 2014; Berry & Glaeser, 2005; Furman et al., 2002; Glaeser & Hausman, 2020). Second, due to a stronger absorptive capacity, it is generally easier for a high-tech region to innovate in traditional fields compared to a region more specialized in a specific traditional category attempting innovation in a different traditional category (Boschma et al., 2015; Hidalgo et al., 2007).

Chapter 5 integrates the overarching theme of this dissertation along with the key findings from the three essays. It offers a concluding summary of common threads linking each essay, highlighting the theoretical contributions and policy implications that emerge from the research.

CHAPTER II

REINFORCING THE ROLE OF OLDER INDUSTRIAL CENTERS? THE PERSISTENCE OF TRADITIONAL TECHNOLOGICAL INNOVATION IN US METROPOLITAN REGIONS

2.1 Introduction

Since the rise of the knowledge economy, most conversations regarding innovation-led economic development have centered around growing metropolitan regions. Much attention has been given to a few leading regions, such as Silicon Valley, Boston, Austin, and Portland, which are known to be specialized in highly innovative industries including semiconductors, information technology, life sciences and pharmaceuticals (Mayer, 2011; Saxenian, 1996). By contrast, the traditional industrial strengths of some established industrial centers are largely blamed for the downward spiral of regional development in almost all social aspects, among which the population drop is perhaps the most noticeable (Wiechmann & Pallagst, 2012). Moreover, in public perception, the policymakers from these regions have struggled to restructure their de-industrialized economic bases in order to “catch up with” the high-tech centers (Bingham & Eberts, 1990; Cooke, 1995; Neumann, 2016).

Canonical economic development theories, such as product cycle theory

(Hekman, 1980; Norton & Rees, 1979) and endogenous growth theory (Krugman, 1991b; Lucas, 1988; Romer, 1986), could be a possible root of these policy choices and public perceptions. According to these canonical theories, the level of output/income a region achieves, the population it attracts, the "technological intensity" of the industries it specializes in (usually measured by STEM jobs), and the knowledge (especially patented innovation) it produces can reinforce each other. These mainline development theories represent the current rationale of growth-oriented development: a region can thrive in every dimension in a knowledge economy by advancing any one of those dimensions. By the same token, a retreat in any of those dimensions most often indicates the same in the others.

Recent scholarship, though, argues that the economic development and restructuring of established industrial regions is much more complex than these canonical explanations allow. For instance, some urban shrinkage scholars have started to challenge the equivalence between economic advancement (or industrial restructuring) and population gain after looking into older industrial cities in Europe and the US (Bartholomae et al., 2017; Hartt, 2018). One stream of the literature includes detailed case studies investigating the innovation activities of single US Rust Belt regions' established industries. The empirical evidence shows that, though usually without substantial population gains, these regions have sustained patenting activities in their traditional specializations. The studies cover industries such as opto-electronics, steel, automobiles, and synthetic rubber (Hannigan et al., 2015; Mudambi et al., 2017; Safford, 2004; Treado, 2010).

This study aims to explore the innovation dynamics in traditional technological fields in the US's metropolitan regions. The past four to five decades are usually considered as the period during which the innovation gap between traditional fields and modern high-tech fields widened (Hall et al., 2001; Rigby, 2015). This process, as mentioned before, coincided with the economic struggles of the host regions. However, with the latest progress in academic conversations, this study questions the equivalence between regional economic growth and the innovative capacity of the region's historically specializations. I examine the generalizability of recent empirical evidence, and contend that regions specializing in traditional fields can sustain innovation activities in their traditional specializations, even for regions experiencing population loss and economic decline.

Using regression analyses and primarily US Patent and Trademark Office (USPTO) patent data, this study tests the hypothesis that, *ceteris paribus, regions with higher original patenting levels in in traditional technological fields experienced greater patenting levels in those fields from 1976-1980 to 2010-2014*. This study further investigates the economic factors that have led to those sustained innovation activities by testing two sub-samples of regions experiencing population loss and slow economic growth during the study period. The findings first show that innovation often persists even when regions experience population and economic decline. Nevertheless, the persistence of innovation is reduced by regional population decline. Second, this study contends that the presence of large manufacturing establishments and a large overall size of the manufacturing industry could be factors contributing to the lower innovation performance of some Shrinking City regions. These findings are followed by specific policy recommendations to address the identified issues. Last, this study advocates for further research to explore the interactions between major economic factors, such as innovation, productivity, and population change, which canonical development theories have not yet thoroughly explained.

2.2 Literature Review

Regional scientists have long realized that the capability of a region's dominant industries to spawn new economic activities impacts the growth of the region. Also, the innovative activities are driven by new knowledge in its various forms (Booth, 1986; Chinitz,1961). The knowledge ranges from being aware of the locational advantages of natural resources and transportation to becoming familiar with the skills and scientific technologies needed for production.

Scholars find that industries where skilled labor and R&D input serve as important sources of innovative activities have a higher propensity to cluster in certain regions than other industries (Audretsch & Feldman, 1996a). These industries include both traditional manufacturing industries (Ellison & Glaeser, 1997; Ellison et al., 2010; Rosenthal & Strange, 2001) and more advanced high-tech industries (Mayer, 2011; Saxenian,1996). The concentration of these innovation-generating industries makes the regions that hold the industries enjoy increasing returns to scale and thus sustained economic growth (Arrow, 1962; Arthur, 1990; Jacobs, 1969; Krugman, 1991a; 1991b; 1994; Marshall, 1920; Romer, 1986). Besides saving costs on operations, firms in these industries co-locate because the economic knowledge is usually produced through intensive interaction and tacit transmission (Bathelt et al., 2004; Maskell & Malmberg, 1999; Morgan, 1997).

Nevertheless, compared to the more advanced high-tech industries, the traditional industries are considered to have lost their innovative momentum in the knowledge economy era. According to the canonical economic development stage theory (Parr, 1999), the dominant (export) industries of a region undergo structural change as the region develops. The change largely follows a systematic, thus predictable, sequence of stages – from resource-based, to manufacturing, and finally to the most innovative information-processing sectors. It is also pointed out by Parr (1999) that since older industries are inevitably subject to decline, it may be more prudent for a region to redirect economic resources towards industrial transformation instead of attempting to sustain innovation or competitiveness in declining industries.

Indeed, since 1975, new patents are increasingly concentrating in fewer patent classes, and not surprisingly the advanced high-tech classes. Hence, the share of patents in the traditional classes is shrinking simultaneously (Hall et al., 2001; Rigby, 2015). Also, in contrast to emerging high-tech regions/cities, many older industrial regions/cities in the US that specialize in these "less-innovative" traditional industries, such as Detroit, Cleveland, Akron, Pittsburgh, and Buffalo, have endured painful economic and social transitions over the last four to five decades (Cochrane et al., 2014; Farley et al., 2000; Fee & Hartley, 2014).

The discussions on urban decline and shrinkage primarily take place at the municipal level, and center around several usually interchangeable terminologies: "older industrial city" or "Rust Belt city", "shrinking city", and "legacy city" (Ganning & Tighe, 2021; Hollander, 2010; Mallach, 2010; 2012). The concept of "older industrial city", or "Rust Belt city" captures the difficulties of these cities in transforming their economies. In a similarly negative tone, "shrinking city" places more emphasis on the population loss these cities usually experience, which usually is, in turn, the precursor of other forms of social decay (Wiechmann & Pallagst, 2012). The “legacy city” concept is weighted more toward the upside of these “challenged” cities, highlighting their assets, including dense and diverse downtown characters, manufacturing bases, and anchor institutions, as the seeds of smart economic revitalization (Mallach, 2012).

The level of municipality is more often adopted in that the literature primarily centers the depopulated urban cores, rather than including the suburban areas of a region (Ganning & Tighe, 2021). Nevertheless, when economic activities are the primary variables, some scholars use shrinking/legacy-city-centered regions. This is primarily because business location, labor, and even housing markets usually operate at a regional scale (Van Leuven & Hill, 2021). Given that this study primarily concerns the economic and innovation data, shrinking/legacy-city-centered region (termed “Shrinking City region” or “shrinking region” in this study) is chosen as the unit of analysis. Among the various definitions for region, Core-based Statistical Areas (CBSAs), including Metropolitan or Micropolitan Statistical Areas, are commonly used in scholarly research, and will also be used in this study.

Scholars have tried to explain what has led to the weakened innovation of the traditional industries in which the Rust Belt regions specialize. From the perspective of market competition, Alder et al. (2014) argue that innovative capacity declined because in the 1950s, the manufacturing industries in these regions lacked competitive pressure in the labor (e.g., high unionization level, high wage premium) and the output market. This devastatingly depressed the incentives of the lead firms to innovate. The innovation deficiency of US firms began to show its detrimental impact on the regional economy as

US firms faced competition from labor-intensive developing countries and innovation-intensive firms from other developed countries in the 1970s. As a result, Rust Belt regions encountered severe urban problems, including high unemployment rates, severe outmigration, weakened land and housing markets, and deteriorated local infrastructure (Partridge et al., 2015; Wiechmann & Pallagst, 2012).

Economists also use the knowledge from industrial and regional studies to explain the failure of these regions to regenerate their industrial innovation. Audretsch and Feldman (1996b), Hekman (1980), and Norton and Rees (1979) apply the life cycle theory of industrial production, which is first proposed by Vernon (1966), to approach the question. According to them, the traditional industries in the Rust Belt regions were highly developed and innovative previously. However, the innovative capacity gradually diminished to the point where it failed to offset the continuous dispersion of standardized production to less developed regions.

Building on the life cycle theory of industry, evolutionary economists introduce the life cycle theory of industrial clusters. Menzel and Fornahl (2010) hold that if industrial clusters maintain high knowledge heterogeneity, they can sustain their innovative capacity and even initiate new industrial life cycles by spawning new industries. This idea resonates with Jacobian externalities (1969) and other works on regional economics (Booth, 1986; Carbonara & Tavassoli, 2013; Chinitz,1961; Duranton & Puga, 2001; Feldman & Audretsch, 1999; Glaeser, 2005; Glaeser et al., 1992). However, they argue that some industrial clusters in the Rust Belt, such as the automobile industry in Detroit, have made their regions mono-structured “company towns” with too little knowledge diversity. They further elaborate that, even though these clusters sometimes maintain high innovation rates, the innovations usually arise within the existing and exhausted technology path. Recent scholarship tends to agree (e.g., Sweeney et al., 2020).

It can be concluded that mainstream literature challenges the idea that traditional industries in established industrial regions can innovate significantly. However, recently, scholars find that in some US Rust Belt regions, the innovation activities related to their specialized industries persist and even grow after the decline of corresponding manufacturing activities. Some notable examples include the automobile industry of Detroit, Michigan (Hannigan et al., 2015), the polymer industry of Akron, Ohio (Mudambi et al., 2017), the steel industry of Pittsburgh, Pennsylvania (Treado, 2010), and the photonics industry of Rochester, New York (Safford, 2004). Another group of studies explores the geography of knowledge-based industrial clusters, innovation activities, and high-tech employment in US. They demonstrate that many older industrial regions remain as innovation hotspots for traditional industries including chemicals, transportation equipment, and machinery (Buzard & Carlino, 2013; Fallah et al., 2014; Koo, 2005).

Ideas from evolutionary economic geography offer us one possible theory to explain the new evidence, which does not fit well into the canonical theories mentioned above. The economic geography community admits that regions did move their knowledge base toward more complex and valuable technologies along the development path (Hidalgo et al., 2007; Petralia et al., 2017). The scholars also agree that the most complex and valuable technologies usually appear in regions with the largest growth (Balland & Rigby, 2017). However, the theory differs from previous theories, such as the stage theory of economic development (Parr, 1999), because the evolutionary theory emphasizes that the knowledge base of each region tends not to converge to a similar mix eventually. On the contrary, the evolution of the knowledge base mostly follows the region's industrial specialization; though some regions transition rapidly from one knowledge core to another, for most regions the process of technological transition is relatively slow (Boschma et al., 2015; Essletzbichler, 2015; Rigby, 2015). Thus, it is suggested that any "one-size-fits-all" economic development policies on enhancing regional R&D should be reassessed (Asheim et al., 2011).

From a microeconomic perspective, regional economists also investigate the mechanisms behind the sustainability of mature industries and their innovative activities in previous industrial centers. After looking at individual manufacturing industries in the US, Dumais et al. (2002) argued that when an industry emerges, the new firms tend to locate away from established industry centers. However, as an industry matures, it experiences a firm closure process which disproportionately preserves firms located in or near the original industrial centers. Similarly, Klepper (2002; 2007; 2010; 2011; 2016) argues that industry and industrial innovation expand geographically through spinoff activities from the lead firms. When an industry declines, the few most innovative lead firms and their early local spinoffs are favored relative to the later entrants located elsewhere. These theories resonate with recent empirical evidence (Hannigan et al., 2015; Mudambi et al., 2017; Safford, 2004; Sturgeon et al., 2008; Treado, 2010), and support the main hypothesis that traditional innovation favors especially leading older industrial centers.

2.3 Methods and Data

This study uses regression analyses to examine whether and to what extent regions that were historically specialized in traditional technological fields sustained their patenting capacities and achieved higher patenting levels in these fields even after industrial decline. I also focus on the sample of shrinking regions – regions with shrinking populations and slow-growth economies over the study period – and explore the factors that led to sustained innovation activities. Hence, this study further tests whether factors like a shrinking population, a slow-growing economy, and the presence of large manufacturing establishments contribute to the increase or decrease of a region's innovation capability in traditional fields. Traditional manufacturing industries in the US started to decline before the 1970s and the decline process has continued (Cochrane et al., 2014; Farley et al., 2000; Fee & Hartley, 2014). This study collects USPTO patent data from 1976-2014 to construct the main innovation variables. USPTO patent data provides rich detail about patent information, including the technological classification and granted (or application) date of the invention, the name and location of inventors, and the ownership of the intellectual property of the invention (Hall et al., 2001)[1].

For every patent granted between 1976-1980 and 2010-2014 respectively, this study uses the location of the first-named inventor as the patent's location. As a result, this study only includes patents whose first-named inventor is in the US. Moreover, out of the three patent types – Utility patents, Design patents, and Plant patents, only Utility patents are included in the sample. This is because they contain the necessary National Bureau of Economic Research (NBER) technological groupings and United States Patent

[1] https://patentsview.org/download/data-download-tables

Classification (USPC) information about what technological field they should be categorized into, which is the standard I refer to when deciding whether a patent belongs to traditional fields. Moreover, about 90% of the patent documents issued by USPTO in recent years have been Utility patents[2].

According to Hall et al. (2001), all patents can be aggregated into 6 main technological categories: Chemical (excluding Drugs); Computers and Communications; Drugs and Medical; Electrical and Electronics; Mechanical; and Others. As shown in Table A.1 in the Appendix, the 6 categories can be further divided into 36 two-digit sub-categories. Of the 6 categories, Chemical, Mechanical, and Others are usually considered as the three traditional fields (this study uses "traditional fields" and "traditional categories" interchangeably). By contrast, Computers and Communications and Drugs and Medical are the high-tech fields (this study uses "high-tech fields" and "high-tech categories" interchangeably), because their patent count grew much more slowly than that of the traditional fields before 1980s, but has significantly surpassed the latter since early 1980s (Hall et al., 2001). It is worth pointing out that regions specializing in traditional fields, like automobiles, are increasingly patenting in high-tech categories such as computers and communications, due to the growing prevalence of the Internet of Things (IoT). Nevertheless, it is important to clarify that this study's outcome variables do not encompass the high-tech patents filed by these regions.

This study further defines the Electrical and Electronics category as the fourth traditional field. Within this category, the sub-category Semiconductor Devices largely

[2] USPTO description of patent types: https://www.uspto.gov/web/offices/ac/ido/oeip/taf/data/patdesc.htm

emerged alongside the Computers and Communications category. However, due to the techniques and human capital requirements of Semiconductor Devices being more aligned with traditional rather than high-tech fields, this study classifies the sub-category as part of the traditional fields (Table 2.1, expanded upon in Appendix Table A.1). It should be also noted that this sub-category had not been established in 1976 yet so it is not included in the samples of this study.

Table 2.1 Traditional Tech Categories and Their Sub-categories Established by 1976

Category Code and Name	Sub-category Code and Name
1 Chemical	11 Agriculture, Food, Textiles; 12 Coating; 13 Gas; 14 Organic Compounds; 15 Resins; 19 Miscellaneous-Chemical
4 Electrical & Electronics	41 Electrical Devices; 42 Electrical Lighting; 43 Measuring & Testing; 44 Nuclear & X-rays; 45 Power Systems; 49 Miscellaneous-Electrical & Electronics
5 Mechanical	51 Materials Processing & Handling; 52 Metal Working; 53 Motors, Engines & Parts; 54 Optics; 55 Transportation; 59 Miscellaneous-Mechanical
6 Others	61 Agriculture, Husbandry, Food; 62 Amusement Devices; 63 Apparel & Textile; 64 Earth Working & Wells; 65 Furniture, House Fixtures; 66 Heating; 67 Pipes & Joints; 68 Receptacles; 69 Miscellaneous-Others

Using the US Census Bureau's 2015 delineation for Core-based Statistical Areas (CBSAs), which includes both Metropolitan and Micropolitan Statistical Areas, and taking the data availability for covariates into consideration, this study identifies 705 CBSAs that produced at least one patent in any of the then-existing sub-categories in the four traditional fields at the beginning of the timeframe (1976). To enhance the reliability of the results, this study compares the patenting levels between two periods instead of two points in time. Therefore, this study computes the average of annual patent counts from 1976 to 1980 for the first period and from 2010 to 2014 for the second period. As for the patent counts after 1976, this study only focuses on each region's traditional patents belonging to their respective patenting sub-categories in 1976. In other words, for patent counts from 1977 to 1980 and from 2010 to 2014, this study ignores each region's traditional patents belonging to the traditional sub-categories not found in each region in 1976[3][4]. The 705 CBSAs produced an annual average of 21,334.6 traditional patents from 1976 to 1980, and 36953.2 traditional patents from 2010 to 2014.

It is also important to note that after May 2016, the USPC classification is no longer assigned to Utility patents (though it is still used for Design and Plant patents)[5]. Instead, USPTO replaces the USPC schemes with the Cooperative Patent Classification (CPC) classification jointly developed by the European Patent Office (EPO) and USPTO to ensure it is understood by a wide international audience. Most of the CPC's subdivisions stem directly from current International Patent Classification (IPC) and World Intellectual Property Organization (WIPO) technological fields used in over 100 countries around the world and managed by WIPO[6].

However, this study still chooses to use USPC classification because a clearer distinction between traditional and high-tech fields is provided under this scheme (Hall et al., 2001). As a result, this study finds that for the patent data reported under the USPC classification, the count of 2014 data peaked, and the count went down year by year since after. This is because there is usually a time gap between when an innovation is granted and when it is organized into the database. For instance, even though USPTO had still

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[3] For instance, if a region patented in sub-category 12 and 15 in 1976, and patented in sub-category 12, 14, and 15 in 2014, this study only includes the patents for sub-category 12 and 15 as the patent count of this region in 2014. This is because this study is more interested in testing whether regions were able to sustain innovation in their original specialization. If all traditional patents produced from 2010 to 2014 are counted, the 705 CBSAs would have produced an annual average of 49475.2 traditional patents during 2010-2014.

[4] This sample selection method might miss economic activities in some sub-categories that could potentially drive innovations in other sub-categories. The Discussions section includes results for a model covering all patents in traditional technological sub-categories in later years, regardless of their presence in 1976.

[5] https://patentsview.org/forum/generalfaq

[6] https://patentsview.org/classification

been reporting patent data under USPC classification until May 2016, some patents granted in 2015 might not yet been included in the database before May 2016 due to the time lag. This leads to the conclusion that the patent data in and before 2014 are complete, because the overall US patent count has kept growing every year, especially since 2008. Hence, I choose 2014 as the end point of the study period.

This study also conducts analyses on two shrinking region sub-samples. First, among the 705 innovating CBSAs, 136 regions are shrinking regions in terms of population, which have experienced a region-wide population loss during 1976-2014. The second sub-sample contains 42 slow-growth regions in terms of regional total income. This is because this study defines the latter group as regions with above-median total income in 1976 and below-median total income increase between 1976 and 2014[7]. Additionally, if we define Rust Belt regions as those located in any of the eight states: New York, Pennsylvania, West Virginia, Ohio, Michigan, Indiana, Illinois, Wisconsin, 65% of the population-shrinking regions and 83% of the slow-growth regions can be classified as Rust Belt regions. Interestingly, as shown in Appendix Table A.2, 29 of the regions in both samples overlap, and almost all of the overlapping regions (27 regions, i.e., 93%) are Rust Belt regions.

Moreover, this study further defines growing regions in terms of population as regions having experienced population growth (569 regions) and growing regions in terms of economy as regions with above-median total income increase (352 regions) from 1976 to 2014. This study runs additional regression models on these two comparative

[7] Data source: Bureau of Economic Analysis. To calculate the total income of each region, this study multiplies the per capita income of each region by its respective population.

sub-samples to provide stronger evidence for the results of the two shrinking region sub-samples. It is also noteworthy that about 91% of the growing regions in terms of total income are also growing regions in terms of population. However, only about 56% of the growing regions in terms of population are also growing regions in terms of total income. It seems reasonable to speculate that an increase in population does not always lead to an increase in total income. These facts reinforce a major argument of this study – progress or regression in any of the dimensions of innovation, population, and economy does not necessarily indicate the same trend in the other dimensions.

This study runs Linear Regression models[8] to examine the main hypotheses: holding all else constant, a region's patenting level in traditional technological fields during 2010-2014 was positively associated with the region's patenting level in these fields in during 1976-1980.[9] Additionally, literature suggests that regions even with a shrinking population or slow-growth economy are also able to sustain innovation activities, and the leading manufacturing firms are likely to be the main contributor.

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[8] Although a Panel Regression approach may provide more reliable results, it is not applied in this study. This is because the patent data show that regional innovation demonstrates very strong serial autocorrelation even within a relatively long timeframe, such as 10-year blocks, so using panel data may require more complex Time-series Regression techniques to adjust for the strong autocorrelation. Given the study compares the innovation level before and after a nearly-40-year time period, OLS Regression is appropriate.

[9] Technological category by region is not chosen as the unit of analysis because many regions have zero observations in more than one technological category, which can lead to biased regression results. Also, using technological category as the unit of analysis might overlook the cross-category influences within each region. Furthermore, assigning category-specific dummy variables to each region is challenging, as the patents of many regions span multiple technological categories. Given the potential for different patterns of innovation evolution across various technological categories, future research could consider conducting in-depth analyses within specific categories or sub-categories. Additionally, incorporating category-specific covariates, such as establishing a crosswalk between technological categories and covariates categorized by industries, poses a considerable challenge that warrants careful consideration in these studies.

Therefore, this study conducts the same regression analyses on the two sub-samples of shrinking regions and further investigates if the large manufacturing corporations indeed lead to the sustained innovation activities in these regions. Two comparative emerging region sub-samples are also tested. This study collects data for each CBSA's population and income covariates from the Bureau of Economic Analysis, and educational attainment and business covariates from the US Census Bureau.

This study uses Equation (1) to fit six sets of models:

$$\ln(PatCt)_{2010\text{-}2014} = \beta_0 + \beta_1 \ln(PatCt)_{1976\text{-}1980} + \beta_2 PopGr_{1976\text{-}2014} + \beta_3 IncGr_{1976\text{-}2014} + \beta_4 MfgEstd_{2014} + \beta_5 HumCap_{2014} + Division' + e \quad (1)$$

Model 1 contains all 705 CBSAs. Models 2 and 3 compare shrinking and growing regions in terms of population. Model 2 contains the 136 CBSAs identified as shrinking regions in terms of population – regions recorded smaller population in 2014 than in 1976. On the contrary, Model 3 is comparative model including the 569 CBSAs with an increased population during 2014-1976. Model 4 and 5 compare slow-growth regions with growing regions in terms of total income. Similarly, Model 4 is the main model containing the 42 CBSAs which had above-median total income in 1976, but experienced a lower-than-median total income increase between 1976 and 2014. By contrast, Model 5 includes the 352 CBSAs that experienced above-median total income increase from 1976 to 2014.

The models control for covariates which may also influence regional innovation[10]. The first covariate controls for the contribution of large manufacturing

[10] To address concerns of potential endogeneity in the main independent variable, i.e., Patent Count Average 1976-1980 (ln), due to possible reverse causality with the error term, I employed a Two-Stage Least Squares (2SLS) analysis. The instrumental variable chosen for this analysis

corporations on traditional innovation, measured by the count of each region's manufacturing establishments with greater than 1,000 employees in 2014. This study defines manufacturing businesses with the classification of North American Industry Classification System (NAICS) codes (2-digit code: 31-33). Contrary to high-tech industries, where smaller startups play a more important role in patenting activities, literature suggests that traditional patents tend to concentrate in large manufacturing corporations (e.g., Hannigan et al., 2015; Mudambi et al., 2017).

The second control variable is human capital, measured by each region's percentage of adults age 25+ with a bachelor's degree or above in 2015[11]. Human capital is a strong predictor of innovation growth (e.g., Florida et al., 2008). Other covariates include regional population growth between 1976 and 2014 and each region's per capita income growth during the same period. These two covariates serve as the measure for agglomeration and urbanization economies. The last set of covariates includes dummy

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was the Patent Count Average 1971-1975 (ln). This variable is significantly correlated with the potentially endogenous independent variable but does not have a direct connection to the dependent variable. Notably, comprehensive datasets on US patent data before 1975 are unavailable in digital format via the USPTO. As a result, I utilized the HistPat dataset, compiled by Petralia et al. (2016) from digitized records of original patent documents issued by the USPTO from 1836 to 1975. This unique dataset provides geographical locations of patents but lacks information on technological categories and sub-categories, leading to the inclusion of all existing patents within each CBSA as the instrumental variable.

The Wald test's F-statistic confirms the chosen instrumental variable's strength. In the second-stage regression, the coefficients and significance levels for both the primary independent variable (Patent Count Average 1976-1980 (ln)), and key control variables – including Population Growth 1976-2014 (%), Per Capita Income Growth 1976-2014 (%), Count of Manufacturing Establishment with > 1,000 Employees in 2014, and Human Capital 2015-2019 (%) – aligned with those observed in the initial regression model. Moreover, the coefficient for the primary independent variable was 1.155, surpassing its original model value, which underscores the study's argument regarding its "pure" direct impact. Additionally, the residual plot from the second-stage model demonstrated homoscedasticity.

[11] Data source: Census Bureau 2015-19 American Community Survey (ACS) 5-year estimates. This study uses 5-year instead of 1-year estimates because the latter leave out many smaller regions in the sample.

variables indicating which one of the 9 US Census Divisions each region is in[12].

Table 2.2 Descriptive Statistics[13]

Variable	Obs.	Mean	Std. Dev.	Min	Max
Patent Count Average 2010-2014 (ln)	705	2.169	1.893	-2.000	8.057
Patent Count Average 1976-1980 (ln)	705	1.710	1.646	-1.609	7.768
Population Growth 1976-2014 (%)	705	0.428	0.563	-0.472	4.515
Per Capita Income Growth 1976-2014 (%)	705	5.635	1.133	2.434	15.246
Count of Manufacturing Establishment with > 1,000 Employees in 2014	705	1.045	2.513	0.000	35.000
Human Capital 2015-2019 (%)	705	24.020	8.377	10.200	67.400
Census Division East North Central (0/1; Baseline)	705	0.213	0.410	0.000	1.000
Census Division New England (0/1)	705	0.037	0.189	0.000	1.000
Census Division Middle Atlantic (0/1)	705	0.087	0.281	0.000	1.000
Census Division West North Central (0/1)	705	0.119	0.324	0.000	1.000
Census Division South Atlantic (0/1)	705	0.152	0.359	0.000	1.000
Census Division East South Central (0/1)	705	0.087	0.281	0.000	1.000
Census Division West South Central (0/1)	705	0.123	0.329	0.000	1.000
Census Division Mountain (0/1)	705	0.082	0.275	0.000	1.000
Census Division Pacific (0/1)	705	0.101	0.301	0.000	1.000

[12] For CBSAs that cross the border between two Census Divisions, this study uses the location of the first-named state in the name of each CBSA.

[13] This study employs logarithm transformation to adjust for the right-skewed distribution of the dependent variables and the main patent independent variables. Given that these variables primarily involve count data, Generalized Linear Model (GLM) Regression techniques may be suitable. This study also examines the data with GLM Poisson regression, but the models fail to pass diagnostic tests. It is important to note that this study sets the results of ln (0) as -2 for the patent count average 2010-2014 dependent variables. This adjustment is made to ensure that all observations are computable even in regions with 0 patent counts for each year from 2010 to 2014. Consequently, these regions have the minimum value across all regions. The next smallest value for this variable would be the regions that had only 1 patent in any single year during 2010-2014. In such case, the 5-year patent count average is 0.2, resulting in a natural logarithm value of ln (0.2) = -1.609.

Table 2.3 Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Patent Count Average 2010-2014 (ln)	1.000													
2	Patent Count Average 1976-1980 (ln)	0.879	1.000												
3	Population Growth 1976-2014 (%)	0.320	0.108	1.000											
4	Per Capita Income Growth 1976-2014 (%)	0.100	0.010	0.111	1.000										
5	Count of Manufacturing Establishment with > 1,000 Employees in 2014	0.551	0.585	0.079	0.026	1.000									
6	Human Capital 2015-2019 (%)	0.546	0.380	0.275	0.298	0.188	1.000								
7	Census Division East North Central (0/1; Baseline)	0.033	0.112	-0.279	-0.226	0.054	-0.127	1.000							
8	Census Division New England (0/1)	0.145	0.124	-0.062	0.164	-0.001	0.260	-0.102	1.000						
9	Census Division Middle Atlantic (0/1)	0.104	0.181	-0.174	-0.014	0.000	0.040	-0.160	-0.060	1.000					
10	Census Division West North Central (0/1)	-0.095	-0.110	-0.138	0.141	-0.028	0.075	-0.191	-0.072	-0.113	1.000				
11	Census Division South Atlantic (0/1)	0.024	-0.004	0.214	0.055	-0.025	-0.014	-0.220	-0.083	-0.130	-0.156	1.000			
12	Census Division East South Central (0/1)	-0.105	-0.127	-0.021	0.055	-0.004	-0.130	-0.160	-0.060	-0.095	-0.113	-0.130	1.000		
13	Census Division West South Central (0/1)	-0.155	-0.133	0.000	0.171	-0.008	-0.203	-0.195	-0.073	-0.115	-0.138	-0.159	-0.115	1.000	
14	Census Division Mountain (0/1)	0.023	-0.051	0.269	0.030	-0.049	0.170	-0.156	-0.059	-0.092	-0.110	-0.127	-0.092	-0.112	1.000
15	Census Division Pacific (0/1)	0.088	0.036	0.249	-0.265	0.043	0.097	-0.174	-0.065	-0.103	-0.123	-0.142	-0.103	-0.126	-0.100

2.4 Results and Findings

Table 2.4 shows the regression results. Due to the heteroskedasticity problem in some of the models, this table presents the robust errors for each model. In addition, since both the dependent and key independent variables have been transformed using the natural logarithm, the coefficients can be interpreted as the elasticity of the dependent variable with respect to the key independent variable. In other words, the coefficient shows the percentage change in the dependent variable expected from a 1% difference in the key independent variable.

We see from Model 1 that for all US regions that produced at least one patent in any of the traditional fields in 1976, their patenting level in those technological sub-categories during 2010-2014 was positively associated with their 1976-1980 patenting level. Specifically, a 1% increase in the patenting level during 1976-1980 was associated with a 1.069% increase in patenting level in 2010-2014. Therefore, the results support the main hypothesis of this study – regions with higher original patenting levels in traditional fields achieved greater innovation levels in their respective specializations during 2010-2014.

Models 2 and 3 use the same regression models as Model 1 to compare the results of shrinking and growing regions in terms of population. Model 2 shows that for regions losing population between 1976 and 2014 (among which 65% are Rust Belt regions), their traditional patenting levels during 2010-2014 were lower than their patenting levels during 1976-1980 – a 1% higher original patenting level during 1976-1980 was associated with a 0.862% higher patenting level during 2010-2014. By contrast, Model 3 shows that the sub-sample of regions gaining population yielded similar results as the full sample – regions with higher levels of traditional innovation during 1976-1980 also achieved higher traditional patenting levels during 2010-2014.

Models 4 and 5 instead compare the results of slow-growth and growing regions in terms of regional total income. Model 4 shows that for regions that had an above-median total income in 1976 but a below-median increase in total income between 1976 and 2014 (among which 83% are Rust Belt regions), their traditional patenting level during 2010-2014 was still positively associated with their patenting level during 1976-1980, and the coefficient was even higher than the full sample. A 1% increase in patenting level during 1976-1980 was associated with a 1.150% increase in patenting level during 2010-2014. Model 5 further demonstrates that regions with an above-median increase in total income during 1976-2014 produced a similar result as the full sample. Therefore, it appears that neither a slow-growth nor a growing total income had a significant impact on changes in traditional innovation.

Focusing on the coefficients for the covariate Count of Manufacturing Establishment with > 1,000 Employees, we see from Model 1 that the presence of large manufacturing corporations with greater than 1,000 employees was not associated with the level of traditional innovations during 2010-2014. Like the full sample, the sub-samples that had higher patenting levels during 2010-2014 than the patenting levels during 1976-1980 (i.e., growing regions in terms of population, slow-growth regions in terms of total income, and growing regions in terms of total income) also indicate that the presence of large manufacturing corporations did not significantly contribute to their traditional innovation during 2010-2014. Nevertheless, the opposite is true for shrinking regions in terms of population, which is the only sub-sample that did not produce more traditional patents during 2010-2014 than during 1976-1980. In these population-shrinking regions, large manufacturing establishments with more than 1,000 employees made a statistically significant contribution to the traditional innovation during 2010-2014.

This study replaces the original business covariate Count of Manufacturing Establishment with more than 1,000 Employees with the count of manufacturing establishments with more than 500 employees, more than 100 employees, and the count of all manufacturing establishments, and re-tests the models. Once again, the covariates consistently show significance only in the sub-sample of shrinking regions in terms population. The coefficients for the three alternative covariates are 0.0485***, 0.0045***, and 0.0004***, respectively. To facilitate cross-model coefficient comparison, I standardized them by calculating the product of each coefficient and the standard deviation ratio of the corresponding independent and dependent variables. Table 2.5 presents these standardized coefficients. The findings indicate that, in population-shrinking regions, larger manufacturing establishments have a marginally more significant role in traditional innovations compared to medium and smaller firms. The results also highlight the need for future studies to investigate whether it is the size of larger establishments or the broader scale of the local industry that influences future patent activity.

Interestingly, the presence of large manufacturing corporations in the 1980s (1986) did not significantly contribute to traditional innovation during 2010-2014 for growing regions in terms of population, slow-growth regions in terms of total income, growing regions in terms of total income. In contrast, for population-shrinking regions, the count of large manufacturing establishments in the1980s is significantly and positively associated with their traditional innovation during 2010-2014, with a coefficient of 0.035***. Again, the same condition is also found if the covariate is replaced with the count of manufacturing establishments with more than 500 employees, more than 100 employees, and the count of all manufacturing establishments. Hence, it is plausible to suggest that among population-shrinking regions, those that had a concentration of large manufacturing businesses and a large size of manufacturing industry in 1980s may have produced more traditional innovations during 2010-2014.

These findings partially resonate with the arguments made by recent empirical studies about traditional innovation in some Rust Belt regions. First, one generalizable finding is that regions that historically specialized in traditional fields have continued to innovate in these specializations at the same or slightly higher level over the last 40 years of industrial decline. Second, it should be noted that the performance of regions with declining populations was less satisfactory than other regions, even including those had a slow-growth regional total income. Specifically, the coefficient shows that population-shrinking regions exhibited no significant growth in the patent level of traditional fields from 1976-1980 to 2010-2014.

However, a note of caution is warranted as the raw patent count data indicates that population-shrinking regions collectively produced an average of 3,286.2 patents annually between 2010 and 2014, representing a 19.60% increase from the 2,747.6 annual patents recorded during 1976-1980. Although this growth rate in annual patent counts for these regions was significantly lower than the overall regional growth rate (which experienced a 73.21% increase from 21,334.6 annual patents during 1976-1980 to

36,953.2 annual patents during 2010-2014), there was still an increase in patent output in traditional fields in these population-shrinking regions. In the regression models, this increase has been accounted for by the change in other covariates such as educational attainment.

Third, recent empirical studies have emphasized the role of large manufacturing firms in some Rust Belt regions in sustaining regional traditional innovation (e.g., Hannigan et al., 2015; Mudambi et al., 2017). This study also reaches a similar finding. However, this study highlights that the role of these large corporations is less significant in most other regions that produce traditional patents. Furthermore, future research could delve deeper and explore whether the presence of large establishments, a large overall industry size, a combination of both factors, or other factors that leads to the lower innovation performance of population-declining regions.

The regression results seem to support that population does play a role in fostering traditional innovation, and it is possible they are endogenous to each other. First, again, regions with a shrinking population over the study timeframe invented fewer traditional patents than other regions. Second, in almost every model, population growth over 1976-2014 was positively associated with the level of regional traditional innovation during 2010-2014. This conclusion also applies to the human capital covariates – most models show a positive association between the percentage of adults (over 25 years old) with a bachelor's degree or above in each region and each region's traditional patenting level. This finding indicates that like innovation in high-tech fields, higher education has also been relevant to innovation in traditional fields.

On the contrary, regional per capita income growth does not appear to significantly impact innovation in the traditional fields. This finding is understandable because not all regions that are experiencing economic growth prioritize innovation as a development strategy. Last, it is surprising that the geographic location of CBSAs in general does not have a significant impact on the current landscape of traditional innovation. The only exception seems to be the Middle Atlantic Census Division, which also contains many Rust Belt regions but exhibited a lower level of traditional innovation during 2010-2014 compared to the East North Central Census Division.

Table 2.4 Regression Results

Model	1	2	3	4	5
Sample	**All CBSAs**	**Population-shrinking CBSAs**	**Population-growing CBSAs**	**Slow-growth CBSAs in Total Income**	**Growing CBSAs in Total Income**
Patent Count Average 1976-1980 (ln)	1.069***	0.862***	1.099***	1.150***	1.096***
	(0.021)	(0.054)	(0.021)	(0.119)	(0.026)
Population Growth 1976-2014 (%)	0.558***	2.155*	0.534***	1.174	0.470***
	(0.057)	(0.967)	(0.060)	(1.060)	(0.059)
Per Capita Income Growth 1976-2014 (%)	0.026	-0.046	0.027	0.495*	-0.013
	(0.031)	(0.119)	(0.031)	(0.241)	(0.040)
Count of Manufacturing Establishment with > 1,000 Employees in 2014	0.029	0.106***	0.015	0.139	0.002
	(0.016)	(0.030)	(0.016)	(0.145)	(0.012)
Human Capital 2015-2019 (%)	0.031***	0.045*	0.030***	-0.015	0.030***
	(0.005)	(0.020)	(0.005)	(0.032)	(0.005)
Census Division East North Central (0/1; Baseline)					
Census Division New England (0/1)	-0.026	-0.493	-0.063	0.707*	-0.135
	(0.135)	(0.345)	(0.136)	(0.343)	(0.166)
Census Division Middle Atlantic (0/1)	-0.236	0.241	-0.480**	0.243	-0.301*
	(0.124)	(0.211)	(0.156)	(0.376)	(0.120)
Census Division West North Central (0/1)	0.018	0.162	-0.059		-0.138
	(0.107)	(0.221)	(0.121)		(0.133)
Census Division South Atlantic (0/1)	-0.140	0.224	-0.208	-0.331	-0.089
	(0.106)	(0.252)	(0.117)	(0.390)	(0.115)
Census Division East South Central (0/1)	-0.099	0.123	-0.173	-0.184	-0.037
	(0.147)	(0.250)	(0.163)	(0.339)	(0.213)
Census Division West South Central (0/1)	-0.051	-0.154	-0.046	0.473	0.038
	(0.119)	(0.293)	(0.125)	(0.475)	(0.143)
Census Division Mountain (0/1)	-0.141	-0.729**	-0.160	0.170	0.074

Model	1	2	3	4	5
Sample	**All CBSAs**	**Population-shrinking CBSAs**	**Population-growing CBSAs**	**Slow-growth CBSAs in Total Income**	**Growing CBSAs in Total Income**
	(0.171)	(0.226)	(0.181)	(0.411)	(0.219)
Census Division Pacific (0/1)	-0.140		-0.186	0.426	-0.160
	(0.110)		(0.114)	(0.759)	(0.123)
Constant	-1.358***	-1.098	-1.282***	-3.185	-0.958***
	(0.165)	(0.565)	(0.174)	(1.363)	(0.213)
Number of Observations	705	136	569	42	352
Adjusted R-squared	0.886	0.828	0.895	0.727	0.905

Note: "***" $p < 0.001$; "**" $p < 0.01$; "*" $p < 0.05$. Values in parentheses are standard errors.

Table 2.5 Cross-model Coefficients Comparison for Covariate Manufacturing Establishments

Covariate	More than 1,000 Employees	More than 500 Employees	More than 100 Employees	All Manufacturing Establishments
Standardized Coefficient	0.117	0.116	0.105	0.103

2.5 Discussions and Conclusion

The first conclusion this study wants to draw is that innovation often persists even in regions facing population decline or sluggish economic growth, and this conclusion perhaps applies more to regions that lead in innovation. This study also demonstrates that even though population-shrinking regions were unable to achieve significant growth in innovation, they were still able to sustain their traditional patenting level in their historical specializations for an extended period. Hence, it comes as no surprise that recent empirical studies have identified several prominent examples of Rust Belt regions that continue to actively engage in patenting activities within traditional fields (Hannigan et al., 2015; Mudambi et al., 2017; Safford, 2004; Treado, 2010). With appropriate investments and improvements in the educational attainment of the local population, these regions hold the potential for growth in future innovation.

Nevertheless, this study acknowledges the broader context of the increasing innovation gap between traditional and high-tech fields. As previously demonstrated, traditional fields have experienced a much slower rate of innovation growth over the last half century compared to the rapid growth of innovation in high-tech fields. The results of this study also show that despite the ability of traditional fields to sustain patenting for a long time amid industrial decline, their growth rate is not particularly high (not far from unit elasticity). Moreover, when one includes all patents in traditional technological sub-categories in subsequent years regardless of whether we observed patents in those sub-categories back in 1976 and retest Model 1, the coefficient for the main independent variable becomes smaller than 1 (0.856***) and even smaller for Model 2 (0.733***). This is consistent with mainstream economic development theories in that traditional fields should embrace the changes brought by the emergence of high-tech fields and continually adopt new knowledge to remain competitive. It is equally important to recognize that the concept of traditional fields is constantly evolving over time. Today's high-tech fields may eventually become traditional fields as newer fields are invented.

The second objective of this study is to examine the role of large manufacturers. It was observed that regions with declining populations had the least satisfactory innovation performance and were the only sample in which large manufacturing establishments played a significant role in traditional patenting. While recent empirical studies have highlighted the importance of large manufacturing firms in sustaining traditional innovation, this study raises questions about this idea. It suggests that the presence of large manufacturing establishments might be a contributing factor to the lower innovation performance observed in some Rust Belt regions. Moreover, this study reveals that the overall size of the manufacturing industry, though slightly less, also plays a significant role in traditional patenting. Exploring whether these factors, or others, lead to reduced innovation performance in population-shrinking regions can be insightful. Here, the standpoint of this study resonates with Menzel and Fornahl's (2010) life cycle theory of industrial clusters and Markusen's (1996) theory on "hub-and-spoke" industrial districts.

The third and last takeaway of this study is the non-parallelism between innovation, economy, and population growth. While economic development scholarship often emphasizes the reinforcing relationship between the three economic factors, this study contends that their interaction may vary, particularly during economic decline. For instance, this study finds that regions experiencing economic decline did not necessarily experience population or innovation decline. This may be because economic development involves complex factors beyond human capital and technological innovation. By contrast, population and human capital seem to play a more important role in fostering innovation. This study demonstrates that population decline can lead to reduced innovation, and *vice versa*.

In conclusion, this study suggests that for many established industrial regions, completely abandoning traditional expertise in favor of pursuing high-tech industries may not be the most efficient use of resources. Instead, regions could integrate their existing industrial strengths into their regional revitalization strategies. For instance, besides designating industrial parks that solely attract and incubate high-tech start-ups, governments can identify and support competitive traditional corporations or clusters that are capable of investing in advanced technologies. Policy-makers may also consider minimizing the potential adverse impact of large or potentially monopolistic traditional firms, as well as the impact of an overly dominant traditional industry on the regional innovation atmosphere.

While patent data is a widely-adopted proxy for innovation in many studies, it has several limitations that merit attention. Three major limitations are worth highlighting. First, patent data does not cover all kinds of traditional innovation, particularly those that are related to process innovation instead of production innovation, and those that are not patented due to company strategies. This could affect the generalizability of the findings. Second, this study assumes equal weight for all patents. However, it is recognized that breakthrough patents typically contribute more significantly than those representing minor improvements. Future research might explore the feasibility of assigning greater weights to patents with a higher number of citations.

Third, there is potential for geographical bias in patent data, as the location of the first-named inventor may not necessarily reflect the major resources utilized in developing the patent, or the locations of companies using the patent or production-related products. Often, this location is chosen based on legal or administrative reasons. In this study, the first-named inventor's location was chosen because they play a pivotal role in the patent's conceptualization and development, and their location typically reflects the place of this work. As the study focuses on regional innovation activity, this approach aids in identifying the geographic distribution of innovation and the leading region in cases of collaborative networks. However, future extended studies might consider including all associated locations of a patent to more comprehensively represent the collaborative nature of modern innovation processes.

CHAPTER III

REGIONAL INNOVATION AND TRANSFORMATION: HIGH TECH INNOVATION GROWTH AND THE KNOWLEDGE STRUCTURE AROUND TRADITIONAL TECHNOLOGIES

3.1 Introduction

Although always striving for long-run economic competitiveness, regions rarely experience perpetual growth. One primary challenge leading to the economic decline of a region is that the region specializes in certain industries but these industries decline (Glaeser, 2005). Rust Belt regions in the US are such examples (Martinez-Fernandez et al., 2012; 2016). Regions respond to industry-led decline with different economic revitalization strategies, and one goal is to reinvent their export base and become competitive again (Bingham & Eberts, 1990; Neumann, 2016). Developing specializations in emerging industries, which refers to the most advanced industries in need of high R&D inputs, is a popular strategy. These so-called “emerging” or “high-tech” industries include, for instance, computers, pharmaceuticals, and biotechnology (Hecker, 2005; Mendonça, 2009). Regions seeking to reinvent their export base often pursue increased innovation capacity in these emerging industries (Fogarty & Garofalo, 2014).

Many modern development theories explain the economic factors leading to regional innovation growth. Agglomeration research argues that regional economic or knowledge structure ushers in new industrial expertise (Feldman & Audretsch, 1999; Glaeser et al., 1992). Two major competing viewpoints within agglomeration research stimulate much discussion. One view explains that agglomeration enables this new industrial expertise through Jacobian externalities, wherein innovation growth occurs through novel combinations of inter-industrial knowledge (Jacobs, 1969). For instance, in their observation of the evolution of regional industries, Menzel and Fornahl (2010) argue that regions can spawn new industries with high innovation rates if local industrial clusters maintain high knowledge heterogeneity. This development pathway is usually considered in contrast to the thesis of Marshall (1920)-Arrow (1962)-Romer (1986) (MAR) externalities, which claims that higher innovation growth is made possible by the intra-industry knowledge spillovers between similar firms. Recent meta-analyses show that both arguments find empirical support (De Groot et al., 2016; Melo et al., 2009).

Despite the fruitful academic discussions, one research gap still exists within this body of literature. Most studies look at the relationship between overall or industry-specific knowledge structure and aggregate or industry-specific innovation growth in a region's economy. This is because their main interest lies in the process of economic and industrial growth. However, few relate the topic to the process of economic and industrial restructuring. Put differently, agglomeration research rationalizes why agglomeration economies and knowledge spillovers play an important role in spurring regional innovation growth. Nevertheless, as suggested by Martin and Sunley (2003), it usually lacks a dynamic perspective regarding how agglomeration is associated with the transformation of regional economies and the emergence of new industrial strengths. To address the research gap, this study instead tests an asymmetric relationship by investigating whether a region's innovation growth in high-tech industries is associated with the pre-existing knowledge structure of its traditional industries.

This study employs the US Patent and Trademark Office (USPTO) technological classification and patent data to define high-tech and traditional technological fields. Through regression analyses, the hypotheses are tested to determine *whether a more specialized or diversified knowledge structure of traditional technological fields better encourages high-tech innovation growth from 1986 to 2014*. The findings indicate that regions with greater diversity in both related and unrelated traditional technological sub-categories tend to perform better in restructuring their knowledge base and fostering high-tech innovation. Conversely, a high degree of specialization in specific traditional technological sub-categories negatively impacts a region's ability to undergo restructuring. The conclusions remain consistent across multiple time periods from 1986 to 2014.

This study also delves into the underlying mechanism of how fostering a diverse knowledge base not only benefits innovation growth but also facilitates the development of entirely new industrial expertise within the region. Scholarship has offered various potential explanations for the observation that knowledge diversity can lead to innovation emerging from radically new industries. One primary objective of this study is to clarify the nuances among these arguments.

Based on the results presented, this study posits, first, that regions with more diverse traditional technologies – whether related or unrelated – offer more opportunities for high-tech companies to identify potential new areas of demand among local industries. Second, more diversified regions, often characterized by larger economies and populations, foster economies of scale that are more supportive for high-tech start-ups, even those that deviate from their initially specialized industries. Third, while scholars may argue that regions known for highly specializing in certain traditional fields have successfully incorporated high-tech expertise, this study contends that the majority of these regions actually belong to the category characterized by high related variety rather than high specialization.

3.2 Literature Review

This paper tests the relationship between a region's industrial or knowledge structure and its capacity to innovate. The research question derives from the theoretical framework concerning the relationship between agglomeration economies and regional innovation growth. This literature serves as an important part of the extensive studies exploring economic factors that generate regional innovation. This review first delves deeper into the three most discussed industrial structure-innovation arguments exploring different aspects of regional knowledge structure (specialization, related variety, and unrelated variety) and their impacts on regional innovation growth. Next, this review identifies the research gap which leads to the main hypotheses. Last, this review briefly introduces the scholarship explaining the plausible mechanisms that the main hypotheses of this study try to capture.

A vast literature examines the economic factors that could lead to a region's innovation growth. Some of the most discussed and interrelated factors include the agglomeration of innovating businesses, the presence of leading R&D institutions, and the pool of educated workers. Macrolevel research finds that businesses tend to agglomerate because knowledge spillovers are facilitated through the co-location of supplier, competitor, and consumer firms, as well as research and economic development institutions (Audretsch & Feldman, 1996; Ellison et al., 2010; Porter, 1998; Saxenian, 1996). Similarly, Morgan (1997), Maskell and Malmberg (1999), and Bathelt et al. (2004) argue that these industrial agglomerations foster the formation of an interactive learning and joint problem-solving environment where businesses can innovate more effectively.

At the micro level, scholarship highlights the role of anchor institutions, including research universities (Anselin et al., 2000; Audretsch et al., 2012; Mayer, 2011), leading innovating corporations (Agrawal & Cockburn, 2003; Klepper, 2016; Mayer, 2011) and government-led industrial initiatives (Bingham, 1998; Klepper, 2016) in developing and commercializing technological innovation. Furthermore, researchers stress that for regions aiming to promote technological innovation, attracting skilled and educated workers is an essential part of all development strategies (Florida, 2003; Glaeser & Hausman, 2020; Glaeser & Resseger, 2010).

The literature on agglomeration research has long debated whether a more specialized or diversified economy (usually measured by the employment of different industries in the region) better encourages regional innovation growth (De Groot et al., 2016; Glaeser et al., 1992). Using patents and patent citation data, scholars also study the issue through directly investigating to what extent intra-industrial and inter-industrial knowledge spillovers, or externalities, impact the creation of new knowledge (Acemoglu et al., 2016; Kekezi et al., 2021). The theory of MAR externalities underlines that a region's innovative capacity particularly benefits from the intra-industrial knowledge spillovers, especially those that occur within the region's industrial specializations. Economists have reasoned that experience gained with one product can make it easier for firms to produce new products incorporating similar technologies (Arthur, 1989; 1990; Patel & Pavitt, 1997). In addition, co-located firms from the same industry can lower operation costs and innovate more efficiently because the industrial agglomeration provides them industry-specific infrastructure and assets (Feldman, 1999; Krugman, 1991; Marshall,1920).

In contrast to MAR externalities, Jacobian (1969) externalities emphasizes that knowledge spillovers are not confined to businesses from the same industries. Rather, important knowledge transmits across industries. Therefore, industrial diversity facilitates the exchange and combination of cross-industry knowledge and in turn fosters regional innovation (Acs, 2002; Duranton & Puga, 2000; Feldman & Audretsch, 1999; Glaeser et al., 1992). Similarly, by exploring patent citation data, Jaffe (1993) finds that a significant portion of the knowledge flow affecting co-located firms' research productivity comes from outside of their immediate technological neighborhood. Recent empirical evidence further suggests that inter-industry knowledge externalities rather than MAR externalities play a significant role in the knowledge creation of US manufacturing industries (Kekezi et al., 2021).

Studies from the evolutionary economic geography community rephrase the term "Jacobian externalities" with the term "related variety", which highlights the kind of regional industrial portfolio in which industries are not only diverse but also technologically proximate (Frenken et al., 2007). In other words, a region with high related variety indicates that the region has diverse sub-level industries within its broad-level industries. As an illustration, consider a region known for its strong manufacturing base in the automotive sector. In addition to hosting manufacturers producing different types of vehicles, it is also home to a multitude of suppliers engaged in the production of diverse automotive components, such as roofs, fenders, tires, and wheels.

This stream of literature further finds that regional economies usually grow by innovating in the industries that are technologically close to the pre-existing industries (i.e., under the same broad-level industries) (Balland et al., 2019; Boschma et al., 2015; Essletzbichler, 2015; Hidalgo et al., 2007; Neffke et al., 2011; Petralia et al., 2017; Rigby, 2015). As a result, it is not surprising that growing evidence shows that regions with higher industrial variety across related industries experience stronger innovation growth (Aarstad et al., 2016; Carbonara & Tavassoli, 2013; Castaldi et al., 2015; Ejdemo & Örtqvist, 2020; Liang & Goetz, 2018; Miguelez & Moreno, 2018; Zhang et al., 2020).

Therefore, two primary insights can be drawn from the regional agglomeration research and the evolutionary economic geography community so far. First, scholars argue that both MAR externalities and Jacobian externalities (or related variety) can be associated with higher innovation growth. Second, MAR externalities and Jacobian externalities (or related variety) exist as two distinct constructs and are measured differently. On the one hand, MAR externalities capture a region's specialization (measured by, for instance, employment share or patenting share) in certain broad-level industries or sub-level industries compared to corresponding national averages. On the other hand, Jacobian externalities, or related variety, focuses on whether a region has a diverse range of sub-level industries under its broad-level industries. Therefore, scholars usually measure the former with location quotient and the latter with variants of an entropy index (Liang & Goetz, 2018). Specifically, an entropy index quantifies the distributional characteristics of elements within a system, determining whether these elements are predominantly concentrated in a limited number of categories or are more uniformly dispersed across a broader array of categories.

Besides the two types of industrial structure, evolutionary economic geography scholars also point out that many technologically-unrelated industries may concentrate in regions with dense population and economic activities. Correspondingly, they see regions with such industrial structure as one with “unrelated variety” (Frenken et al., 2007). There is little theoretical reason to suspect that unrelated variety engenders inter-industrial knowledge spillovers. However, scholars still find that in a few occasions the combination of radically different knowledge fields can lead to break-through innovations or even the birth of entirely new fields (Barbieri & Consoli, 2019; Castaldi et al., 2015; Miguelez & Moreno, 2018). These studies also measure “unrelated variety” with the variants of an entropy index at the broad industrial level.

A notable gap in this literature is the focus on economic or industrial growth, with less attention to economic or industrial restructuring. Most studies examine either the link between a region’s overall industrial structure and its aggregate innovation growth, or the connection between a region’s industry-specific structure and innovation in corresponding industries. Evolutionary economic geographers point out that mainstream agglomeration research often overlooks the relationship between agglomeration and the transformation of regional economies or the development of new industrial strengths (Martin and Sunley, 2003). This study aims to bridge this gap by exploring economic/industrial restructuring, specifically investigating how the knowledge structure of traditional technological fields in a region influences its innovation capacity in technologically unrelated, high-tech fields.

Most scholarship utilizes the level of R&D intensity of an industry to distinguish these high-tech, science-based industries from the more traditional, non-high-tech industries. For instance, the Organization for Economic Cooperation and Development (OECD) uses the ratio of R&D expenditures to output to categorize industries into four groups – high-technology, medium-high-technology, medium-low-technology, and low-technology industries. High-tech industries are therefore defined as those with the highest R&D intensity, covering industries including pharmaceuticals, aerospace, computers, communications, and scientific instruments (Hansen & Winther, 2011; Mendonça, 2009). The identified industries highly overlap with the "Level I" high-tech industries classified by the US Bureau of Labor Statistics. The BLS defines Level I as industries with the highest R&D employment intensity, or with the highest occupation proportions of scientists, engineers, and technicians (Hecker, 2005). Other scholars employ the concept of technological proximity to categorize industrial patents into distinct groups. They further identify high-tech technological categories based on their observation of higher innovation output (i.e., patent) growth in recent decades when compared to traditional categories (e.g., chemicals and mechanicals) (Hall et al., 2001). This study follows the approach of Hall et al. (2001). The identified high-tech technological categories are shown in the Methods and Data section.

To reiterate, the main objective of this study is to see if the industrial/knowledge structure-innovation hypotheses developed by canonical agglomeration research and furthered by economic geography scholars explain the process of industrial restructuring. To achieve this goal, this paper studies whether the knowledge structure around US metropolitan areas' traditional technological fields is associated with their innovation capacity in the high-tech fields. In order to innovate in the high-tech fields, regions need to absorb drastically different high-tech knowledge and integrate it into their industrial base. Hence, this study investigates whether a more specialized or a more diversified industrial/knowledge structure encourages the growth of innovation which is new to a region.

Connecting to pre-existing scholarship, it is conventional to speculate that established industrial regions with a more diversified structure of traditional fields should perform better than their counterparts which are too specialized in a few traditional sub-categories. The rationale can be that businesses in regions with diverse and even unrelated technological sub-categories have better opportunity to integrate high-tech knowledge into the regional knowledge base (Ebert et al., 2019; Tsvetkova et al., 2020). Moreover, existing literature provides other plausible explanations regarding why regions can take advantage of a diversified knowledge structure to develop radical innovation. For instance, scholars argue that industrial diversity provides the entrepreneurial climate that benefits the entry and survival of innovative start-ups (Capozza et al., 2018; Renski et al., 2011).

However, recent scholarship also finds that regions with a very strong specialization in certain traditional industries, such as Detroit, have started to integrate technologies from high-tech industries into their regional innovation portfolio (Hannigan et al., 2015). One explanation is that in order to stay competitive, traditional monopolistic corporations are more willing to and capable of investing in advanced technologies (Hannigan et al., 2015; Mendonça, 2009).

3.3 Methods and Data

This study uses regression analyses to explore the relationship between the knowledge structure of traditional technological fields and innovative capacity in high-tech fields within US metropolitan areas. More specifically, this study investigates whether a more specialized or a more diversified knowledge structure of traditional technological fields better encourages industrial restructuring, or the development of high-tech fields that are entirely different than the traditional fields in a region. Among the different approaches to measuring knowledge structure and defining traditional and high-tech fields, this study primarily uses innovation output data, i.e., patent data, from the USPTO. This study chooses 1986-2014 as the timeframe, taking the availability of patent data into account. USPTO patent data provides rich detail about patent information, including the technological classification and granted (or application) date of the invention, the name and location of inventors, and the ownership of the intellectual property of the invention (Hall et al., 2001)[14].

The location of the first-named inventor on patents granted in 1986, 1996, 2006, and 2014 (with 1996 and 2006 chosen as midpoints within the timeframe to analyze long-, mid-, and short-term effects) is used to designate the patent's geographic origin. Hence, the analysis is limited to patents with their first-named inventor based in the US. Moreover, out of the three patent types – Utility patents, Design patents, and Plant patents, only Utility patents are included in the sample. According to USPTO definitions,

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[14] https://patentsview.org/download/data-download-tables

a Utility patent is issued for the invention of new and useful process, machine, manufacture, or composition of matter, or a new and useful improvement. Therefore, they contain the necessary United States Patent Classification (USPC) information about what technological field they should be categorized into, which is the standard I refer to when deciding whether a patent belongs to traditional or high-tech fields. Moreover, about 90% of the patent documents issued by USPTO in recent years have been Utility patents[15].

Table 3.1 Traditional and High-tech Technological Categories and Their Sub-categories

Traditional Category Code and Name	**Traditional Sub-category Code and Name**
1 Chemical	11 Agriculture, Food, Textiles; 12 Coating; 13 Gas; 14 Organic Compounds; 15 Resins; 19 Miscellaneous-Chemical
4 Electrical & Electronics	41 Electrical Devices; 42 Electrical Lighting; 43 Measuring & Testing; 44 Nuclear & X-rays; 45 Power Systems; 46 Semiconductor Devices; 49 Miscellaneous-Electrical & Electronics
5 Mechanical	51 Materials Processing & Handling; 52 Metal Working; 53 Motors, Engines & Parts; 54 Optics; 55 Transportation; 59 Miscellaneous-Mechanical
6 Others	61 Agriculture, Husbandry, Food; 62 Amusement Devices; 63 Apparel & Textile; 64 Earth Working & Wells; 65 Furniture, House Fixtures; 66 Heating; 67 Pipes & Joints; 68 Receptacles; 69 Miscellaneous-Others
High-tech Category Code and Name	**High-tech Sub-category Code and Name**
2 Computers & Communications	21 Communications; 22 Computer Hardware & Software; 23 Computer Peripherals; 24 Information Storage
3 Drugs & Medical	31 Drugs; 32 Surgery & Medical Instruments; 33 Biotechnology; 39 Miscellaneous-Drugs & Medical

According to Hall et al. (2001), all patents can be aggregated into 6 main technological categories: Chemical (excluding Drugs); Computers and Communications; Drugs and Medical; Electrical and Electronics; Mechanical; and Others. As shown in Table A.1 in Appendix, the 6 categories can be further divided into 36 two-digit sub-categories and 431 three-digit patent classes. Of the 6 categories, Chemical, Mechanical,

[15] USPTO description of patent types:
https://www.uspto.gov/web/offices/ac/ido/oeip/taf/data/patdesc.htm

and Others are usually considered as the three traditional fields (this study uses "traditional fields" and "traditional categories" interchangeably). By contrast, Computers and Communications and Drugs and Medical are the high-tech fields (this study uses "high-tech fields" and "high-tech categories" interchangeably). Their patent count grew much more slowly than that of the traditional fields before 1980s, but has significantly surpassed the latter since early 1980s (Hall et al., 2001). This study further classifies the Electrical and Electronics category as the fourth traditional field. Within this category, the sub-category Semiconductor Devices largely emerged alongside the Computers and Communications category. However, due to the techniques and human capital requirements of Semiconductor Devices being more aligned with traditional rather than high-tech fields, this study classifies the sub-category as part of the traditional fields (Table 3.1, expanded upon in Appendix Table A.1).

This study utilizes the US Census Bureau's 2015 delineation for Core-based Statistical Areas (CBSAs). This geographic scale is chosen as it effectively represents the operational sphere of regional economic activities and captures the socio-economic integration within these areas. Nevertheless, when constructing the spatial lagged covariates for regression analyses, I find that the lack of high-tech patents in many Micropolitan Statistical Areas may lead to biases in model estimations. This is because the substantial zero values may skew the distribution and violate the underlying assumptions of the regression models. Hence, this study only includes Metropolitan Statistical Areas (MSAs). Moreover, due to the lack of data for the other regression covariates for some MSAs, this study only includes 357 MSAs in the three main regression models. The earliest available USPTO patent data dates back to 1976.

However, again, considering the scarcity of high-tech patents (which are used to construct spatial lagged covariates) before 1980s, choosing 1986 as the earliest year for data collection helps minimize potential bias in regression results. In total, these regions produced 54,054 high-tech patents in 2014, which is the end year of the study period.

Table 3.2 Definition of Primary Independent Variables

Variable	Description
Specialization (SPEC)	The SPEC index for each region is calculated as the location quotient of each region's most specialized traditional technological sub-category. The below equation shows how to calculate the location quotient of each traditional sub-category within each region. $pattrad_s$ is the patent count of traditional sub-category s within region i; $pattrad_i$ is the total patent count of all traditional sub-categories within region i; $PatTrad_s$ is the total patent count of traditional sub-category s in all regions; $PatTrad$ is the total patent count of all traditional sub-categories in all regions. A higher SPEC index indicates a greater level of innovation specialization for each traditional sub-category. SPEC = $\left(\frac{pattrad_s}{pattrad_i}\right) / \left(\frac{PatTrad_s}{PatTrad}\right)$
Related Variety (RV)	The RV index for region is calculated as the weighted sum of the entropy at the three-digit patent class level within each two-digit technological sub-category for each region. The below equation shows how to calculate the weighted-sum entropy for traditional sub-categories for each region. $pattrad_s$ is the patent count of traditional sub-category s within region i; $pattrad_i$ is the total patent count of all traditional sub-categories within region i; e_s is the entropy at the three-digit patent class level within every two-digit traditional sub-category s within region i; $pattrad_c$ is the patent count of patent class c within traditional sub-category s within region i. Note that the entropy for each traditional sub-category within each region is a sum of values across all patent classes within each sub-category. The RV index for each region is a weighted sum of entropy values across all traditional sub-categories within each region. A higher RV index indicates a greater innovation variety within traditional sub-categories for each region. This suggests a more balanced distribution of patents among interconnected patent classes within sub-categories, rather than concentration in just a few unrelated patent classes. RV = $\sum_{s=1}^{n}\left(\frac{pattrad_s}{pattrad_i}\right) e_s$, where: $e_s = \sum_{c=1}^{n}\left(\frac{pattrad_c}{pattrad_s}\right) \ln\left(\frac{1}{pattrad_c/pattrad_s}\right)$
Unrelated Variety (UV)	The UV index for each region is calculated as the entropy at the two-digit technological sub-category level within each region. The below equation shows how to calculate the entropy for traditional sub-categories for each region. $pattrad_s$ is the patent count of traditional sub-category s within region i; $pattrad_i$ is the total patent count of all traditional sub-categories within region i. Note that the entropy for each region is a sum of values across all traditional sub-categories within each region. A higher UV index indicates a greater innovation variety of unrelated traditional sub-categories for each region. This suggests a more balanced distribution of patents across various sub-categories, rather than concentration in just a few sub-categories. UV = $\sum_{s=1}^{n}\left(\frac{pattrad_s}{pattrad_i}\right) \ln\left(\frac{1}{pattrad_s/pattrad_i}\right)$

It is also important to note that after May 2016, the USPC classification is no longer assigned to Utility patents (though it is still used for Design and Plant patents)[16].

[16] https://patentsview.org/forum/generalfaq

Instead, USPTO replaces the USPC schemes with the Cooperative Patent Classification (CPC) classification jointly developed by the European Patent Office (EPO) and USPTO to ensure it is understood by a wide international audience. Most of the CPC's subdivisions stem directly from current International Patent Classification (IPC) and World Intellectual Property Organization (WIPO) technological fields used in over 100 countries around the world and managed by WIPO[17].

However, I still choose to use USPC classification because a clearer distinction between traditional and high-tech fields is provided under this scheme (Hall et al., 2001). As a result, this study finds that for the patent data reported under the USPC classification, the count of 2014 data had peaked, and the count went down year by year after. This is because there is usually a time gap between when an innovation is granted and when it is organized into the database. For instance, even though USPTO had still been reporting patent data under USPC classification until May 2016, some patents granted in 2015 might not yet have been included in the database before May 2016 due to the time lag. This suggests that the patent data in and before 2014 are complete, because the overall US patent count has grown every year, especially since 2008. Hence, I choose 2014 as the end point of the study period.

Again, the primary goal of this study is to examine which type(s) of knowledge structure is more likely to lead regions with traditional expertise to restructure their economy and innovate in the high-tech fields. Three main hypotheses are tested: holding all else constant, regions 1) with a higher traditional technological specialization, 2) that have a traditional knowledge structure with higher related variety, and 3) that have a

[17] https://patentsview.org/classification

traditional knowledge structure with higher unrelated variety at the beginning of the timeframes were associated with higher patenting level in high-tech fields in 2014. As discussed in the literature review section, theoretical foundations exist to support each of the three hypotheses presented. To determine the temporal variation in the association between traditional knowledge structure and high-tech innovation, this study employs three linear regression models using different starting points and the same end point: 1986-2014, 1996-2014, and 2006-2014[18]. Table 3.2 describes how to measure the three primary independent variables for each model[19].

This study uses Equation (1) to fit three regression models:

$$\ln(PatTech)_{2014} = \beta_0 + \beta_1 SPEC_{1986} + \beta_2 RV_{1986} + \beta_3 UV_{1986} + \beta_4 PopGr_{1986\text{-}2014} + \beta_5 IncGr_{1986\text{-}2014} + \beta_6 EduGr_{1986\text{-}2014} + \beta_7 \ln(PatTech)_{1986} + \beta_8 Spatlag_{1986} + Division' + e \quad (1)$$

The models have a common dependent variable – the patent count in high-tech fields in 2014 – and vary in the timing of independent variables. Models (1), (2), and (3)

[18] This study examines the traditional patent counts in each region during the periods of 1 and 2 years leading up to 1986, 1996, and 2006 respectively and finds that the patent counts largely remain stable. In other words, the standard deviation of patent counts across multiple years is not dispersed for more than half of the regions. According to standard power analysis, a sample size of 26 is sufficient for accurate estimation, and the sample of this study contains 357 MSAs. Hence, constructing the variables using one-year patent counts should be acceptable.

[19] In my analysis, I utilized the location quotient of a region's most specialized traditional technological sub-category to measure its level of specialization. The location quotient was selected for its capacity to underscore the regional concentration in specific technological sub-categories relative to the average of all studied regions. While this method aligns well with regional economic analysis, I acknowledge the potential utility of alternative measures like the Herfindahl-Hirschman Index (HHI) or the market share of the four largest firms or inventors within a sub-category. These metrics, commonly used to assess industry concentration and market dominance, could offer additional insights into the intensity of regional specialization.
The reason for not adopting the HHI in this study is its conceptual proximity to the entropy index, which I used to assess related and unrelated variety, essentially measuring diversification rather than concentration. Regarding the market share of the top four firms or inventors, this was not used due to the absence of inventor-specific data in the patent information collected for this analysis. However, I recognize the value of exploring these alternative metrics in future research to validate and enhance the findings of this study.

test the relationship between high-tech patent level in 2014 and traditional knowledge structure in 1986, 1996, and 2006, respectively. The timing of control variables, such as population growth, income growth, human capital growth, high-tech patent spatial lag, and original high-tech patenting level, change accordingly.

The first set of covariates control for the contribution of population growth, per capita income growth, and human capital growth on high-tech innovation during the study timeframes. More specifically, human capital growth is measured by the difference of each region's percentage of adults age 25+ with a bachelor's degree or above between the starting and end time[20]. The second set of covariates includes dummy variables indicating which one of the 9 US Census Divisions each region is in[21]. The models also account for each region's high-tech patenting level at the beginning of the timeframes studied.

This study takes into account the impact of high-tech innovation from neighboring regions by creating a spatial lagged variable for each region. The purpose is to control for the potential spillover effects of high-tech innovation within nearby regions. To begin, shapefiles for all MSAs were obtained from the Census Bureau. These shapefiles were then projected to the World Geodetic System 1984 (WGS84) coordinate reference system using R programming language within RStudio. Next, in order to construct the spatial weights matrices for calculating spatial lagged variables, two

[20] I collect data for population and income covariates from the Bureau of Economic Analysis, and for educational attainment covariates from the Census Bureau. To construct educational attainment covariates, this study uses 1980, 1990, 2000 Population Censuses, and the 2015-19 American Community Survey (ACS) 5-year estimates. This study uses 5-year instead of 1-year estimates because the latter leave out many smaller regions in the sample.

[21] For MSAs that cross the border between two Census Divisions, this study uses the location of the first-named state in the name of each MSA.

approaches were considered: the k-nearest neighbors (KNN) approach and distance-based neighbors (DBN) approach.

For the KNN approach, the scenarios tested include k values of 1 and 4, meaning the high-tech patenting level of the 1 and 4 nearest neighboring regions are taken into account for each region. For the DBN approach, a cut-off distance of 200km (~124mile) and 400km (~248mile) was chosen, indicating that the high-tech patenting levels of all neighboring regions within the respective buffer distances are considered[22]. I chose these proximity ranges because the spillover effects under study might no longer be relevant beyond these distance thresholds (Ganning et al., 2013; Partridge & Rickman, 2008). The spatial lagged variable for each region was computed as the weighted sum of high-tech patents from included neighbors. The weights were given by the corresponding spatial weights matrix, allocating greater weight to nearer neighbors. This approach aligns with Tobler's First Law of Geography, which asserts that nearby entities are more likely to influence each other than those that are farther apart.

[22] In this study, Great Circle distance is used instead of Euclidean distance for all involved distance measurements. In addition, the obtained distances are converted into row-standardized inverse distances when constructing the spatial weights matrices. The high-tech patenting counts of all neighboring regions are collected at the beginning of each study timeframe. Additionally, it should be noted that in the DBN approach, a cut-off distance of 200km results in 12 regions with no neighboring regions. Similarly, for the cut-off distances of 400km and 600km, there are 2 regions with no neighboring regions, respectively.

Table 3.3 Descriptive Statistics[23]

Variable	Obs.	Mean	Std. Dev.	Min	Max
High-tech Patent Count in 2014 (ln)	357	2.507	2.191	-1.000	8.984
Traditional Fields Specialization (SPEC) Index 1986	357	11.094	15.504	1.636	171.056
Traditional Fields Specialization (SPEC) Index 1996	357	8.463	5.981	1.716	35.965
Traditional Fields Specialization (SPEC) Index 2006	357	10.479	11.315	1.761	140.732
Traditional Fields Related Variety (RV) Index 1986	357	0.572	0.526	0.000	2.134
Traditional Fields Related Variety (RV) Index 1996	357	0.687	0.520	0.000	2.105
Traditional Fields Related Variety (RV) Index 2006	357	0.635	0.482	0.000	2.037
Traditional Fields Unrelated Variety (UV) Index 1986	357	1.862	0.728	0.000	2.983
Traditional Fields Unrelated Variety (UV) Index 1996	357	2.093	0.649	0.000	3.059
Traditional Fields Unrelated Variety (UV) Index 2006	357	2.028	0.702	0.000	3.040
Population Growth 1986-2014 (%)	357	0.396	0.367	-0.181	2.509
Population Growth 1996-2014 (%)	357	0.199	0.174	-0.120	0.853
Population Growth 2006-2014 (%)	357	0.068	0.060	-0.075	0.283
Per Capita Income Growth 1986-2014 (%)	357	2.027	0.379	1.167	5.497
Per Capita Income Growth 1996-2014 (%)	357	0.885	0.229	0.475	3.329
Per Capita Income Growth 2006-2014 (%)	357	0.246	0.089	0.007	0.946
Human Capital Growth 1986-2014 (%)	357	12.45	4.228	3.30	25.70
Human Capital Growth 1996-2014 (%)	357	9.600	3.192	1.800	20.000
Human Capital Growth 2006-2014 (%)	357	6.251	2.018	1.400	11.950
High-tech Patent Spatial Lag 1986 (KNN = 1)	357	5.779	18.138	0.000	157.000
High-tech Patent Spatial Lag 1996 (KNN = 1)	357	25.680	83.004	0.000	701.000
High-tech Patent Spatial Lag 2006 (KNN = 1)	357	80.540	350.070	0.000	3949.000
High-tech Patent Count in 1986 (ln)	357	0.412	1.558	-1.000	6.231
High-tech Patent Count in 1996 (ln)	357	1.386	1.923	-1.000	7.033
High-tech Patent Count in 2006 (ln)	357	2.013	2.135	-1.000	8.281
Census Division East North Central (0/1; Baseline)	357	0.163	0.369	0.000	1.000
Census Division New England (0/1)	357	0.042	0.201	0.000	1.000
Census Division Middle Atlantic (0/1)	357	0.092	0.290	0.000	1.000
Census Division South Atlantic (0/1)	357	0.207	0.406	0.000	1.000
Census Division West North Central (0/1)	357	0.087	0.282	0.000	1.000
Census Division East South Central (0/1)	357	0.078	0.269	0.000	1.000
Census Division West South Central (0/1)	357	0.106	0.309	0.000	1.000
Census Division Mountain (0/1)	357	0.092	0.290	0.000	1.000
Census Division Pacific (0/1)	357	0.132	0.339	0.000	1.000

[23] This study employs logarithm transformation to adjust for the right-skewed distribution of the dependent variable using patent count in 2014, and sets the results of ln (0) as -1.

3.4 Results and Findings

Table 3.4 shows the correlation matrix, and Table 3.5 shows the regression results[24]. We see from Table 3.5 that all three models that the results support the second and the third main hypotheses but not the first hypothesis of this study. In other words, holding all else constant, regions that have a traditional knowledge structure with higher related variety, and that have a traditional knowledge structure with higher unrelated variety at the beginning of the timeframes were associated with higher patenting level in high-tech fields in 2014. By contrast, regions with a higher traditional specialization were associated with a lower patenting level in high-tech fields in 2014.

For the included 357 US MSAs, their patenting level in high-tech fields in 2014 was positively associated with their preexisting related diversity level and unrelated diversity level of traditional fields in 1986, 1996, and 2006. According to Model (1), after accounting for other variables in the model, each unit increase in the traditional fields RV index in 1986 was associated with a 0.864% increase in high-tech patent count in 2014. In addition, each unit increase in the traditional fields UV index in 1986 was associated with a 0.684% increase in high-tech patent count in 2014.

The results show that regions with a traditional knowledge structure characterized by either a greater diversity of related technological sub-categories producing patents or a greater diversity of unrelated sub-categories producing patents tended to patent more in high-tech fields in later periods. By contrast, regions that focused more heavily on their top technological sub-category in terms of patenting level (as suggested by the first

[24] Due to the heteroskedasticity problem in the models, the robust errors for each model are presented. All models pass diagnostic tests.

hypothesis) ended up with lower high-tech patenting levels in the future. This point will be considered in more detail later.

The regression results also indicate the consistency and stability of the relationship across various time periods. Model (2) and Model (3) show that as the beginning time approached 2014, the coefficients for both the traditional fields RV index and the traditional fields UV index consistently maintained a positive and statistically significant sign. These models were also retested after replacing the dependent variable (the high-tech patent count in 2014) with the high-tech patent growth between the starting and end time[25]. The new models produced consistent coefficients for all explanatory variables as the reported three models, except for the high-tech patent count variables at the baseline time, which exhibited negative coefficients[26]. This additional information indicates that even though more innovative high-tech regions in general recorded higher patent counts during the periods studied, their growth tended to be slower.

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[25] As for the dependent variables using patent growth during different timeframes, this study measures them by calculating the log difference between the patent count at the end time and the beginning time.

[26] This group of three models is not reported in this study due to their relatively smaller r-squared values (0.427; 0.286; 0.160) compared to the reported three models.

Table 3.4 Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	High-tech Patent Count in 2014 (ln)	1.000																
2	Traditional Fields Specialization (SPEC) Index 1986	-0.283	1.000															
3	Traditional Fields Related Variety (RV) Index 1986	0.737	-0.229	1.000														
4	Traditional Fields Unrelated Variety (UV) Index 1986	0.721	-0.314	0.720	1.000													
5	Population Growth 1986-2014 (%)	0.207	0.028	-0.086	-0.058	1.000												
6	Per Capita Income Growth 1986-2014 (%)	0.000	-0.079	-0.058	-0.089	-0.034	1.000											
7	Human Capital Growth 1986-2014 (%)	0.590	-0.185	0.437	0.447	0.074	0.106	1.000										
8	High-tech Patent Spatial Lag 1986 (KNN = 1)	0.105	0.073	0.067	0.066	-0.065	-0.060	0.073	1.000									
9	High-tech Patent Count in 1986 (ln)	0.814	-0.209	0.788	0.688	0.029	-0.039	0.505	0.124	1.000								
10	Census Division East North Central (0/1; Baseline)	0.009	-0.097	0.165	0.157	-0.307	-0.204	-0.006	0.024	0.077	1.000							
11	Census Division New England (0/1)	0.138	-0.064	0.169	0.140	-0.138	0.028	0.312	0.122	0.142	-0.092	1.000						

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
12	Census Division Middle Atlantic (0/1)	0.011	0.060	0.109	0.086	-0.196	-0.092	0.139	0.055	0.119	-0.141	-0.067	1.000					
13	Census Division South Atlantic (0/1)	-0.060	0.050	-0.109	-0.071	0.195	-0.075	0.069	-0.117	-0.082	-0.225	-0.107	-0.163	1.000				
14	Census Division West North Central (0/1)	0.026	0.004	-0.084	-0.022	-0.066	0.143	0.115	0.001	-0.060	-0.136	-0.065	-0.098	-0.158	1.000			
15	Census Division East South Central (0/1)	-0.130	0.021	-0.045	-0.092	-0.033	0.058	-0.083	-0.061	-0.129	-0.128	-0.061	-0.093	-0.149	-0.090	1.000		
16	Census Division West South Central (0/1)	-0.111	0.069	-0.079	-0.104	-0.014	0.395	-0.295	-0.042	-0.077	-0.152	-0.072	-0.110	-0.176	-0.106	-0.101	1.000	
17	Census Division Mountain (0/1)	0.036	0.007	-0.078	-0.092	0.342	-0.030	-0.063	-0.030	-0.030	-0.141	-0.067	-0.102	-0.163	-0.098	-0.093	-0.110	1.000
18	Census Division Pacific (0/1)	0.123	-0.056	0.000	0.022	0.152	-0.125	-0.085	0.106	0.076	-0.171	-0.082	-0.124	-0.199	-0.120	-0.114	-0.134	-0.124

Note: Only the correlation matrix for Model (1) (1986-2014) is reported in this paper. The correlation matrices for Model (2) (1996-2014) and Model (3) (2006-2014) demonstrate no significant variation from the correlation matrix for Model (1).

Table 3.5 Regression Results

Model	(1)	(2)	(3)
Timeframe	1986-2014	1996-2014	2006-2014
Dependent Variable	Patent Count in 2014 (ln)		
Traditional Fields Specialization (SPEC) Index 1986	-0.007*		
	(0.003)		
Traditional Fields Specialization (SPEC) Index 1996		0.002	
		(0.010)	
Traditional Fields Specialization (SPEC) Index 2006			0.002
			(0.004)
Traditional Fields Related Variety (RV) Index 1986	0.864***		
	(0.176)		
Traditional Fields Related Variety (RV) Index 1996		0.552**	
		(0.179)	
Traditional Fields Related Variety (RV) Index 2006			0.624**
			(0.189)
Traditional Fields Unrelated Variety (UV) Index 1986	0.684***		
	(0.120)		
Traditional Fields Unrelated Variety (UV) Index 1996		0.782***	
		(0.122)	
Traditional Fields Unrelated Variety (UV) Index 2006			0.491***
			(0.111)
Population Growth 1986-2014 (%)	1.055***		
	(0.173)		
Population Growth 1996-2014 (%)		1.239**	
		(0.375)	
Population Growth 2006-2014 (%)			1.240
			(0.968)
Per Capita Income Growth 1986-2014 (%)	0.069		
	(0.211)		
Per Capita Income Growth 1996-2014 (%)		0.241	
		(0.311)	
Per Capita Income Growth 2006-2014 (%)			-0.294
			(0.570)
Human Capital Growth 1986-2014 (%)	0.105***		
	(0.018)		
Human Capital Growth 1996-2014 (%)		0.070***	
		(0.021)	
Human Capital Growth 2006-2014 (%)			0.083**
			(0.032)
High-tech Patent Spatial Lag 1986 (KNN = 1)	0.003		

Model	(1)	(2)	(3)
Timeframe	1986-2014	1996-2014	2006-2014
Dependent Variable		Patent Count in 2014 (ln)	
	(0.002)		
High-tech Patent Spatial Lag 1996 (KNN = 1)		0.000	
		(0.001)	
High-tech Patent Spatial Lag 2006 (KNN = 1)			0.000
			(0.000)
High-tech Patent Count in 1986 (ln)	0.538***		
	(0.061)		
High-tech Patent Count in 1996 (ln)		0.607***	
		(0.052)	
High-tech Patent Count in 2006 (ln)			0.652***
			(0.052)
Census Division East North Central (0/1; Baseline)			
Census Division New England (0/1)	-0.110	0.134	0.016
	(0.249)	(0.225)	(0.182)
Census Division Middle Atlantic (0/1)	-0.273	-0.272	-0.133
	(0.229)	(0.195)	(0.179)
Census Division South Atlantic (0/1)	0.057	0.009	0.019
	(0.216)	(0.185)	(0.173)
Census Division West North Central (0/1)	0.609*	0.461*	0.224
	(0.251)	(0.227)	(0.245)
Census Division East South Central (0/1)	0.001	-0.063	-0.133
	(0.246)	(0.199)	(0.206)
Census Division West South Central (0/1)	0.319	-0.127	0.123
	(0.263)	(0.261)	(0.230)
Census Division Mountain (0/1)	0.454.	0.381	0.190
	(0.258)	(0.247)	(0.209)
Census Division Pacific (0/1)	0.610**	0.507*	0.310.
	(0.204)	(0.202)	(0.174)
Constant	-1.478**	-1.619***	-0.824*
	(0.458)	(0.391)	(0.323)
Number of Observations	357	357	357
Adjusted R-squared	0.801	0.838	0.860

Note: “***” $p < 0.001$; “**” $p < 0.01$; “*” $p < 0.05$; “.” $p < 0.10$. Values in parentheses are standard errors.

It is important to note that in the retest models, the correlations between the high-tech patent count independent variables at the initial time and the dependent variables of high-tech patent growth in 2014 (e.g., the correlation coefficient for the 1986 model is 0.174) were much lower compared to the correlations with the dependent variables of high-tech patent count in 2014 (as shown in the Correlation Matrix in Table 3.4, for instance, the correlation coefficient for the 1986 model is 0.814) in the original models. As a result, the coefficients of the independent variables that are of primary interest in the original models are not affected by autocorrelation concerns.

Regarding the last type of regional knowledge structure (the first hypothesis of this paper), two of the three models detected no significant association between the traditional fields specialization index and the high-tech patenting level for the US MSAs analyzed. The third detected only a slight negative correlation, it was statistically significant but economically insignificant and therefore contains no meaningful information. Consequently, the first main hypothesis of this study is not supported, indicating that a region's patenting in high-tech fields does not generally benefit from strong specialization in its most specialized traditional technological sub-category. As further discussed in the next section, high-tech innovations in regions with strong specialization in specific traditional industries, as highlighted in recent scholarship, are likely driven by knowledge spillovers among lower-tier industries within their area of strong specialization, or related variety, rather than by strong specialization in a broader sense general.

Table 3.4 reveals a negative correlation between the traditional fields SPEC index and both the RV and UV indexes. This suggests that regions with a high SPEC index, denoting a concentration in top traditional technological sub-categories, typically do not align with regions having high RV and UV indexes, which represent a diversified traditional knowledge structure. Evidently, regions with larger populations, typically characterized by expansive market and labor pools, are associated with higher RV and UV indexes, reflecting a variety of patenting industries, but show a low SPEC index[27]. In contrast, smaller regions, possibly due to resource constraints or historical factors, often show specialization in a few technological sub-categories, indicated by a high SPEC index. This trend may explain the more frequent occurrence of industrial restructuring in larger, economically diversified regions compared to smaller, highly specialized ones.

The coherence of these empirical observations become evident upon considering the mathematical relationships among the SPEC, RV, and UV indexes. The SPEC index derives from the location quotient of a region's most specialized traditional technological sub-category. In essence, the SPEC index shows how concentrated the most specialized sub-category of a region is compared to the national average. Hence, a high SPEC index indicates a proportionally smaller share of other technological sub-categories. Conversely, elevated UV and RV indexes both signify more evenly distributed shares among diverse technological sub-categories and among diverse patent classes within each sub-category. Therefore, it is reasonable to observe a negative correlation between the SPEC index and both the UV and RV indexes.

Moreover, the decomposable nature of entropy measures enhances our

[27] The correlation coefficients between population size and traditional fields RV index are 0.590, 0.582, and 0.582 for the years 1986, 1996, and 2006, respectively. Those between population size and traditional fields UV index are 0.381, 0.377, and 0.373 for the same respective years. In contrast, the correlation coefficients between population size and traditional fields SPEC index are -0.121, -0.255, and -0.181, respectively, for the years 1986, 1996, and 2006.

understanding of the connection between the UV and RV indexes. Again, the RV index captures the variety of 3-digit patent classes within each 2-digit sub-category (using a weighted sum), and the UV index captures the variety across different 2-digit sub-categories. Hence, the RV index and the UV index of a region sum up to the entropy value of 3-digit patent classes (without a weighted sum). In other words, the total innovation variety of 3-digit patent classes within a region's economy can be expressed as a combination of the innovation variety among related patent classes under each unrelated technological sub-category (RV index) and the innovation diversity across those unrelated technological sub-categories (UV index). In this study, the total innovation variety of 3-digit patent classes within each region is also calculated. It has been demonstrated that this total variety index equates to the sum of the RV index and the UV index for each region.

Additionally, in my analysis, I replaced the RV and UV indexes with a single total variety index across each of the three models. I observed that the regression coefficient for this total variety index does not match the sum of the coefficients of the RV and UV indexes; it was generally smaller, but still significant. There are several potential explanations for this. First, the RV and UV indexes may exhibit a high degree of correlation. When both are in the model, their individual coefficients are usually adjusted for the shared variance. This adjustment might differ when the total variety index, a combination of both, is used instead. Second, there could be interaction effects between the RV and UV indexes that are not captured when they are simply combined to create a total variety index. Such interactions might influence the coefficients in non-linear ways. Third, merging two variables into one alters the variable's scale, potentially impacting the size of the coefficient.

One surprising finding revealed in the regression results is the lack of statistical significance in the coefficients for the high-tech patent spatial lag variables. This study only reports the results of the K =1 scenario in the KNN approach. Despite testing various scenarios, such as the K = 1 and K = 4 scenarios in the KNN approach, as well as cut-off distances of 200km and 400km in the DBN approach, none of these scenarios demonstrate significant coefficients. This suggests that a region's ability to restructure its knowledge base through proximity to high-tech innovative neighboring regions and the associated spillover effects is limited.

In addition to the primary findings, the regression results indicate a positive correlation between high-tech innovation and both regional population growth and human capital development. This is consistent with existing regional economics literature. In contrast, this study finds no significant association between regional per capita income growth and high-tech innovation, echoing the minimal correlation observed between income growth and the level of high-tech patenting in Table 3.4. Last, in terms of geographic location, the regression results show that MSAs situated in the Pacific Census Division and West North Central Census Division experienced higher levels of high-tech innovation growth during the study periods in comparison to MSAs located in the East North Central Census Division.

3.5 Discussions and Conclusion

This study aims to establish several generalizable arguments regarding the relationship between the knowledge structure of US MSAs in traditional fields and their innovation capacity in high-tech fields. First, the findings of this study provide support for the notion that regions with greater diversity in related traditional technological sub-categories tend to excel in restructuring their knowledge base and fostering high-tech innovation. Second, this study suggests that the colocation of diverse unrelated traditional technological sub-categories also contributes positively to regional economic restructuring and the development of high-tech fields. Third, this study asserts that a high degree of specialization in specific traditional technological sub-categories has a negative impact on a region's ability to undergo restructuring.

The benefits of cultivating a diverse economic or knowledge base have long been recognized as a fundamental strategy in regional or local economic development. Previous studies have extensively explored the advantages that economic and knowledge diversity bring to a region, such as increased productivity, employment opportunities, and growth in innovation (De Groot et al., 2016). However, most of the existing literature has primarily focused on the process of economic development and recovery. This study seeks to contribute further to the scholarship by examining the context of economic restructuring. I contend that fostering a diverse knowledge base is not only beneficial for the economic development process but also facilitates the development of entirely new industrial expertise within the region. In other words, maintaining a more diversified knowledge structure encourages regions to assimilate knowledge from emerging industries that may be vastly different and subsequently integrate this new knowledge into their industrial base.

This study also refers to pre-existing scholarship and discusses the potential mechanism underlying the presented arguments. First, regions with diverse industries are more likely to provide ample opportunities for high-tech companies to identify new market demands and niches among local industries, as opposed to specialized regions. Additionally, diversified regions often benefit from larger economies and populations, which lead to economies of scale by virtue of their increased market size and access to financial and human resources. This environment is highly conducive to the establishment and success of high-tech start-ups. Recent empirical studies have highlighted instances where regions known for their specialization in traditional industries have begun to develop innovation capacity in high-tech industries and revitalize their regional industrial base (Hannigan et al., 2015; Mudambi et al., 2017). This study posits that such regions typically do not belong to the category of most specialized regions. Instead, they are often regions with strong related diversity, which enables them to adapt novel knowledge from high-tech industries into their existing economic landscape. Furthermore, I infer that regions characterized by strong specialization but low related variety are unlikely to witness significant growth in high-tech innovation.

It is important to note that the identification of traditional and high-tech industries in this study is based on the classification of technological rather than industrial categories. As a result, only two categories – Computers & Communications and Drug & Medical – are included as high-tech fields. Readers might perceive that certain advanced manufacturing technologies included in the traditional fields should be considered high-tech, as they require extensive human intelligence. This study acknowledges the progress made in traditional fields and recognizes potential shortcomings in the selected classification. However, I contend that adhering to this classification ensures that the identified high-tech fields are “radically new” to regions specialized in traditional fields.

Moreover, other categorizations of high-tech industries are not comprehensive as well. For instance, defining high-tech industries based on the highest R&D intensity may include only those technologies driven by endogenous industry R&D activities, while neglecting those influenced by exogenous factors.

Relatedly, achieving an exceptionally diverse knowledge base and pursuing expertise in the most popular high-tech industries may not be feasible for every region. For many regions, a more prudent approach would be to leverage their existing industrial strengths and diversify into related, more advanced industries. By doing so, these regions also enhance their possibilities of adopting high-tech industries in the future. Moreover, even regions located near high-tech centers should be prepared to compete with other regions if they aim to restructure their knowledge base for high-tech industries.

The regression results of this study also underscore the role of regional population growth and human capital growth in fostering high-tech innovation. On the other hand, regional per capita income growth does not have a significant impact on high-tech innovation. These findings are reasonable, as regions can pursue economic growth without necessarily specializing in high-tech industries, and high levels of wealth do not automatically translate into suitable conditions for high-tech development. Also, the economic benefits of innovation are not always shared with the workforce.

Admittedly, there are several limitations when using patent data, although it is one of the most widely-adopted proxies for innovation in relevant studies. Two major weaknesses worth highlighting. First, patent data does not cover all kinds of innovation, particularly those that are related to process innovation instead of production-related innovation, and those that are not patented due to company strategies. Hence, my findings primarily reflect a subset of innovations, specifically those that are patentable and have been patented. Future studies, utilizing surveys, case studies, or industry reports to quantify non-patentable innovations, might uncover different relationships between traditional technological fields structuring and high-tech innovation.

Second, there is potential for geographical bias in patent data, as the location of the first-named inventor may not necessarily reflect the major resources utilized in developing the patent, or the locations of companies using the patent or manufacturing related products. Often, this location is chosen based on legal or administrative reasons. In this study, the first-named inventor's location was chosen because they play a pivotal role in the patent's conceptualization and development, and their location typically reflects the place of this work. As the study focuses on regional innovation activity, this approach aids in identifying the geographic distribution of innovation and the leading region in cases of collaborative networks. However, future extended studies might consider including all associated locations of a patent to more comprehensively represent the collaborative nature of modern innovation processes.

The possibility of including additional covariates that could influence high-tech patenting level was also considered in this study. These covariates encompassed the quantity of R&D public institutions and private labs, as well as the levels of R&D expenditure and venture capital within each region. However, collecting complete datasets, particularly concerning R&D institutions and labs, presented impractical challenges. Moreover, certain data, such as R&D expenditure and venture capital, were not available early enough prior to the end point of the study timeframes, and it was also unavailable at a geography smaller than the MSA.

CHAPTER IV

HIGH-TECH REGIONS AS INNOVATORS OF TRADITIONAL TECHNOLOGIES: CAN HIGH-TECH INNOVATION CAPABILITY FOSTER TRADITIONAL INNOVATION?

4.1 Introduction

In the knowledge economy, a region's economic development often hinges on the innovation capacity of its specialized industries. Therefore, regions specializing in high-tech industries such as information technology and bioscience receive much attention from urban researchers and practitioners (Mayer, 2011; Saxenian,1996). Other popular research interests broaden the scope of innovation beyond high-tech industries to include cultural and professional service industries, examining the locations where these industries thrive. In contrast, studies on innovation- and especially technology-led development have largely overlooked traditional industries and regions specializing in these industries. Instead, the academic focus for these industries and regions centers on employment decline and urban shrinkage (Doussard & Schrock, 2015; Ganning & Tighe, 2021; Wiechmann & Pallagst, 2012). However, besides labor and output, technology also represents one of the evolving characteristics of traditional industries and their host regions (Vanchan et al., 2015).

Perhaps regions prefer high-tech industries because they believe it represents progress in both technological advancement and economic standing. Indeed, high-tech industries are characterized by higher knowledge intensity (Hall et al., 2001; Rigby, 2015), experience greater market demand (NRC, 1996) and consequently, offer higher compensation to their employees. However, generations of scientists have commented that technological progress or economic development is more complex than moving away from traditional fields and toward high-tech fields. Rather, the high-tech and the non-high-tech industries are highly symbiotic and their innovation impacts cut across economic activities. These theorists come from different schools of thought, including but not limited to evolutionary economics (Dosi et al., 1988; Nelson & Winter, 1982) and evolutionary economic geography (Asheim et al., 2011; Asheim et al., 2017). Recent empirical evidence also indicates that companies and regions specializing in traditional industries have been engaging in innovation within high-tech industries. This shift is leading to a revitalization of their traditional expertise through the integration of cutting-edge knowledge (Hannigan et al., 2015; Mendonça, 2009; Mudambi et al., 2017).

There remains a research gap regarding the regional innovation dynamics between high-tech and traditional fields. Relatively few studies have studied whether or how regions with more "advanced" specialized industries innovate in traditional industries. To my understanding, the only existing analyses similar to this proposed study are focused either on the national level or differentiating between urban and rural areas. For example, Robertson & Patel (2007) discovered that countries exhibiting robust innovation in high-tech industries tend to outperform less innovative countries in traditional industries as well. Similarly, Hansen et al., (2014) found that, compared to less innovative rural regions, urban regions with higher innovation levels also demonstrated stronger innovation in traditional industries. They further argue that this is perhaps because innovations in both high-tech emerging industries and non-high-tech traditional industries are increasingly influenced by some common factors, such as human capital and global competition, that transcend industrial influences (Berry & Glaeser, 2005; Glaeser & Hausman, 2020). Nevertheless, relevant studies are still scarce and inconclusive.

This study aims to address this research gap by exploring whether US regions with more robust innovation capabilities in high-tech fields also demonstrate elevated patenting activity in traditional fields from 1996 to 2014. Utilizing technological classifications and patent data from the US Patent and Trademark Office (USPTO), the study tests a key hypothesis: *regions with higher patenting levels in high-tech fields between 1996-2000 had greater patenting levels in traditional fields between 2010-2014*, while accounting for the impact of historical traditional specializations and other confounding variables. Additionally, this study replaces general patenting levels in the high-tech and traditional fields with specific technological categories, thereby providing a more detailed view of the hypothesized relationship.

This study enriches the growing body of research on innovation development processes beyond the extensively studied high-tech and cultural industries. Firstly, the regression analysis results support the primary hypothesis – regions that demonstrated higher patenting levels in high-tech fields during 1996-2000 subsequently exhibited greater patenting levels in traditional fields between 2010 and 2014. The study delves into potential explanations for these findings, linking them with insights from both the current study's results and existing literature.

Secondly, when examining the relationship by technological category, the study uncovers a positive association between the overall patenting levels in traditional categories and both of the two high-tech categories: Computers & Communications, and Drugs & Medical. Additionally, this study investigates the correlation between overall patenting in high-tech categories and three individual traditional technological categories: Chemical, Electrical & Electronics, and Mechanical. Although the relationships are positive across all three traditional categories, the Mechanical category seems to have been the least influenced by advancements in high-tech innovation. Lastly, the analysis indicates that regional innovation, including in traditional fields, is predominantly influenced by path dependency, with the high-tech fields' impact being more complementary.

4.2 Literature Review

This literature review starts with background information regarding the mainstream innovation studies within the domain of regional economic development. The main body of this review synthesizes the important academic milestones (both theoretical and empirical) exploring innovation activities in the traditional industries. Most studies have focused on how regions and firms from traditional industries have maintained or developed innovation capacity in both traditional and high-tech industries. However, fewer studies cover how regions with specializations in more advanced and innovative high-tech industries have chosen to innovate in traditional industries. Last, this review introduces scholarship which might shed light on the mechanisms behind the hypothesis of this paper, i.e., regions with higher innovation capacity in high-tech fields are more likely to innovate in traditional fields.

From neoclassical growth theory (Solow, 1956; 1962) to endogenous growth theory (Lucas, 1988; Romer, 1986), economists have attributed long-term economic growth to technological innovation. Schumpeter's (1942) innovation and entrepreneurship theory holds that innovation introduces entirely new products and new markets to the regional production system, facilitating economic development rather than merely incremental economic growth. Particularly in the face of various macro-economic trends like mechanization, neoliberal corporate strategies, global outsourcing, and the de-concentration of domestic production, high-wage industrialized countries have been pressured to uphold their competitive advantage by fostering innovation. As a result, discussions on regional economic development have predominantly centered on high-tech industries and a limited number of high-tech regions (David & Foray, 2002; Freeman, 2004; Mayer, 2011; Saxenian,1996).

Indeed, since the 1990s, high-tech fields have out-performed traditional fields in terms of patent growth rates, which shows their superior capacity for innovation (Hall et al., 2001; Rigby, 2015). This trend in patenting often correlates with increased levels of research and development (R&D) intensity in research-intensive high-tech industries. Hence, research institutions and academics rely on both R&D intensity-related metrics and patenting levels as criteria to differentiate high-tech industries from traditional industries.

For instance, the Organization for Economic Cooperation and Development (OECD) divides industries into four categories: high-technology, medium-high-technology, medium-low-technology, and low-technology industries, based on their R&D expenditures (input) to output ratio. Industries with lower R&D intensity, such as basic metals, rubber and plastic products, food products, and chemicals, are classified as non-high-tech (Hansen & Winther, 2011; Mendonça, 2009). Similarly, the US Bureau of Labor Statistics (BLS) categorizes industries into Levels I, II, III, using criteria such as R&D employment intensity or the proportion of scientists, engineers, and technicians in the workforce (Hecker, 2005). Scholars at the National Bureau of Economic Research (NBER) refer to high-tech fields as "emerging" fields, acknowledging their growing innovation output, particularly in terms of patents, relative to traditional fields (Hall et al., 2001).

Considering innovation's impact in economic development, technological progress is often envisioned as a linear process toward preferred outcomes. However, generations of economists have argued against this viewpoint. In Schumpeter's (1942) model of innovation, entrepreneurs rearrange pre-existing factors of production, thereby creating markets that align new production methods with consumer preferences. In other words, innovation stems from novel combinations of knowledge and is propelled by emerging market demand, rather than being solely the product of individual knowledge with greater technology intensity. Likewise, evolutionary economists argue that the advancement of technological innovations is more likely rooted in firm-specific routines and practices than in R&D strategies aimed at finding optimal solutions (Amin & Cohendet, 2004; Dosi et al., 1988; Edquist, 1997; Nelson & Winter, 1982; Patel & Pavitt, 1997).

Furthermore, evolutionary economic geographers contend that innovations in traditional fields are just as crucial as those in high-tech fields, despite their reliance on distinct knowledge bases. Innovations in high-tech fields typically stem from the creation of knowledge through scientific research, whereas those in traditional fields are more frequently the result of re-combining existing knowledge (Asheim et al., 2011; Asheim et al., 2017).

Scholars highlight the importance of the synthesis-based innovation method used by traditional industries, as it enhances the innovative capacity of not only these industries but also the broader economy. Traditional industries utilize innovation from high-tech industries in two primary ways. First, they adopt high-tech products or sophisticated machinery to enhance their production processes. This adoption not only improves their efficiency but also spurs further R&D activities, contributing to the sustainable growth of high-tech industries (Hansen & Winther, 2011; Heidenreich, 2009; Kirner et al., 2009; Robertson & Patel, 2007). Second, these industries may incorporate new high-tech components into their products, leading to market-oriented modifications that enhance their offerings (Hirsch-Kreinsen, 2015; Mulhall, 2015). Some traditional companies also gain competitive advantages through innovations in design and service, often targeting adaptations in response to evolving dynamics within the supply chain (Vanchan et al., 2015; Walcott, 2015; Warren & Gibson, 2015).

Another set of empirical studies reveals that firms in traditional industries are taking an increasingly proactive role in regional innovation. They not only patent products in their own fields but also venture into high-tech fields. For instance, some firms in traditional industries like optics and photonics, metal processing, automotive, textiles, and synthetic rubber continue to vigorously patent in their traditional specialties (Hannigan et al., 2015; Mudambi et al., 2017; Ronayne, 2015; Safford, 2004; Treado, 2010). Simultaneously, major companies in traditional industries like food, chemicals, and machinery are increasingly engaging in knowledge creation within advanced fields like biotechnology and information technology (Mendonça, 2009; Robertson & Patel, 2007).

The literature reviewed above discusses how companies and regions specializing in traditional industries contribute to high-tech innovation in two ways: 1) by integrating these innovations into their production processes and 2) by acting as innovators in high-tech industries alongside their traditional areas of expertise. This body of work clarifies that technological progress goes beyond moving from traditional to high-tech industries. Rather, a significant symbiotic relationship exists between high-tech and non-high-tech industries, with their innovations having impacts across various economic activities. Despite this understanding, there is a notable research gap: the investigation into how regions known for advanced and innovative high-tech fields innovate within traditional fields. Addressing this gap is the primary focus of this study. The following paragraphs offer several explanations to support the main hypothesis of this paper, namely, why regions known for high-tech patenting also engage in traditional innovation.

Attempts have been undertaken to explore why regions with greater innovation capacity in high-tech industries are also capable of innovating within traditional industries. Researchers suggest that innovations in both high-tech and non-high-tech industries are not separate entities requiring entirely different catalysts. Common factors, such as human capital, which are not bound by industrial boundaries or technology intensity levels, can be crucial for the innovation capacity of traditional industries as well (Autor & Dorn, 2013; Berry & Glaeser, 2005; Glaeser & Hausman, 2020; Hansen et al., 2014). This reasoning aligns with observations that regions heavily investing in education tend to produce higher levels of overall patenting compared to other regions (Glaeser & Hausman, 2020). Other shared factors affecting innovation encompass a region's innovation infrastructure, which includes elements like R&D spending, intellectual property rights protection, openness to international trade, and research activities conducted by academic institutions with funding and commercialization efforts undertaken by the private sector (Acs et al., 2014; Fagerberg & Srholec, 2008; Furman et al., 2002).

The evolutionary economic geography literature offers another explanation for why regions strong in high-tech innovation can also excel in innovation within traditional fields. Their theories of path dependency suggest that when regions expand their innovation into more complex technologies, they usually opt for industrial categories that are technologically similar to their existing industrial strengths (Balland et al., 2019; Boschma et al., 2015; Essletzbichler, 2015; Hidalgo et al., 2007; Neffke et al., 2011; Petralia et al., 2017; Rigby, 2015). One reason can be that prior related knowledge equips firms with the ability to recognize and utilize technological opportunities effectively (Cohen & Levinthal, 1990, Zahra & George, 2002). Hence, it is challenging for a typical region to assimilate and make use of knowledge that is significantly different from its existing expertise. However, this finding applies less clearly to very innovative regions. Here, researchers find that regions with rich technological resources, sophisticated research facilities, skilled workforce, and strong collaboration networks, can develop new technologies that diverge from their current knowledge bases (Petralia et al., 2017).

To summarize, while there is a scarcity of research on whether and how regions proficient in high-tech innovation also develop innovation capabilities in traditional fields, various theoretical frameworks offer insights into the potential mechanisms underlying this interaction. In brief, first, innovations in both high-tech and traditional fields are increasingly influenced by common factors such as education, research institution, innovation infrastructure, and global competition. Second, due to a stronger absorptive capacity, it is generally easier for a high-tech region to innovate in traditional fields compared to a region more specialized in a specific traditional category innovating in a different traditional category. In the discussion section, I will explore the potential mechanisms further, linking them with findings from this study and existing literature.

4.3 Methods and Data

This study investigates the hypothesis that US metropolitan areas with higher patenting levels in high-tech fields have been more likely to patent in traditional fields since the 1996-2000 period. The period has traditionally been thought of as the first high-growth period of the US high-tech fields. According to USPTO patent data, the period between 1996 and 2000 marked a significant shift in patent trends, with high-tech fields beginning to exceed traditional fields in annual patent filings (Hall et al., 2001).

Additionally, this study replaces general patenting levels in the high-tech and traditional fields with patenting in specific technological categories, providing a more detailed examination of the hypothesized relationship. It specifically assesses whether higher patenting levels in the two high-tech categories (Computers & Communications, and Drugs & Medical) result in increased overall patenting levels in traditional fields. It also investigates whether elevated overall patenting in high-tech fields translates into greater patenting levels in the three individual traditional technological categories: Chemical, Electrical & Electronics, and Mechanical. This study further evaluates whether the effect of high-tech on traditional technological innovation is consistent across these various technological categories. These additional analyses are conducted because, to the best of my knowledge, there are no definitive conclusions about how patenting in individual high-tech sub-technologies may impact traditional technologies differently, or how high-tech technologies may have varied effects on patenting in individual traditional technological sub-categories.

Among the different approaches to defining traditional and high-tech fields, this study primarily uses the NBER categorization, which is also used by the USPTO under the United States Patent Classification (USPC) scheme. USPTO patent data provides rich detail about patent information, including the technological classification and granted (or application) date of the invention, the name and location of inventors, and the ownership of the intellectual property of the invention (Hall et al., 2001)[28].

This study uses 2010-2014 as the end period due to the availability of complete patent data after this date. After May 2016, the USPC classification is no longer assigned to Utility patents[29][30] (though it is still used for Design and Plant patents)[31]. Instead, USPTO replaces the USPC scheme with the Cooperative Patent Classification (CPC) classification jointly developed by the European Patent Office (EPO) and USPTO to

[28] https://patentsview.org/download/data-download-tables
[29] USPTO description of patent types: https://www.uspto.gov/web/offices/ac/ido/oeip/taf/data/patdesc.htm
[30] Out of the three patent types – Utility patents, Design patents, and Plant patents, only Utility patents are included in the sample. According to USPTO definitions, a Utility patent is issued for the invention of new and useful process, machine, manufacture, or composition of matter, or a new and useful improvement. Therefore, they contain the necessary USPC information about what technological field they should be categorized into, which is the standard I refer to when deciding whether a patent belongs to traditional or high-tech fields. Moreover, about 90% of the patent documents issued by USPTO in recent years have been Utility patents.
[31] https://patentsview.org/forum/generalfaq

ensure it is understood by a wide international audience[32][33]. However, this study still chooses to use USPC scheme due to the clearer distinction between traditional and high-tech fields provided under this scheme (Hall et al., 2001)[34].

As a result, this study finds that for the patent data reported under the USPC classification, the count of 2014 data peaked, and the count went down year by year since after. This is because there is usually a time gap between when an innovation is granted and when it is organized into the database. For instance, even though USPTO had still been reporting patent data under USPC classification until May 2016, some patents granted in 2015 might not yet been included in the database before May 2016 due to the time lag. This leads to the conclusion that the patent data in and before 2014 are complete, because the overall US patent count has kept growing every year, especially since 2008. Hence, I choose 2014 as the end point of the study period. For every patent granted between 1996-2000 and 2010-2014 respectively, this study uses the location of

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[32] https://patentsview.org/classification

[33] Most of the CPC's subdivisions stem directly from current International Patent Classification (IPC) and World Intellectual Property Organization (WIPO) technological fields used in over 100 countries around the world and managed by WIPO.

[34] It is important to note that the most common distinctions between traditional and high-tech industries typically rely on industrial and occupation classifications, rather than patent categories. Bridging industrial classifications with patent categories is challenging due to its complexity. (A crosswalk for this purpose is available on the USPTO website.) Given the primary interest in patent data, this study uses patent categorization, specifically focusing on emerging technologies as defined by NBER scholars Hall et al. (2001). The most recent and relevant update by NBER scholars, which utilizes the CPC scheme to analyze patents in areas such as software, communication, cloud computing, artificial intelligence, semiconductor, self-driving and drone technology, pharmaceuticals, medical technology, and other related emerging technologies, is documented in Webb et al., 2018. It should be noted, however, that these identified categories may not fully encompass all emerging technologies. Nevertheless, given the fast-paced evolution of high-tech fields, it would be insightful to revisit and conduct this study using the CPC scheme in the future.
Additionally, alternative high-tech industry classifications have their own limitations. For example, defining high-tech industries solely based on high R&D intensity might only capture technologies driven by internal industry R&D efforts, overlooking those influenced by external factors.

the first-named inventor as the patent's location[35]. As a result, this study only includes patents whose first-named inventor is in the US.

Table 4.1 Traditional and High-tech Technological Categories and Their Sub-categories

Traditional Category Code and Name	**Traditional Sub-category Code and Name**
1 Chemical	11 Agriculture, Food, Textiles; 12 Coating; 13 Gas; 14 Organic Compounds; 15 Resins; 19 Miscellaneous-Chemical
4 Electrical & Electronics	41 Electrical Devices; 42 Electrical Lighting; 43 Measuring & Testing; 44 Nuclear & X-rays; 45 Power Systems; 46 Semiconductor Devices; 49 Miscellaneous-Electrical & Electronics
5 Mechanical	51 Materials Processing & Handling; 52 Metal Working; 53 Motors, Engines & Parts; 54 Optics; 55 Transportation; 59 Miscellaneous-Mechanical
6 Others	61 Agriculture, Husbandry, Food; 62 Amusement Devices; 63 Apparel & Textile; 64 Earth Working & Wells; 65 Furniture, House Fixtures; 66 Heating; 67 Pipes & Joints; 68 Receptacles; 69 Miscellaneous-Others
High-tech Category Code and Name	**High-tech Sub-category Code and Name**
2 Computers & Communications	21 Communications; 22 Computer Hardware & Software; 23 Computer Peripherals; 24 Information Storage
3 Drugs & Medical	31 Drugs; 32 Surgery & Medical Instruments; 33 Biotechnology; 39 Miscellaneous-Drugs & Medical

According to Hall et al. (2001), all patents can be aggregated into 6 main technological categories: Chemical (excluding Drugs); Computers and Communications; Drugs and Medical; Electrical and Electronics; Mechanical; and Others. As shown in Table 4.1, the 6 categories can be further divided into 36 two-digit sub-categories. Of the 6 categories, Chemical, Mechanical, and Others are considered as the three traditional

[35] Patent data may exhibit geographical bias, as the location associated with the first-named inventor might not accurately represent the primary resources involved in the patent's development, or the locations of companies utilizing the patent or manufacturing related products. Often, this location is selected for legal or administrative reasons. In this study, the first-named inventor's location was used because it often reflects where the conceptualization and development of the patent occurred, and this individual plays a crucial role in these processes. Given the study's focus on regional innovation activity, this method helps in mapping the geographic spread of innovation and identifying dominant regions in collaborative networks. Nevertheless, future in-depth research could benefit from incorporating all associated locations of a patent, providing a more complete picture of the collaborative characteristic inherent in contemporary innovation processes.

fields (Hall et al., 2001). These fields are considered as traditional in the context of USPTO patent data because they have a long history of patenting activities that predates and underpins many modern technological advancements. Furthermore, unlike newer fields that may emerge or evolve rapidly due to technological changes, the filing rates of these categories have remained relatively stable over time. This stability allows for consistent classification and analysis of patents within these fields[36]. While the main focus of this study is on “traditional technologies”, underscored by the use of patent data, it also refers to these technological fields as “traditional categories”.

This study further classifies the Electrical and Electronics category as the fourth traditional field. As noted by Hall et al. (2001), this category has shown a slightly greater growth compared to the three previously mentioned traditional fields. However, the field has been central to technological innovations since the late 19th and early 20th centuries, paving the way for the emergence and advancement of contemporary technologies such as information technology, nanotechnology, and quantum computing. Yet, compared to the high-tech fields, the classification of this field in the patent database has also remained stable and the patenting activities have been less frequent in recent decades.

An example illustrates. The sub-category Semiconductor Devices rapidly emerged alongside the Computers and Communications category. However, the inclusion of Semiconductor Devices within the Electrical and Electronics category stems from their historical development and core role in controlling, amplifying, and generating electrical signals within electronic circuits and systems, a foundational aspect of electrical and

[36] Hall et al. (2001) note that the process of developing an aggregation system and categorizing patent classes into technological categories involves some inherent arbitrariness, potentially limiting this study.

electronic engineering. Patents related to semiconductors predominantly pertain to manufacturing techniques (e.g., wafer fabrication, doping, etching, and lithography) and essential building blocks of electronic devices (e.g., integrated circuits, transistors, and diodes). Initially, these components found their applications in simple electronic systems, power systems, and industrial machinery, later extending to encompass computer and communication devices[37]. Therefore, due to the techniques and human capital requirements of Semiconductor Devices, this study classifies the sub-category as part of the traditional fields (Table 4.1, expanded upon in Appendix Table A.1)[38]. This example illustrates the challenge of categorizing technological sub-categories as either traditional or high-tech, while simultaneously illustrating that the rise of high-tech likely increased patenting activities within a traditional field—precisely the scenario this study tests for.

By contrast, Computers and Communications and Drugs and Medical are the emerging fields, because their patent count grew much more slowly than that of the traditional fields before the 1980s, but has significantly surpassed the traditional fields since the early 1980s (Hall et al., 2001). These two emerging fields mainly include high-tech patenting in information and communication technologies, computer software, artificial intelligence, medical technologies, pharmaceuticals, and biotechnology. Therefore, these two emerging fields are collectively referred to as "high-tech fields" or

[37] Additionally, patents related to the design, simulation, and verification of semiconductors fall under the "Computers and Communications" category because of their reliance on advanced software and computing techniques. Therefore, Computer-aided design and analysis of circuits and semiconductor masks (Patent Class 716) is classified under the Computers and Communications technological category.

[38] As mentioned in Appendix Table A.1, several other advanced technologies that might be categorized under the Electrical and Electronics category or other traditional fields, such as robots (Patent Class 901), electric vehicles (Patent Class 903), nuclear technology (Patent Class 976), and nanotechnology (Patent Class 977), were not included in this dataset due to the unavailability of such data on the USPTO database at the time of data collection.

"high-tech categories" within this research. The term "emerging fields" also reflect the common pattern of rapid development evolution associated with these advanced technologies.

Using the US Census Bureau's 2015 delineation for Core-based Statistical Areas (CBSAs), which includes both Metropolitan and Micropolitan Statistical Areas, and taking the data availability for covariates into consideration, this study identifies 425 CBSAs that produced at least one patent in any of the sub-categories in the two traditional fields at the beginning of the timeframe (1996). To enhance the reliability of the results, this study compares the patenting levels between two periods instead of two points in time. Therefore, this study computes the average of annual patent counts from 1996 to 2000 for the first period and from 2010 to 2014 for the second period. Collectively, the 425 CBSAs produced an annual average of 18,517.8 high-tech patents from 1996 to 2000, and 48,238.2 traditional patents from 2010 to 2014.

This study employs Linear Regression models to test the extent to which the variation in regional patenting levels in traditional fields from 2010 to 2014 are explained by variation in patenting levels in high-tech fields between 1996 and 2000. In addition to the primary model, this study examines five supplementary models to understand the dynamics within various technological categories.

The first two of these additional models exclusively consider regions that generated patents in the Computers & Communications and Drugs & Medical ("high-tech") categories at the beginning of the timeframe (1996). The objective here is to investigate whether an increase in traditional patents is positively linked to a rise in the number of patents in each of these high-tech categories. The remaining three models differ in their dependent variables; they focus on patents in three of the four traditional categories – Chemical, Electrical & Electronics, and Mechanical categories – rather than encompassing all traditional patents[39]. The goal is to understand the causal relationship between these specific traditional technological categories and high-tech patenting activity. This study uses Equation (1) to calibrate the six models.

$$\ln(PatTrad)_{2010\text{-}2014} = \beta_0 + \beta_1 \ln(PatTech)_{1996\text{-}2000} + \beta_2 \ln(PatTrad)_{1996\text{-}2000} + \beta_3 PopGr_{1996\text{-}2014} + \beta_4 IncGr_{1996\text{-}2014} + \beta_5 EduChg_{1996\text{-}2014} + Division' + e \quad (1)$$

Model 1 contains all 425 CBSAs. The dependent variable uses the logarithmic transformation of the average annual number of traditional patents in each region from 2010 to 2014. The primary independent variable is the logarithmic form of the average annual count of all high-tech patents in each region during the period from 1996 to 2000. Models 2 to 6, while structurally similar to Model 1, differ specifically in terms of their dependent and primary independent variables.

Models 2 and 3 retain the same dependent variable as Model 1. However, they differ in their primary independent variable. Model 2 includes only the average annual count of patents filed in the Computers & Communications category from 1996 to 2000, while Model 3 focuses on the Drugs & Medical category for each region. Consequently, these models only consider regions that produced patents in these specific high-tech categories in 1996. As a result, Model 2 analyzes 270 CBSAs, and Model 3 includes 351 CBSAs. Models 4 through 6 maintain the same primary independent variable and the

[39] The traditional category "Others" is excluded from the analysis because this field is designed to cover a wide range of inventions that do not neatly fit into the more narrowly defined categories such as Chemical, Mechanical, and Electrical & Electronics. This diversity results in a lower relevance for policy reference purposes.

same sample size as Model 1. However, their dependent variables differ, each concentrating on the average annual count of patents in one of the three traditional categories – Chemical for Model 4, Electrical & Electronics for Model 5, and Mechanical for Model 6 – during the 2010-2014 period. Table 4.2 summarizes the dependent variable and the primary independent variable for each of the six models.

Table 4.2 Summary of Regression Models

Model	**1**	**2**	**3**	**4**	**5**	**6**
Dependent variable	Traditional Patent Count Average 2010-2014 (ln)	Traditional Patent Count Average 2010-2014 (ln)	Traditional Patent Count Average 2010-2014 (ln)	Chemical Category Patent Count Average 2010-2014 (ln)	Electrical & Electronics Category Patent Count Average 2010-2014 (ln)	Mechanical Category Patent Count Average 2010-2014 (ln)
Primary Independent Variable	High-tech Patent Count Average 1996-2000 (ln)	Computers & Communications category Patent Count Average 1996-2000 (ln)	Drugs & Medical Category Patent Count Average 1996-2000 (ln)	High-tech Patent Count Average 1996-2000 (ln)	High-tech Patent Count Average 1996-2000 (ln)	High-tech Patent Count Average 1996-2000 (ln)

Each of the six models incorporates a set of covariates to account for factors that may impact patenting levels in traditional fields. The first control variable across all models is the logarithmic transformation of the average annual count of all traditional patents in each region from 1996 to 2000. This covariate is included to control for the influence of a region's historical patenting specialization in traditional fields on its subsequent patenting levels within these fields. In Models 4 to 6, where the dependent variable is the patenting level in the specific categories of Chemical, Electrical & Electronics, and Mechanical, the first control variable is adapted to reflect the earlier patenting levels in these respective categories.

The second to fourth covariates in the models are designed to control for the impact of population growth, per capita income growth[40], and changes in education

[40] Considering the potential endogeneity problem between the dependent variable and the

attainment on traditional innovation during the study timeframe (1996-2014). Specifically, the change in educational attainment is quantified by the difference in the percentage of adults aged 25 and over with at least a bachelor's degree in each region, measured between the start and end of the study period[41]. These three covariates are used to gauge the effects of agglomeration and urbanization economies and regional human capital. Additionally, the models include a set of dummy variables that identify the specific US Census Division each region falls into, making up the final set of covariates[42].

This study further tests two joint models combined with the Wald test to evaluate whether the influence of high-tech innovation on traditional innovation remains consistent across different technological categories. The first joint model combines the key explanatory variables from Models 2 and 3, including the patenting levels from 1996-2000 in the high-tech categories of Computers & Communications and Drugs & Medical, along with other shared covariates. This model aims to determine if one high-tech

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explanatory variables of Population Growth 1996-2014 (%) and Per Capita Income Growth 1996-2014, I conducted a Two-Stage Least Squares (2SLS) analysis. This involved using Population Growth 1976-1996 (%) and Per Capita Income Growth 1976-1996 (%) as instrumental variables for the corresponding explanatory variables. The F-statistics from the Wald test indicate that these are strong instruments for the potentially endogenous variables. In the second-stage model, the coefficients and significance levels of the primary independent variable (High-tech Patent Count Average 1996-2000 (ln)) and main control variables, including Traditional Patent Count Average 1996-2000 (ln), Population Growth 1996-2014 (%), Education Attainment Change 1996-2014 (%), and Per Capita Income Growth 1996-2014 (%), remain consistent with those in the original regression model. Further discussions of the results are provided in the results and discussions section. The residual plot from the second-stage model exhibits homoscedasticity.

[41] This study collects data for population and income covariates from the Bureau of Economic Analysis, and for educational attainment covariates from the Census Bureau. To construct educational attainment covariates, this study uses 1990 Population Censuses, and the 2015-19 American Community Survey (ACS) 5-year estimates. This study uses 5-year instead of 1-year estimates because the latter leave out many smaller regions in the sample.

[42] For CBSAs that cross the border between two Census Divisions, this study uses the location of the first-named state in the name of each CBSA.

category exerts a more substantial influence on traditional patenting activity compared to the other. This model contains all 425 CBSAs, with the patenting levels for the two high-tech categories are set to 0 in regions that did not patent in either or both of these categories between 1996 and 2000. Equation (2) is employed to calibrate the first joint model, facilitating a structured approach to this comparative analysis.

$\ln(PatTrad)_{2010\text{-}2014} = \beta_0 + \beta_1 \ln(PatCom)_{1996\text{-}2000} + \beta_2 \ln(PatMed)_{1996\text{-}2000} + \beta_3 \ln(PatTrad)_{1996\text{-}2000} + \beta_4 PopGr_{1996\text{-}2014} + \beta_5 IncGr_{1996\text{-}2014} + \beta_6 EduChg_{1996\text{-}2014} + Division' + e$

(2)

The second joint model, building on Models 4, 5, and 6, examines the 2010-2014 patenting levels in the individual traditional categories of Chemical, Electrical & Electronics, and Mechanical. It considers these dependent variables alongside their respective historical patenting levels from 1996-2000 (as category-specific covariates), the aggregate high-tech patenting levels from 1996-2000, and other common covariates, to test if high-tech patenting differentially impacts the patenting levels in these traditional categories. Notably, the dependent variable in this model is the natural logarithm of the average annual traditional patent counts for each of the three traditional categories in each region during 2010-2014. Therefore, this model contains 1,275 observations, representing three observations for each of the 425 CBSAs. Within this model, *Category* acts as a factor variable that signifies the technological category. Hence, the interaction term quantifies the variance in the effect of the main independent variable on the dependent variable across different technological categories, or in comparison to the baseline category (Chemical). Equation (3) is used to calibrate the second joint model.

$\ln(PatTrad')_{2010\text{-}2014} = \beta_0 + \beta_1 \ln(PatTech)_{1996\text{-}2000} * Category' + \beta_2 \ln$

$(PatChem)_{1996\text{-}2000} + \beta_3\ln\,(PatElec)_{1996\text{-}2000} + \beta_4\ln\,(PatMech)_{1996\text{-}2000} + \beta_5 PopGr_{1996\text{-}2014} +$

$\beta_6 IncGr_{1996\text{-}2014} + \beta_7 EduChg_{1996\text{-}2014} + Division' + e$ (3)

Table 4.3 Descriptive Statistics[43]

Variable	Obs.	Mean	Std. Dev.	Min	Max
Traditional Patent Count Average 2010-2014 (ln)	425	2.993	1.840	-2.000	8.057
High-tech Patent Count Average 1996-2000 (ln)	425	1.591	1.951	-1.609	7.768
Traditional Patent Count Average 1996-2000 (ln)	425	3.121	1.694	-2.000	8.048
Population Growth 1996-2014 (%)	425	0.176	0.189	-0.239	1.177
Per Capita Income Growth 1996-2014 (%)	425	0.902	0.231	0.475	3.329
Education Attainment Change 1996-2014 (%)	425	9.716	3.404	0.700	22.100
Census Division East North Central (0/1; Baseline)	425	0.207	0.406	0.000	1.000
Census Division New England (0/1)	425	0.049	0.217	0.000	1.000
Census Division Middle Atlantic (0/1)	425	0.096	0.295	0.000	1.000
Census Division West North Central (0/1)	425	0.099	0.299	0.000	1.000
Census Division South Atlantic (0/1)	425	0.165	0.371	0.000	1.000
Census Division East South Central (0/1)	425	0.078	0.268	0.000	1.000
Census Division West South Central (0/1)	425	0.096	0.296	0.000	1.000
Census Division Mountain (0/1)	425	0.092	0.289	0.000	1.000
Census Division Pacific (0/1)	425	0.118	0.323	0.000	1.000

[43] This study employs logarithm transformation to adjust for the right-skewed distribution of the dependent variables and the main patent independent variables. It is important to note that this study sets the results of ln (0) as -2 for the patent count average 2010-2014 dependent variables. This adjustment is made to ensure that all observations are computable even in regions with 0 patent counts for each year from 2010 to 2014. Consequently, these regions have the minimum value across all regions. The next smallest value for this variable would be the regions that had only 1 patent in any single year during 2010-2014. In such case, the 5-year patent count average is 0.2, resulting in a natural logarithm value of ln (0.2) = -1.609.

Table 4.4 Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Traditional Patent Count Average 2010-2014 (ln)	1.000													
2	High-tech Patent Count Average 1996-2000 (ln)	0.909	1.000												
3	Traditional Patent Count Average 1996-2000 (ln)	0.957	0.904	1.000											
4	Population Growth 1996-2014 (%)	0.255	0.204	0.184	1.000										
5	Per Capita Income Growth 1996-2014 (%)	-0.074	-0.095	-0.115	0.099	1.000									
6	Education Attainment Change 1996-2014 (%)	0.475	0.455	0.411	0.273	0.051	1.000								
7	Census Division East North Central (0/1; Baseline)	-0.008	-0.077	-0.001	-0.319	-0.252	-0.076	1.000							
8	Census Division New England (0/1)	0.138	0.149	0.133	-0.116	0.073	0.213	-0.117	1.000						
9	Census Division Middle Atlantic (0/1)	0.075	0.081	0.114	-0.242	-0.047	0.053	-0.167	-0.074	1.000					
10	Census Division West North Central (0/1)	-0.080	-0.045	-0.122	-0.042	0.074	0.079	-0.169	-0.075	-0.108	1.000				
11	Census Division South Atlantic (0/1)	-0.004	0.015	0.005	0.229	-0.141	0.116	-0.227	-0.101	-0.145	-0.147	1.000			
12	Census Division East South Central (0/1)	-0.117	-0.097	-0.108	0.004	-0.079	-0.131	-0.148	-0.066	-0.095	-0.096	-0.129	1.000		
13	Census Division West South Central (0/1)	-0.080	-0.082	-0.062	0.063	0.455	-0.259	-0.167	-0.074	-0.107	-0.108	-0.145	-0.095	1.000	
14	Census Division Mountain (0/1)	0.023	0.003	-0.009	0.385	0.078	0.115	-0.162	-0.072	-0.104	-0.105	-0.141	-0.092	-0.104	1.000
15	Census Division Pacific (0/1)	0.078	0.101	0.068	0.069	-0.016	-0.059	-0.187	-0.083	-0.119	-0.121	-0.162	-0.106	-0.119	-0.116

4.4 Results and Discussions

Table 4.5 displays the regression results, addressing the heteroskedasticity via robust errors for each model. Diagnostic graphs indicated that extreme outliers in the sample skewed these results. By calculating Cook's Distances for Model 1, 21 influential outliers were identified. However, re-evaluating Model 1 after their exclusion showed minimal impact on the regression coefficients' value and significance, as well as the adjusted R-squared[44]. Notably, 18 of these outliers are micropolitan statistical areas, typically generating fewer patents than metropolitan statistical areas. Given the minor influence of these outliers and no compelling reasons for their exclusion, Table 4.5 incorporates all regions in the respective models.

The inclusion of the variable representing earlier patenting levels in both the overall traditional fields and individual traditional categories results in very high R-squared values for each model. Consequently, I performed a block entry analysis on Model 1 to more clearly identify the explanatory power of other variables. This analysis was conducted to verify that the high-tech patent counts (overall and in specific sub-categories) significantly contribute to the model by improving its fit as indicated by the R-squared value.

The results of block entry analysis presented in Table 4.6 offer several key insights. Initially, the 1st Block Model, which only includes the independent variable of past traditional patenting levels, accounts for 91.7% (adjusted R-squared) of the variance in traditional patenting levels. However, the introduction of the main variable of interest,

[44] After eliminating influential outliers, the model successfully met all diagnostic criteria. The sample size remains adequate for model fitting after the removal of influential observations.

i.e., the overall levels of high-tech patents, in the 2nd Block Model, further enhances the model's fit (compared to 1st Block Model), as evidenced by the increase in R-squared from 91.7% to 92.5%. The ANOVA F-test statistic validates the statistical significance of this enhancement. Furthermore, adding other covariates to the model also leads to additional improvements, as shown in 3rd and 4th Block Models[45].

These results suggest that while the main independent variable, i.e., overall high-tech patenting levels, does account for a portion of the explained variance, the most significant explanatory factor is the covariate representing previous patenting levels in the traditional fields. This conclusion is supported by comparing the standardized coefficients of the two predictors in Model 1 (Table 4.5), where the standardized coefficient for the covariate of previous traditional patenting levels is 0.736, in contrast to 0.206 for high-tech patenting levels. This disparity underscores the critical influence of historical trends or path dependency in regional patent production.

Referring to the regression results in Table 4.5, where both the dependent and key independent variables are transformed using the natural logarithm, the coefficients should be interpreted as the elasticities of the dependent variable in relation to the key independent variable. This means that each coefficient represents the expected percentage change in the dependent variable resulting from a 1% change in the key independent variable.

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[45] Table 4.6 also includes a Baseline Model, which incorporates solely the primary independent variable. The purpose is to further show the independent effect of the high-tech patenting levels on traditional patenting levels. This model demonstrates that the primary independent variable alone explains 82.7% (adjusted R-squared) of the variance in the dependent variable.

We see from Model 1 that for CBSAs that produced at least one high-tech patent in 1996, there was a positive correlation between their patenting levels in traditional categories from 2010-2014 and their high-tech patenting levels from 1996 to 2000. Specifically, a 1% increase in the high-tech patenting level during 1996-2000 corresponded to a 0.195% rise in traditional patenting level from 2010 to 2014. These findings affirm the primary hypothesis of this study: regions with higher initial patenting in high-tech fields tend to exhibit increased patenting in traditional fields in the second period.

Models 2 and 3 explore the influence of specific high-tech categories on the subsequent overall patenting levels in traditional categories for each region. Table 4.5 indicates that a 1% increase in the Computers & Communications category's patenting level during 1996-2000 is associated with a 0.082% increase in traditional patenting from 2010 to 2014. Furthermore, a 1% increase in the Drugs & Medical category's patenting level in the same period corresponds to a 0.130% rise in traditional patenting from 2010 to 2014.

Models 4 to 6 focus on the effects of each region's overall high-tech patenting levels from 1996 to 2000 on the subsequent patenting levels in specific traditional categories. Table 4.5 shows that, even after accounting for earlier patenting levels in each traditional category and other covariates, a positive association persists between high-tech patenting levels and patenting in the Chemical, Electrical & Electronics, and Mechanical categories. Specifically, a 1% increase in high-tech patenting levels during 1996-2000 is linked to respective increases of 0.310%, 0.336%, and 0.205% in the patenting levels of these three traditional categories from 2010 to 2014.

The two joint models combined with the Wald test enable a consistent comparison of coefficients across different models. Again, the first joint model incorporates the main explanatory variables from Models 2 and 3, specifically, the 1996-2000 patenting levels of the individual high-tech categories, Computers & Communications and Drugs & Medical, alongside other common covariates. The regression results are demonstrated in Table 4.7. The p-value of the Wald test's F-statistic, which is 0.694, indicates that the two high-tech categories had statistically equivalent impacts on traditional patenting levels observed from 2010 to 2014.

Where the first joint model tested whether either high-tech category influences traditional patenting more, the second joint model tests whether any of the traditional categories experience more impact from high-tech patenting than do others. To reiterate, the second joint model includes the dependent variables from Models 4, 5, and 6, specifically, the 2010-2014 patenting levels of the individual traditional categories, Chemical, Electrical & Electronics, and Mechanical, along with their respective historical (1996-2000) patenting levels (as a category-specific covariate), the shared independent variable of 1996-2000 high-tech patenting levels, and other shared covariates.

As shown in Table 4.7, analysis of the interaction terms' regression coefficients reveals that the effect of high-tech patenting on the Electrical & Electronics category (0.038) is statistically comparable to its effect on the Chemical category. Its impact on the Mechanical category (the coefficient of the interaction term is -0.117*) is modestly yet significantly lower than on the Chemical category (the coefficients for the primary independent variable and other covariates remain consistent as the original individual models). The significance of the difference is supported by a p-value of 0.006 for the

Wald test's F-statistic, suggesting that the Mechanical category is the least affected by high-tech patenting levels among the traditional fields.

In an extended comparative analysis, I investigate the relationship between the patenting levels in high-tech and traditional fields during 2010-2014 across the six models. This analysis reveals that the regression coefficients, indicative of tandem relationships, are generally slightly higher than those in the original models, which depicted longer-term relationships. Nonetheless, the significance levels of the main variables remain consistent across all models. While these findings are not explicitly detailed in the report, they serve to strengthen the conclusions drawn from the original regression analysis.

It is important to reiterate that, in all of the six analyzed models, the regression coefficients for the covariates representing earlier patenting levels in the traditional fields – both overall and in each specific traditional category – consistently exceed those for the primary variables related to high-tech patenting levels. This observation aligns with the results obtained from the block entry analysis, which shows that the explanatory power of previous traditional patenting levels on the current traditional patenting is more pronounced than the influence of the high-tech patenting levels. Essentially, this further suggests that historical patterns in traditional fields have a stronger impact on current traditional patenting trends than the high-tech fields' influence.

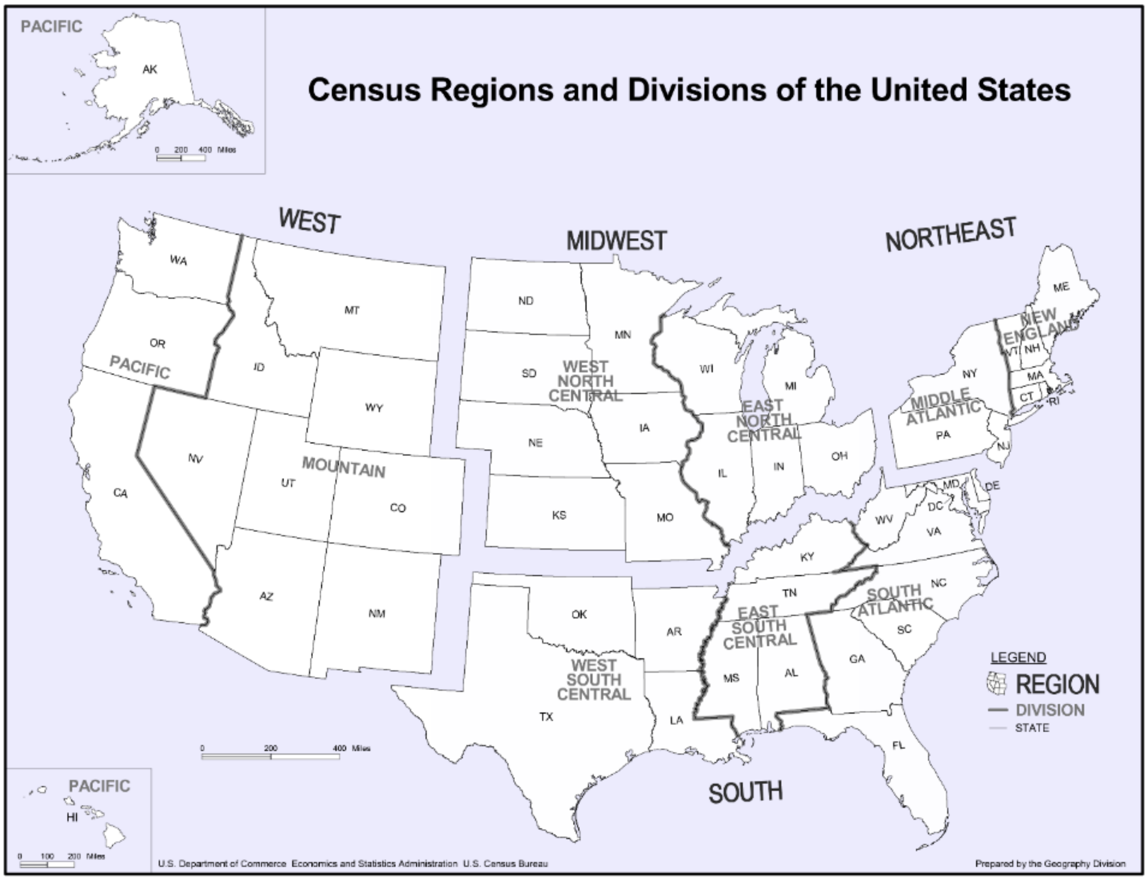
The regression findings further suggest that population growth contributes to the advancement of traditional innovation. In all six models, population growth from 1996 to 2014 exhibited a positive correlation with the level of regional traditional innovation during 2010-2014. This conclusion extends to the covariates related to education attainment changes – the majority of the models demonstrate a positive link between the change in the percentage of adults (aged 25 and above) with at least a bachelor's degree in each region and the region's traditional patenting level. This result indicates that, akin to the high-tech industry, higher education plays a significant role in fostering innovation in traditional fields.

Conversely, regional per capita income growth between 1996 and 2014 does not seem to have a significant effect on innovation in the traditional fields during 2010-2014. This observation can be rationalized by considering that regions undergoing economic growth may not necessarily focus on innovating within the traditional industries as a part of their broader development strategy. Additionally, regions that specialize in traditional innovation do not always align with those experiencing growth in other socioeconomic areas. For example, the economic benefits derived from traditional innovation may not be equitably distributed among the workforce. This could lead to a scenario where the financial gains from such innovation are concentrated at the top, without a corresponding increase in the per capita income of the region.

Furthermore, in each of the six models, I examined the interaction terms between the primary independent variables and factors such as population growth, income growth, and changes in education attainment. However, no systematic effects were observed. Finally, the geographic location of CBSAs appears to influence the contemporary landscape of traditional innovation. The Middle Atlantic Census Division, encompassing many Rust Belt regions, showed a lower level of traditional innovation during 2010-2014 compared to the East North Central Census Division. A similar trend is observed in several southern Census Divisions, namely the South Atlantic, East South Central, and

West South Central Census Divisions[46]. Figure 1 illustrates the geographical locations of all US Census Divisions.

Figure 4.1 Census Divisions of the United States[47]



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46 However, in 2SLS analysis, only the South Atlantic Census Division is statistically significant. Therefore, we should interpret the regression results for the regional dummy variables with caution.

47 The map was retrieved from the U.S. Census Bureau.

Table 4.5 Regression Results

Model	1	2	3	4	5	6
Dependent Variable	**Traditional Patent Count Average 2010-2014 (ln)**	**Traditional Patent Count Average 2010-2014 (ln)**	**Traditional Patent Count Average 2010-2014 (ln)**	**Chemical Category Patent Count Average 2010-2014 (ln)**	**Electrical & Electronic Category Patent Count Average 2010-2014 (ln)**	**Mechanical Category Patent Count Average 2010-2014 (ln)**
High-tech Patent Count Average 1996-2000 (ln)	0.195***			0.310***	0.336***	0.205***
	(0.038)			(0.042)	(0.051)	(0.035)
Computers & Communications category Patent Count Average 1996-2000 (ln)		0.082*				
		(0.032)				
Drugs & Medical Category Patent Count Average 1996-2000 (ln)			0.130***			
			(0.035)			
Traditional Patent Count Average 1996-2000 (ln)	0.800***	0.940***	0.873***			
	(0.047)	(0.039)	(0.044)			
Chemical Category Patent Count Average 1996-2000 (ln)				0.626***		
				(0.042)		
Electrical & Electronics Category Patent Count Average 1996-2000 (ln)					0.663***	
					(0.051)	
Mechanical Category Patent Count Average 1996-2000 (ln)						0.750***
						(0.046)
Population Growth 1996-2014 (%)	0.806***	0.940***	0.684***	0.640*	0.937***	0.910***
	(0.165)	(0.172)	(0.187)	(0.248)	(0.203)	(0.203)
Per Capita Income Growth 1996-2014 (%)	0.268*	0.453*	0.169	0.405*	0.115	0.220
	(0.109)	(0.202)	(0.110)	(0.164)	(0.187)	(0.163)
Education Attainment Change 1996-2014 (%)	0.029***	0.024*	0.028**	0.042***	0.036**	0.009
	(0.008)	(0.011)	(0.009)	(0.013)	(0.013)	(0.010)
Census Division East North Central (0/1; Baseline)						

Model	**1**	**2**	**3**	**4**	**5**	**6**
Dependent Variable	**Traditional Patent Count Average 2010-2014 (ln)**	**Traditional Patent Count Average 2010-2014 (ln)**	**Traditional Patent Count Average 2010-2014 (ln)**	**Chemical Category Patent Count Average 2010-2014 (ln)**	**Electrical & Electronic Category Patent Count Average 2010-2014 (ln)**	**Mechanical Category Patent Count Average 2010-2014 (ln)**
Census Division New England (0/1)	-0.131	-0.108	0.008	-0.408*	0.152	-0.043
	(0.099)	(0.110)	(0.101)	(0.170)	(0.158)	(0.104)
Census Division Middle Atlantic (0/1)	-0.209*	-0.266**	-0.101	-0.487***	-0.061	-0.104
	(0.091)	(0.102)	(0.092)	(0.134)	(0.129)	(0.121)
Census Division West North Central (0/1)	-0.081	-0.184	0.082	-0.416**	-0.138	-0.008
	(0.098)	(0.106)	(0.112)	(0.133)	(0.150)	(0.131)
Census Division South Atlantic (0/1)	-0.300***	-0.297**	-0.121	-0.288*	-0.141	-0.268*
	(0.084)	(0.101)	(0.083)	(0.133)	(0.134)	(0.105)
Census Division East South Central (0/1)	-0.227*	-0.276*	-0.050	-0.294	-0.193	-0.412**
	(0.099)	(0.126)	(0.099)	(0.159)	(0.172)	(0.136)
Census Division West South Central (0/1)	-0.306*	-0.443***	-0.206	-0.455*	-0.164	-0.494**
	(0.123)	(0.128)	(0.136)	(0.183)	(0.175)	(0.163)
Census Division Mountain (0/1)	-0.241*	-0.257	-0.085	-0.231	-0.099	-0.426**
	(0.105)	(0.131)	(0.107)	(0.172)	(0.155)	(0.149)
Census Division Pacific (0/1)	-0.141	-0.122	0.023	-0.215	0.103	-0.261*
	(0.089)	(0.105)	(0.090)	(0.126)	(0.143)	(0.112)
Constant	-0.307*	-0.600**	-0.363*	-0.665***	-0.613***	-0.317
	(0.150)	(0.185)	(0.164)	(0.179)	(0.176)	(0.169)
Number of Observations	425	270	351	425	425	425
Adjusted R-squared	0.935	0.948	0.938	0.867	0.893	0.882

Note: "***" $p < 0.001$; "**" $p < 0.01$; "*" $p < 0.05$. Values in parentheses are standard errors.

Table 4.6 Block Entry Analysis Results

Model	**Baseline**	**1st Block**	**2nd Block**	**3rd Block**	**4th Block**
Dependent Variable	**Traditional Patent Count Average 2010-2014 (ln)**				
High-tech Patent Count Average 1996-2000 (ln)	0.857***		0.229***	0.189***	0.195***
	(0.019)		(0.029)	(0.028)	(0.029)
Traditional Patent Count Average 1996-2000 (ln)		1.039***	0.801***	0.805***	0.800***
		(0.015)	(0.034)	(0.032)	(0.033)
Population Growth 1996-2014 (%)				0.574***	0.806***
				(0.128)	(0.158)
Per Capita Income Growth 1996-2014 (%)				0.171	0.268*
				(0.101)	(0.119)
Education Attainment Change 1996-2014 (%)				0.033***	0.029***
				(0.008)	(0.009)
Census Division East North Central (0/1; Baseline)					
Census Division New England (0/1)					-0.131
					(0.119)
Census Division Middle Atlantic (0/1)					-0.209*
					(0.090)
Census Division West North Central (0/1)					-0.081
					(0.093)
Census Division South Atlantic (0/1)					-0.300***
					(0.082)
Census Division East South Central (0/1)					-0.227*
					(0.099)
Census Division West South Central (0/1)					-0.306**
					(0.110)
Census Division Mountain (0/1)					-0.241*
					(0.024)

Model	**Baseline**	**1st Block**	**2nd Block**	**3rd Block**	**4th Block**
Dependent Variable			**Traditional Patent Count Average 2010-2014 (ln)**		
Census Division Pacific (0/1)					-0.141
					(0.088)
Constant	1.629***	-0.251***	0.130	-0.401**	-0.307*
	(0.048)	(0.055)	(0.071)	(0.129)	(0.138)
Number of Observations			425		
Adjusted R-squared	0.827	0.917	0.925	0.934	0.935
ANOVA F-test Statistic			61.069***		
				18.457***	
					2.390*

Note: "***" $p < 0.001$; "**" $p < 0.01$; "*" $p < 0.05$. Values in parentheses are standard errors.

Table 4.7 Joint Models Regression Results

Model	**1**	**2**
Dependent Variable	**Traditional Patent Count Average 2010-2014 (ln)**	**Traditional Patent Count Average 2010-2014 (ln)**
High-tech Patent Count Average 1996-2000 (ln)		0.307***
		(0.035)
Computers & Communications category Patent Count Average 1996-2000 (ln)	0.094***	
	(0.025)	
Drugs & Medical Category Patent Count Average 1996-2000 (ln)	0.079**	
	(0.026)	
Traditional Patent Count Average 1996-2000 (ln)	0.852***	
	(0.031)	
High-tech Patent Count Average 1996-2000 (ln) * Category (Chemical Category Patent Count Average 2010-2014 (ln)) (Baseline)		
High-tech Patent Count Average 1996-2000 (ln) * Category (Electrical & Electronics Category Patent Count Average 2010-2014 (ln))		0.038
		(0.053)

Model	1	2
Dependent Variable	**Traditional Patent Count Average 2010-2014 (ln)**	**Traditional Patent Count Average 2010-2014 (ln)**
High-tech Patent Count Average 1996-2000 (ln) * Category (Mechanical Category Patent Count Average 2010-2014 (ln))		-0.117*
		(0.048)
Category Chemical Category Patent Count Average 2010-2014 (ln) (Baseline)		
Category Electrical & Electronics Category Patent Count Average 2010-2014 (ln)		-0.037
		(0.063)
Category Mechanical Category Patent Count Average 2010-2014 (ln)		-0.021
		(0.065)
Chemical Category Patent Count Average 1996-2000 (ln)		0.627***
		(0.034)
Electrical & Electronics Category Patent Count Average 1996-2000 (ln)		0.669***
		(0.039)
Mechanical Category Patent Count Average 1996-2000 (ln)		0.753***
		(0.040)
Population Growth 1996-2014 (%)	0.841***	0.828***
	(0.162)	(0.134)
Per Capita Income Growth 1996-2014 (%)	0.243*	0.247*
	(0.122)	(0.102)
Education Attainment Change 1996-2014 (%)	0.033***	0.029***
	(0.009)	(0.007)
Census Division East North Central (0/1; Baseline)		
Census Division New England (0/1)	-0.130	-0.100
	(0.122)	(0.101)
Census Division Middle Atlantic (0/1)	-0.198*	-0.218**
	(0.092)	(0.077)
Census Division West North Central (0/1)	-0.043	-0.185*
	(0.095)	(0.079)

Model	1	2
Dependent Variable	**Traditional Patent Count Average 2010-2014 (ln)**	**Traditional Patent Count Average 2010-2014 (ln)**
Census Division South Atlantic (0/1)	-0.294***	-0.231**
	(0.084)	(0.070)
Census Division East South Central (0/1)	-0.211*	-0.298***
	(0.101)	(0.084)
Census Division West South Central (0/1)	-0.304**	-0.370***
	(0.112)	(0.094)
Census Division Mountain (0/1)	-0.262*	-0.251**
	(0.110)	(0.090)
Census Division Pacific (0/1)	-0.126	-0.123
	(0.091)	(0.075)
Constant	-0.361*	-0.513***
	(0.143)	(0.106)
Number of Observations	425	1275
Adjusted R-squared	0.933	0.882

Note: “***” $p < 0.001$; “**” $p < 0.01$; “*” $p < 0.05$. Values in parentheses are standard errors.

4.5 Conclusion

Urban and economic development practitioners often focus on advancing high-tech industries in their industrial and business policies, driven by the assumption that these industries catalyze higher market demand, better worker compensation, and ultimately, regional prosperity. Consequently, regions specializing in high-tech industries have garnered more attention from scholars in urban and economic development than those in traditional industries. This trend might stem from a prevailing belief that innovation progresses in a unidirectional manner, moving from less advanced to more advanced industries. Despite a general scientific consensus that technological progress is nonlinear, empirical evidence demonstrating the symbiotic relationship and cross-industrial interplay between high-tech and traditional technologies remains limited.

Specifically, research on whether the patenting levels of regions in advanced specialized fields lead to increased patenting activities in traditional fields is currently limited. This gap persists despite some studies exploring this relationship at various geographic scales, including countries and urban/rural areas. This study seeks to fill this gap by examining U.S. CBSAs and investigating whether regions with a stronger innovation capacity in high-tech fields also show higher patenting levels in traditional fields between 1996 and 2014. Utilizing USPTO patent data and regression analysis that accounts for various covariates, including the impact of historical traditional specializations, the models support the main hypothesis: regions with higher patenting levels in 1996-2000 in high-tech fields tend to have increased patenting in traditional fields in 2010-2014.

I concur with insights from existing literature, as previously discussed, that innovations in both high-tech fields and traditional fields are increasingly influenced by common factors such as human capital and global competition, transcending industrial boundaries (Berry & Glaeser, 2005; Glaeser & Hausman, 2020). As a result, traditional innovation now requires higher levels of educational attainment, positioning regions with a strong capacity for high-tech innovation at an advantage. This perspective is also supported by the regression analysis variables related to population growth and changes in educational attainment in this study.

I further propose that despite the continuous decline in the employment share of traditional industries, strategically supporting these industries is meaningful for balanced economic growth. As the workforce increasingly moves towards cutting-edge industries like information technology and biotechnology, there emerges a reciprocal demand for traditional industries. Policy interventions should therefore specifically aim to enhance collaborations between advanced and traditional industries. This could involve creating platforms for knowledge exchange, joint research and development projects, and cross-industrial training programs to foster innovation and leverage the strengths of both industries. The viability and sustainability of all industries hinge on their ability to adapt to market needs effectively. Therefore, developing policies that encourage collaborative innovation and adaptation in high-tech and traditional industries could play a vital role in maintaining a dynamic and diverse economic landscape.

Future research might consider whether the link between information technology and traditional industries has strengthened with the rising adoption of AI and cloud technologies. Additionally, the emergence of electric vehicles, self-driving cars, and drones in the last decade might introduce new dynamics between high-tech industries and mechanical-related technologies in traditional industries. Furthermore, the analyses and models employed in this study could be expanded to evaluate each pairing of high-tech and traditional categories. This extension would facilitate a deeper understanding of the influence of specific high-tech categories on specific traditional categories, yielding more nuanced insights that can inform policies and strategies for economic and business development.

It is important to note that the identification of traditional industries and high-tech emerging industries in this study is based on the classification of technological rather than industrial categories. Consequently, only two categories – Computers & Communications and Drug & Medical – are classified as high-tech industries. This might lead to the perception that certain advanced manufacturing technologies within traditional fields, demanding significant human intelligence, ought to be categorized as high-tech. This study acknowledges advancements in traditional industries and is aware of possible limitations in the chosen classification. Nevertheless, I maintain that this classification is essential to ensure the identified high-tech industries represent innovations that are distinctly different from traditional industries, which lends a more conservative approach to the study's results.

Although patent data is a commonly used proxy for innovation in numerous studies, it presents several notable limitations. Firstly, patent data may not encompass all types of manufacturing innovation, especially those related to process innovations or those not patented due to specific corporate strategies. This limitation could impact the broader applicability of the study's findings. Secondly, the study treats all patents as equal, which overlooks the fact that groundbreaking patents often have a more substantial impact than those representing minor advancements. Future research should consider the potential benefits of attributing greater significance to patents that receive a higher number of citations, thereby acknowledging their relative importance.

CHAPTER V

CONCLUSION

This dissertation expands the current understanding of innovation-led economic development, which has predominantly centered on high-tech industries and their host regions, to also encompass traditional industries and their specialized regions. It adopts the lens of patented technological innovations to reexamine these regions and industries, particularly those that have undergone significant restructuring in the past fifty years. The core thesis posits that the interplay among key economic factors – such as population, income, and innovation – as well as the relationship between high-tech and traditional technologies is more complex during economic restructuring than mainline economic development theories fully capture. In what follows, I synthesize three common themes emerging from the analyses presented in the three essays.

The first theme addresses the lack of parallelism among major economic factors – population, income, and technological innovation – within a region during its economic development and restructuring. This observation is supported by all three essays. Specifically, the first essay reveals that innovation can continue in regions undergoing population decline or sluggish economic growth, challenging the mainstream scholarship's emphasis on a reinforcing relationship among these economic factors.

Furthermore, regression analyses across the essays indicate that while population and human capital appear to contribute to innovation in regions, the presence of economic growth in regions does not necessarily lead to an increase in population or innovation. This suggests that the dynamics among key economic factors are not yet fully comprehended.

Mainline economic development theories have largely aimed at identifying the types of economic factors or activities that drive population and income growth. This focus has naturally drawn scholarly attention towards regions experiencing a positive cycle of economic development, spurred by technological advancements and innovations that not only attract people and financial investment but also create a feedback loop that further fuels innovation. However, this concentration overshadows the need for research into the resilience mechanisms at play in regions facing population and overall income declines as they navigate the complex process of economic restructuring. These overlooked economic dynamics are key to informing successful economic restructuring strategies. The sustained technological innovation highlighted in this dissertation serves as one of the potential factors capable of providing good employment opportunities and improving quality of life for local residents even amidst less favorable conditions.

Some regions may continue to experience growth and avoid significant population declines during periods of industrial restructuring, thanks to enduring regional advantages such as substantial economic size, strategic location, and strong connectivity. Nevertheless, the majority of regions and cities confront uncertainties due to technological changes and demographic shifts. Therefore, this dissertation supports a broader and more inclusive view of economic development that includes restructuring and adaptability as key components for regional success. In addition, it is heartening to observe a growing body of research focused on urban shrinkage and restructuring, which explores how regions and cities can leverage their strengths in specialized knowledge bases, community development, land repurposing, and innovative governance strategies to adapt and flourish, even in the face of adversities.

Nevertheless, this study also acknowledges the broader context of the widening innovation gap between traditional and high-tech fields, despite the enduring capacity of traditional fields to maintain patenting activities amid industrial decline. Consequently, regions like Gary (IN), Flint (MI), and Wheeling (WV), have experienced significant economic downturns as their foundational industries have contracted and efforts to diversify beyond these deeply entrenched sectors have faltered. This observation aligns with mainstream economic development theories, which argues that traditional industries should adapt to the market shifts prompted by the emergence of high-tech technologies and advance innovation within traditional fields to stay competitive. It is equally important to adopt a dynamic perspective, acknowledging that the definition of traditional fields is constantly evolving over time. What is considered high-tech fields today may eventually become tomorrow's traditional fields as newer technologies are invented.

The second theme highlights that the trajectory of economic and technological development is inherently non-linear and is deeply influenced by path dependency. The third essay especially illustrates this, where the interaction between high-tech and traditional technologies is shown to be symbiotic rather than one-directional, predominantly moving from traditional towards high-tech. Technological innovations in high-tech industries do, in fact, spur technological innovations in traditional industries.

Additionally, this essay points out that regional innovation, including that within traditional industries, is significantly shaped by path dependency. This means that historical trends in traditional innovation play a more significant role in shaping current patenting trends in these fields than the influence of the high-tech fields. This observation echoes the findings of the first essay, which demonstrates that regions, regardless of their performance in terms of population and income growth, can maintain innovation in their historical areas of specialization for prolonged periods.

This second theme provides implications for economic development planning aimed at restructuring older industrial regions through a balance between high-tech advancements and leveraging the inherent strength of traditional fields. It suggests that policymakers should recognize the symbiotic relationship between high-tech and traditional technologies and introduce interventions which would capitalize on the combined strength of both. Entirely abandoning traditional technological strengths to chase a narrow range of high-tech technologies may not be the most resource-efficient strategy. Hence, this approach extends beyond the establishment of industrial parks solely for high-tech startups. Instead, it entails identifying and backing competitive traditional firms or clusters that have the potential to integrate advanced technologies as well as to invent technologies that high-tech fields require to meet market demands. To further this integration, policy interventions could include establishing platforms for knowledge sharing, joint research and development initiatives, and workforce training programs across high-tech and traditional fields.

Regions such as Pittsburgh, St. Louis, and Baltimore have transitioned from their traditional manufacturing bases to become hotbeds of innovation in fields like robotics, artificial intelligence, and biotechnology, and autonomous vehicles. This transformation has been largely facilitated by the development of synergistic relationships between cutting-edge technologies and their respective established fields such as steel production, automotive manufacturing, and mechanical engineering. In Pittsburgh, for example, the Benjamin Franklin Technology Partners significantly contributed to bridging academia and industries like robotics and advanced manufacturing. Similarly, supporting collaborative research centers focused on technologies with direct applications to sectors like Detroit's automotive industry can strengthen the innovation ecosystem within traditionally specialized regions. Moreover, establishing specialized training programs in community colleges to upskill the existing workforce in digital literacy, robotics maintenance, health technologies, and green energy solutions is crucial. Such strategies require a comprehensive understanding of the distinct strengths and economic fabric of each region, along with an exploration into a broader spectrum of cutting-edge technologies. Through making appropriate investments and enhancing the workforce's skills, regions with a legacy in traditional fields can stimulate innovation growth and generate new employment opportunities locally.

Furthermore, technological progress is more effectively fostered through a regional governance model that prioritizes collaboration over competition, especially given the importance of collaboration across high-tech and traditional fields. This perspective also broadens the academic discourse on innovation, which moves beyond the confines of high-tech sectors alone. It is vital to acknowledge that high-tech inventions often rely on the foundational elements provided by traditional technologies, which in turn can open new opportunities for advancements in these technologies.

Recognizing the interconnectedness of innovations significantly contributes to economic resilience of regions with specializations in traditional fields, and it helps counteract the negative impact associated with a narrowly focused pro-growth development mindset.

The third theme posits that promoting economic diversity is the preferable approach for regional economic development and restructuring. The key findings of the second essay indicate that regions with a diversified knowledge structure are better positioned to integrate knowledge from emerging industries, even those markedly distinct from the region’s traditional area of specialization, into their current knowledge base. This insight is reinforced by observations from the first essay, which reveals that regions where large traditional establishments or a substantial overall industrial size played a significant role in traditional innovation exhibited the lowest levels of innovation performance across all studied regions. This underscores the importance of economic diversity in fostering a resilient and innovation regional economy.

For economic developers and decision makers, this theme advocates that regions should refrain from concentrating solely on one or two targeted industrial areas, and should place greater emphasis on broader sectors that encompass a variety of related sub-industries. This strategy not only diversifies their economic activities but also positions them to more readily adopt high-tech industries or other new opportunities as they arise in the future. Policy measures might include creating incentives to adopt and develop technologies adjacent to but outside the traditional economic stronghold of the region, and investing in education and training programs that equip the workforce with versatile skills applicable across various sectors. By promoting an ecosystem that values strategically diverse economic activities, regions can lessen their dependency on any single focused area and mitigate the risks associated with economic downturns in specialized sectors.

This dissertation opens several pathways for future research. The first direction involves delving into the inventing organizations responsible for significant advancements in traditional technologies and those leading the transition towards high-tech knowledge creation. Moving beyond the aggregate perspective of this work, future studies could examine innovation at a more granular level. This would entail exploring whether patents in traditional fields have consistently been held by a particular set of innovative institutions or corporations, or if there has been a dynamic shift, incorporating a diverse mix of inventors including new entrants from research institutions and high-tech corporations. Utilizing USPTO patent data, which provides detailed information about inventors and assignees, would facilitate tracking the evolution of patent ownership and the key players in innovation over time.

This analysis could also extend to regions known for their strength in traditional fields but are now actively revitalizing their knowledge bases and venturing into high-tech knowledge creation. A potential focus could be to investigate whether patents in high-tech domains originate from traditional innovators or through partnerships with high-tech firms. Additionally, the investigation could delve into the geographic or cognitive proximity of these partnerships, exploring whether and how physical closeness and shared knowledge bases influence the progress in traditional technologies, and the innovation process at the intersection of traditional and high-tech knowledge.

This research trajectory could further explore the complexity of innovation-related institutions in these regions. For instance, the analyses could extend to cover stakeholders from the public, private and nonprofit sectors who, while not directly engaged in patenting, have facilitated innovation and industrial transformation. Examples include local venture capital organizations and entities involved in the recruiting businesses that innovate or supply products in both traditional and high-tech fields, or in training and attracting the relevant workforce in these regions. These inquiries are particularly intriguing given the substantial institutional innovations within the realms of economic and community development in these regions. In addition, related policy domains such as state and local economic development policies, training and educational policies, and land use policies are also highly pertinent to these regions and warrant examination.

The second avenue for future research involves conducting deeper analyses into specific characteristics of regions that significantly impact their innovation capabilities in both traditional and high-tech fields. This dissertation has identified several factors, such as population decline and the presence of large corporations or significant industrial size, that may impede technological innovation. Further studies could use case studies chosen from the data used in this dissertation to investigate regions with these characteristics. Moreover, this study has observed that some micropolitan areas, while sustaining innovation in traditional fields, encounter barriers in fostering new innovative capabilities within high-tech domains. Detailed studies could also assess whether a region's economic size plays a role in the cultivation of new specializations. Conversely, exploring the conditions under which innovations in both the traditional and high-tech fields can symbiotically reinforce each other's growth could provide valuable guidelines for crafting more effective and inclusive economic development policies.

The third potential research trajectory proposes a more forward-looking examination of regions that have transitioned from highly specialized to more economically diversified portfolios. This involves conducting in-depth analysis into whether such regions have achieved their diversification goals, such as increasing innovation, drawing in a more educated workforce, and generating high-paying jobs within the new industries. Moreover, there is a need to scrutinize how the interplay between high-tech and traditional technologies evolves with the emergence of technologies like artificial intelligence, cloud computing, autonomous vehicles, and drones, which were not covered by the patent data in this study. This inquiry would also explore the extent to which older industrial regions have managed to integrate high-tech innovations into their traditional knowledge base, and the impact of this integration on their overall restructuring endeavors.

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CHAPTER IV

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APPENDIX

Table A.1 Classification of Patent Classes into Tech Categories and Sub-Categories

Category Code	Category Name	Sub-Category Code	Sub-Category Name	Patent Classes
1	**Chemical**	11	Agriculture, Food, Textiles	8, 19, 71, 127, 442, 504
		12	Coating	106, 118, 401, 427
		13	Gas	48, 55, 95, 96
		14	Organic Compounds	532, 534, 536, 540, 544, 546, 548, 549, 552, 554, 556, 558, 560, 562, 564, 568, 570
		15	Resins	520, 521, 522, 523, 524, 525, 526, 527, 528, 530
		19	Miscellaneous-Chemical	23, 34, 44, 102, 117, 149, 156, 159, 162, 196, 201, 202, 203, 204, 205, 208, 210, 216, 222, 252, 260, 261, 349, 366, 416, 422, 423, 430, 436, 494, 501, 502, 506, 510, 512, 516, 518, 585, 588
2	Computers & Communications	21	Communications	178, 333, 340, 342, 343, 358, 367, 370, 375, 379, 385, 398, 455
		22	Computer Hardware & Software	341, 380, 382, 395, 700, 701, 702, 703, 704, 705, 706, 707, 708, 709, 710, 712, 713, 714, 715, 716, 717, 718, 719, 726
		23	Computer Peripherals	345, 347
		24	Information Storage	360, 365, 369, 711
3	Drugs & Medical	31	Drugs	424, 514
		32	Surgery & Medical Instruments	128, 600, 601, 602, 604, 606, 607
		33	Biotechnology	435, 800
		39	Miscellaneous-Drugs & Medical	351, 433, 623
4	**Electrical & Electronics**	41	Electrical Devices	174, 200, 327, 329, 330, 331, 332, 334, 335, 336, 337, 338, 392, 439
		42	Electrical Lighting	313, 314, 315, 362, 372, 445
		43	Measuring & Testing	73, 324, 356, 374
		44	Nuclear & X-rays	250, 376, 378
		45	Power Systems	60, 136, 290, 310, 318, 320, 322, 323, 361, 363, 388, 429
		46	Semiconductor Devices	257, 326, 438, 505
		49	Miscellaneous-Electrical & Electronics	191, 218, 219, 307, 346, 348, 377, 381, 386, 725

Category Code	Category Name	Sub-Category Code	Sub-Category Name	Patent Classes
5	**Mechanical**	51	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
		52	Metal Working	29, 72, 75, 76, 140, 147, 148, 163, 164, 228, 266, 270, 413, 419, 420
		53	Motors, Engines & Parts	91, 92, 123, 185, 188, 192, 251, 303, 415, 417, 418, 464, 474, 475, 476, 477
		54	Optics	352, 353, 355, 359, 396, 399, 720, 850
		55	Transportation	104, 105, 114, 152, 180, 187, 213, 238, 244, 246, 258, 280, 293, 295, 296, 298, 301, 305, 410, 440
		59	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, 508
6	**Others**	61	Agriculture, Husbandry, Food	43, 47, 56, 99, 111, 119, 131, 426, 449, 452, 460
		62	Amusement Devices	273, 446, 463, 472, 473
		63	Apparel & Textile	2, 12, 24, 26, 28, 36, 38, 57, 66, 68, 69, 79, 87, 112, 139, 223, 450
		64	Earth Working & Wells	37, 166, 171, 172, 175, 299, 405, 507
		65	Furniture, House Fixtures	4, 5, 30, 70, 132, 182, 211, 256, 297, 312
		66	Heating	110, 122, 126, 165, 237, 373, 431, 432
		67	Pipes & Joints	138, 277, 285, 403
		68	Receptacles	53, 206, 215, 217, 220, 224, 229, 232, 383
		69	Miscellaneous-Others	1, 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

Note: The list of patent classes as of the date of data collection includes 9 additional new classes that are not to be found in the data: 901, 902, 903, 930, 968, 976, 977, 984, and 987.

Table A.2 Shrinking Regions in terms of Population and in terms of Per Capita Income

Shrinking Regions in terms of Population (136 Obs.)		Slow-growth Regions in terms of Total Income (42 Obs.)	
GEOID	**CBSA Name**	**GEOID**	**CBSA Name**
10660	Albert Lea, MN Micro Area	**10300**	Adrian, MI Micro Area
10980	Alpena, MI Micro Area	**11780**	**Ashtabula, OH Micro Area**
11020	Altoona, PA Metro Area	**13020**	**Bay City, MI Metro Area**
11220	Amsterdam, NY Micro Area	**13180**	Beaver Dam, WI Micro Area
11780	**Ashtabula, OH Micro Area**	**14100**	Bloomsburg-Berwick, PA Metro Area
12180	Auburn, NY Micro Area	**17220**	**Clarksburg, WV Micro Area**
12380	Austin, MN Micro Area	**18500**	**Corning, NY Micro Area**
12820	Bastrop, LA Micro Area	**19060**	**Cumberland, MD-WV Metro Area**
12860	Batavia, NY Micro Area	**19180**	**Danville, IL Metro Area**
12980	Battle Creek, MI Metro Area	**20180**	DuBois, PA Micro Area
13020	**Bay City, MI Metro Area**	**21300**	**Elmira, NY Metro Area**
13220	Beckley, WV Metro Area	**23460**	Gadsden, AL Metro Area
13620	Berlin, NH-VT Micro Area	**24500**	**Great Falls, MT Metro Area**
13700	Big Spring, TX Micro Area	**25840**	Hermiston-Pendleton, OR Micro Area
13720	Big Stone Gap, VA Micro Area	**26860**	**Indiana, PA Micro Area**
13780	Binghamton, NY Metro Area	**29020**	**Kokomo, IN Metro Area**
14180	Blytheville, AR Micro Area	**30340**	Lewiston-Auburn, ME Metro Area
14420	Borger, TX Micro Area	**30620**	**Lima, OH Metro Area**
14620	Bradford, PA Micro Area	**31820**	**Manitowoc, WI Micro Area**
15340	Bucyrus, OH Micro Area	**31980**	**Marion, IN Micro Area**
15380	Buffalo-Cheektowaga-Niagara Falls, NY Metro Area	**32100**	**Marquette, MI Micro Area**
15460	Burlington, IA-IL Micro Area	**32740**	**Meadville, PA Micro Area**
15580	Butte-Silver Bow, MT Micro Area	**33220**	Midland, MI Metro Area
15740	Cambridge, OH Micro Area	**34620**	**Muncie, IN Metro Area**
15780	Camden, AR Micro Area	**35260**	**New Castle, PA Micro Area**
16460	Centralia, IL Micro Area	**35420**	New Philadelphia-Dover, OH Micro Area
16620	Charleston, WV Metro Area	**36300**	**Ogdensburg-Massena, NY Micro Area**
16660	Charleston-Mattoon, IL Micro Area	**36340**	**Oil City, PA Micro Area**
17220	**Clarksburg, WV Micro Area**	**36460**	**Olean, NY Micro Area**
17380	Cleveland, MS Micro Area	**37140**	Paducah, KY-IL Micro Area
17460	Cleveland-Elyria, OH Metro Area	**37620**	**Parkersburg-Vienna, WV Metro Area**
17540	Clinton, IA Micro Area	**38220**	**Pine Bluff, AR Metro Area**
17700	Coffeyville, KS Micro Area	**39500**	**Quincy, IL-MO Micro Area**
18220	Connersville, IN Micro Area	**39980**	**Richmond, IN Micro Area**
18500	**Corning, NY Micro Area**	**40660**	Rome, GA Metro Area
19060	**Cumberland, MD-WV Metro Area**	**40700**	Roseburg, OR Micro Area
19180	**Danville, IL Metro Area**	**41400**	**Salem, OH Micro Area**
19340	Davenport-Moline-Rock Island, IA-IL Metro Area	**43740**	**Somerset, PA Micro Area**

Shrinking Regions in terms of Population (136 Obs.)		Slow-growth Regions in terms of Total Income (42 Obs.)	
19500	Decatur, IL Metro Area	**44580**	**Sterling, IL Micro Area**
19820	Detroit-Warren-Dearborn, MI Metro Area	**44980**	**Sunbury, PA Micro Area**
19940	Dixon, IL Micro Area	**48260**	**Weirton-Steubenville, WV-OH Metro Area**
20260	Duluth, MN-WI Metro Area	**49780**	Zanesville, OH Micro Area
21300	**Elmira, NY Metro Area**		
21500	Erie, PA Metro Area		
21540	Escanaba, MI Micro Area		
21900	Fairmont, WV Micro Area		
22420	Flint, MI Metro Area		
22700	Fort Dodge, IA Micro Area		
22800	Fort Madison-Keokuk, IA-IL-MO Micro Area		
23300	Freeport, IL Micro Area		
23380	Fremont, OH Micro Area		
23660	Galesburg, IL Micro Area		
24100	Gloversville, NY Micro Area		
24460	Great Bend, KS Micro Area		
24500	**Great Falls, MT Metro Area**		
24820	Greenville, OH Micro Area		
24900	Greenwood, MS Micro Area		
25760	Helena-West Helena, AR Micro Area		
25820	Hereford, TX Micro Area		
26340	Houghton, MI Micro Area		
26700	Huron, SD Micro Area		
26860	**Indiana, PA Micro Area**		
26940	Indianola, MS Micro Area		
27420	Jamestown, ND Micro Area		
27460	Jamestown-Dunkirk-Fredonia, NY Micro Area		
27780	Johnstown, PA Metro Area		
28820	Kinston, NC Micro Area		
29020	**Kokomo, IN Metro Area**		
30620	**Lima, OH Metro Area**		
30660	Lincoln, IL Micro Area		
30900	Logansport, IN Micro Area		
31380	Macomb, IL Micro Area		
31820	**Manitowoc, WI Micro Area**		
31900	Mansfield, OH Metro Area		
31980	**Marion, IN Micro Area**		
32020	Marion, OH Micro Area		
32100	**Marquette, MI Micro Area**		
32260	Marshalltown, IA Micro Area		
32380	Mason City, IA Micro Area		

Shrinking Regions in terms of Population (136 Obs.)		Slow-growth Regions in terms of Total Income (42 Obs.)	
32740	Meadville, PA Micro Area		
33020	Mexico, MO Micro Area		
33060	Miami, OK Micro Area		
34020	Morgan City, LA Micro Area		
34620	**Muncie, IN Metro Area**		
35220	New Castle, IN Micro Area		
35260	**New Castle, PA Micro Area**		
35580	New Ulm, MN Micro Area		
35660	Niles-Benton Harbor, MI Metro Area		
36300	**Ogdensburg-Massena, NY Micro Area**		
36340	**Oil City, PA Micro Area**		
36460	**Olean, NY Micro Area**		
36860	Ottawa-Peru, IL Micro Area		
36900	Ottumwa, IA Micro Area		
37420	Pampa, TX Micro Area		
37620	**Parkersburg-Vienna, WV Metro Area**		
37660	Parsons, KS Micro Area		
37780	Pecos, TX Micro Area		
38220	**Pine Bluff, AR Metro Area**		
38300	Pittsburgh, PA Metro Area		
38340	Pittsfield, MA Metro Area		
38380	Plainview, TX Micro Area		
38620	Ponca City, OK Micro Area		
38700	Pontiac, IL Micro Area		
39060	Pottsville, PA Micro Area		
39500	**Quincy, IL-MO Micro Area**		
39980	**Richmond, IN Micro Area**		
40260	Roanoke Rapids, NC Micro Area		
40980	Saginaw, MI Metro Area		
41400	**Salem, OH Micro Area**		
41780	Sandusky, OH Micro Area		
42380	Sayre, PA Micro Area		
42540	Scranton--Wilkes-Barre--Hazleton, PA Metro Area		
42820	Selma, AL Micro Area		
43660	Snyder, TX Micro Area		
43740	**Somerset, PA Micro Area**		
43980	Spencer, IA Micro Area		
44220	Springfield, OH Metro Area		
44580	**Sterling, IL Micro Area**		
44980	**Sunbury, PA Micro Area**		
45020	Sweetwater, TX Micro Area		

Shrinking Regions in terms of Population (136 Obs.)		Slow-growth Regions in terms of Total Income (42 Obs.)	
45380	Taylorville, IL Micro Area		
45460	Terre Haute, IN Metro Area		
45660	Tiffin, OH Micro Area		
45780	Toledo, OH Metro Area		
46460	Union City, TN-KY Micro Area		
46540	Utica-Rome, NY Metro Area		
46740	Valley, AL Micro Area		
46980	Vicksburg, MS Micro Area		
47340	Wabash, IN Micro Area		
47420	Wahpeton, ND-MN Micro Area		
47620	Warren, PA Micro Area		
47940	Waterloo-Cedar Falls, IA Metro Area		
48260	**Weirton-Steubenville, WV-OH Metro Area**		
48540	Wheeling, WV-OH Metro Area		
48700	Williamsport, PA Metro Area		
49660	Youngstown-Warren-Boardman, OH-PA Metro Area		

Note: Overlapping regions are highlighted in the table.