THESIS/DISSERTATION APPROVED BY

June 27, 2019
Date

Kristie Briggs, Ph.D., Dissertation Chair

Eric Neuman, Ph.D., Committee Member

Kristie Briggs, Ph.D., DBA Director

Gail M. Jensen, Ph.D., Dean

INNOVATION'S IMPACT ON COUNTY-LEVEL POPULATION HEALTH

By

NICHOLAS S. BALDETTI

A dissertation submitted to the faculty of the Graduate School of Creighton University in partial fulfillment of the requirements for the degree of Doctor of Business Administration in the Heider College of Business.

Omaha, NE

June 27, 2019

ABSTRACT

This dissertation investigates the importance of innovative economic activity and its impact on health outcomes at the county level. The influence of patent assignment activity per county in the United States from 2010 - 2014 on all-cause and specific type mortality rates per 100,000 per county was analyzed. Previous studies have only looked at this relationship at a national or regional level. Here innovation is found to have a statistically significant impact on affecting mortality rates at the county level. This study also suggests that the impact innovation has on mortality rates differs depending on the type of mortality and maintains significance when controlling for medical specific innovation versus non-medical innovative activity. Additionally, evidence shows that the timing effect of innovation is strongest within the year of assignment when impacting mortality rates at the county level, suggesting that the effects of that innovation's assignment has the strongest impact on the health of the community within the assignment year. Further, results suggest that the innovation of neighboring counties has positive implications for their own population as well as the surrounding counties population by decreasing mortality rates for both that county and counties bound by geographic contiguity. These results highlight important policy implications toward health production and provide a path forward for continued research into health production theory as well as the use of empirical methods to be used to evaluate economic policy and its benefit to population health. Given these results, county officials can better make economic policy decisions based on the positive impact innovation plays in growing local economies while also understanding the role economic innovation plays in impacting their constituencies stock of health.

Keywords: Innovation, Population Health, Patents, Mortality, Health Production

ACKNOWLEDGEMENTS

I would like to take a moment to express my sincere gratitude to a number of individuals. The adage that it takes a village could not be truer. While there are countless others that may not be mentioned here, I wish to express my sincere thanks to everyone who assisted me along the way. Your kind words, contributions, listening ears, and understanding has not gone unnoticed!

First, I'd like to thank some of my fellow Creighton DBA cohort members. I'd like to thank Chandu Valluri for exemplifying academic persistence and rigor. I have learned much by embarking on this journey with you. Keith Olsen, for his unwavering optimism and positivity. Your outlook on life is infectious and I am blessed to have shared in this journey with you. Martha Stillwell for the many conversations. You have offered more benefit than you know! And Derek Kruse, who has been a trusted friend and confidant through this process. His professionalism and grounded pragmatism have both provided motivation and comfort throughout the entirety of this journey. Finally, I'd like to thank the administrative staff and faculty of the DBA program. It is not without your commitment to your craft that I would have been able to reach this point. To all my other cohort members, I am grateful for the many shared experiences. I know that we will forever share in a bond that will not break.

Next, I'd like to attempt to express my sincere gratitude to my dissertation committee. Without their guidance, leadership, advice and (lots of) patience, this process would be far less fulfilling. Eric Neuman has been a trusted mentor and a fantastic representative of the Creighton program. I hope that our interaction together spans far past that of the outcome of this work. Thank you, Eric. It is not without strong leadership

that anything truly leads to accomplishment. Kristie Briggs has been that leader for me and has been more than I could have asked for as my chair. Kristie is a rarity, whose dedication only rivals her professionalism and commitment to her craft. I am eternally grateful and humbled to have had the opportunity to be mentored by someone so talented and giving. It is not without her leadership that I would have been able to reach this point. She has pushed me beyond what I thought I was capable of. Needless to say, I am indebted to you and no amount of thanks is thanks enough. Your dedication to your students, your profession, to Creighton and to the DBA program is difficult to articulate appropriately. Kristie, my sincerest thanks and gratitude for your commitment and belief in me.

A great many thanks is owed to many of those that fall outside of academic circles. To all of my employees, coworkers, colleagues and friends who have listened, guided and sacrificed, I owe you many thanks. While calling each and every one of you out individually would be a dissertation in its own right, I will simply say thank you for your patience, understanding and support.

I must also recognize with the utmost sincerity and emotion my family. “Thanks” hardly seems like enough in terms of the support and sacrifices you all have made along this journey with me. To my in-laws Janel, Brad, Chris and Jody thank you for listening, sacrificing on my behalf and helping my family while I was absent. I thank you from the bottom of my heart for your unwavering support and the examples you set for my children in what a loving and supportive family means. To my Mom and Dad, thank you for always believing in me, encouraging me to chase my goals, and supporting me no matter how crazy you think I am. To my brother Stephn, thank you for being the persistent reminder that someone is always watching, and it is just as much about the action as it is the word.

Thank you to my children Blayne, Liam and Lahna. Your support and love mean more then you'll ever know. Please know not letting you three down was often the motivation that kept this journey true. I am so proud of you all and how you have persisted with my absences over the last few years. You three truly are the most inspirational and life changing features of my entire life. I always have, and always will be your biggest fan and will continue to love you unconditionally, without question. Thank you.

Finally, and this may well be the most difficult paragraph to write. To my wife, my best friend, and my soul mate. There is no possible way to articulate effectively my gratitude for your unwavering support, sacrifice and love. The weekends away, the early mornings, the countless hours at the office were often difficult to tolerate. You maintained your support through my best moments as well as my worst. You were, and always will be, the first to pick me up from the dirt and the first to celebrate with me at the mountain top. To the love of my life, Kylee, it is with every ounce of truth and every fiber of my being that I say thank you. Without you by my side, I am certain that this dissertation would not have been written. I love you.

Table of Contents

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

ACS	American Community Survey
AIC	Akaike Information Criterion
AIDS	Acquired Immunodeficiency Syndrome
BID	Business Development District
CTE	Chronic Traumatic Encephalopathy
CTIA	Cellular Telecommunication Industry Association
DELTA	Domestic Violence Prevention Enhancement and Leadership Through Alliances
FAO	Food and Agriculture Organization
GDP	Gross Domestic Product
HIPAA	Health Insurance Portability and Accountability Act
HIV	Human Immunodeficiency Virus
IHME	Institute of Health Metrics and Evaluation
M&P	Medical and Pharmaceutical
MSA	Metropolitan Statistical Area
NTD	Neglected and Tropical Disease
NVSS	National Vital Statistics System
OECD	Organization for Economic Co-Operation and Development
OLS	Ordinary Least Squares
R&D	Research and Development
SAR	Spatial Autoregression
SES	Socioeconomic Status

SRHS	Self-Reported Health Status
USPTO	United States Patent and Trademark Office
VIF	Variance Inflation Factor
WHO	World Health Organization
WIPO	World Intellectual Property Organization
WTO	World Trade Organization

CHAPTER 1: INTRODUCTION

While the benefits to innovation are diverse, one important influence is the impact of innovation on improved health. Much of the literature examining the relationship between innovation and improved health has been highly micro in nature, examining the impact of specific innovations on health outcomes. The intention of this dissertation is to fill an important gap currently present in the literature. It seeks to examine the causal effect of county-level innovation on county-level health outcomes. This study also briefly explores the timing effects of innovative activity impacting county-level health outcomes. Despite the popular notion that innovation conducted anywhere can equally impact people everywhere, evidence exists that geographical proximity to the innovation source remains important to the reach of knowledge embedded in the innovative processes (Camagni, 1985; Morgan, 2004). Concurrently, research suggests that public health services, such as those championed at the local jurisdictional level, effect community-wide strategies toward the control of chronic diseases (Bishai et al., 2016). Product and process innovations in multiple sectors (not just in pharmaceuticals and biomedical engineering) may play an important role in enhancing ease and effectiveness of population health strategies. That influence of change on health outcomes can be because of innovation of public goods and how such innovations diffuse through different localities (Mokyr, 1993).

It is difficult to refute that, as a country, the United States has a healthcare crisis on its hands. Per the National Center for Health Statistics (2017), in 2015 the United States per capita spending on healthcare was near $10,348. At that time, the total national health expenditure was equal to $3.3 trillion. Thus, the total national health expenditures as a percent of gross domestic product (GDP) was near 17.9% (National Center for Health Statistics, 2017). Taking $3.3 trillion and dividing it by 3,110 counties in the United States equates to an average per county health expenditure of over $1 billion. Unfortunately, much of that cost inevitably falls upon U.S. employers (Stewart, Ricci, Chee, & Morganstein, 2003).

If only from a monetary perspective, evaluating the practice of impacting, and policy adoption toward better health outcomes would seem a noble endeavor. Further, the United Nations Development Report (2009) and World Economic Forum (2011) report that countries who have enhanced technological accomplishments and more positive health outcomes tend to have the strongest economies. Often times, technological accomplishment becomes synonymous with innovation. However, innovation is also understood to be an alternative way of addressing prevailing problems with existing resources. Examining the relationship between the indicators of innovation and their relationships with health outcomes becomes essential in determining how these factors interact to facilitate a strong economy.

There are instances in the public health literature that have attempted to research the general impact of innovation either by how it spreads (Greenberg, 2006), its association to individual property rights (World Health Organization (WHO), 2006) or as a result of policy intervention (Adams et al., 2006). However, the literature appears brief in analyzing the greater, macro level relationship between general indicators of innovation and its direct impact toward population level health outcomes.

Gill (2012; 2013) attempts to build an understanding of the impact innovation has on health outcomes by evaluating innovation's influence in the four large U.S. Census

Regions (Northeast, South, West, and Midwest). While Gill has laid a foundation for analysis, there is room for a more granular analysis when distilling down to the county level.

The work of this dissertation strives to build on previous literature by continuing to analyze the relationship between innovation and health outcomes from an econometric perspective. The potential impact of this study could lead to better economic development and health policy making at the county-level, and subsequently at the regional- and state- levels.

The remainder of this dissertation is organized as follows. In Chapter 2, I conduct a literature review that details theoretical concepts and motivations for my empirical analysis. I start with reviewing existing health production models and useful theoretical extensions for the purposes of this study. I also review the literature on innovation's influence on health outcomes, the geographic scope of innovation and mortality rates as a measure of health outcomes. Chapter 3 is the methodology section. Here I present my empirical model, provide support for included explanatory variables and provide statistical and data gathering specifications in addition to hypothesis relating to my main analysis. In Chapter 4, I provide thorough results where I showcase my findings, how they support my predicted hypothesis as well as discuss the results of additional robustness tests. I conclude this dissertation in Chapter 5 where I discuss the contributions, limitations and potential extension for future study.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The purpose of this chapter is to review the external literature on health production, innovation and mortality. After establishing the theoretical underpinnings of innovation's impact on the household stock of health and the micro vs macro links between innovation and health, I go on to explore obvious versus non-obvious innovative influences on health outcomes. I then discuss the geographic scope of innovation's influence and the known influences of innovation on health. A discussion on the importance of mortality rates as a measure of health outcomes precludes a summary of Chapter 2.

2.2 Theories of Health Production

Being that human capital is a fundamental asset to active economies, it stands to reason that strengthening human capital will have positive economic implications. Grossman (1972) created the demand for health model whereas the demand for healthcare shifts along a downward sloping marginal efficiency of investment. For every additional unit of healthcare cost there is a shift to the stock of health for the individual. The utility function is:

$$U(\phi_t H_t, C_t), \quad t = 0, 1, \ldots, n \tag{1}$$

whereas (1) shows the utility of an individual as the function of $\phi_t H_t$. This function is the product of H_t, which is health stock at age t (or in time period t), times ϕ_t, which is the service flow of health services per unit stock. Utility also depends on C_t, which is the consumption of another composite commodity (Grossman, 2000).

$$H_{t+1} = H_t + I_t - \delta_t H_t \quad (2)$$

Equation 2 represents the signal of the health stock where I_t is investment in health and δ_t is the depreciation rate per unit of time of the health stock during the tth period.

$$I_t = I_t(M_t, TH_t; E) \quad (3)$$

$$C_t = C_t(X_t, T_t; E) \quad (4)$$

Equation 3 represents the production function of investment in health stock. The equation shows that health is created from medical commodities (M_t) and the individual's time spent on getting healthy (TH_t). Both are conditional on the individual's level of knowledge (E).[1] Equation 4 is a symmetrical production function of composite commodities where X_t is a vector of goods that contribute to production, T_t is the time vector and as with investment in health production, the consumption function is conditioned by knowledge (E).

Within Grossman's model however, the consumer's choice is always positioned by the allocation of time and purchases. This approach only allows policy change to exogenously affect prices of health inputs. For the traditional models of health production, the explicit health inputs are commodities that affect only one person at a time and are accessed through healthcare (Bashai et al., 2016). However, in local communities, policy choices are being made that can directly affect the health of many independently of consumer choice. In its pure form, the health demand model provides little opportunity for non-rival health inputs like walkable environment, clean air and water, and shared cultural memes to affect health (Bishai et al., 2016).

[1] Grossman (2000) assumes that E does not vary over the life cycle.

An appropriate starting point would be with equation 2 and 3 when trying to evaluate external health inputs outside of the control of the individual.

Some authors have sought to expand Grossman's model to the household such as Jacobson (2000) who modeled family members within a household's ability to share health-enhancing time amongst residents. Jacobson's model also allows the knowledge of family members to impact the production function. However, this model does not satisfactorily explain differences in health across political boundaries and communities. Basing health production on a foundation of individual human choice makes it difficult to explain geographical health differences as anything other than health input price differences that somehow never balance (Bishai et al, 2016).

It is at this junction that Mokyr (1993) offers a useful theory of health production that can be adapted to allow for health to occur as a direct result of public goods chosen outside of the household. For Mokyr's theory, the health stock is determined by the household production function where:

$$H_j = E_1 + E_2 + F(X_{ij}) \tag{4}$$

Since F is not entirely known to the individual household, Mokyr suggests that its behavior can be determined by:

$$e(H_j) = E_1 + E_2 + F[(A_i - \varepsilon_{ij})X_{ij}] \tag{5}$$

where the household production function F transforms goods consumed into years lived. A_i is a common technology shift factor that measures the efficient use of household technology for good i, and $A_i - \varepsilon_{ij}$ is the equation that the consumer j turns X_i into H. Since households may not be optimally leveraging the use of A_i, ε represents below optimal use from the household. E_1 and E_2 make up the two elements of the environment where E_1 is purely exogenous, and

$$E_2 = G(B_i - \phi_i)Z_i \qquad (6)$$

where as E_2 is contingent on Z_i which is the amount of governmental spending toward policy in i-th county and $G()$ being the efficacy of that governmental spending. $G()$ is contingent on B_i which is the best set of practices available to county i in response to technology or innovation and ϕ_i is the gap failure to perfectly implement that best practice within that county. The full theoretical equation equates to

$$H_j = E_1 + G(B_i - \phi_i)Z_i + F[(A_i - \varepsilon_{ij})X_{ij}] \qquad (7)$$

The second term within the equation is the impact of policy driven influences on health. The third term is the household contribution to health which is the function F of the resources devoted to health X_{ij} in the j-th household in i-th county[2]. This is multiplied by the efficacy of household spending on health. Like policy spending, this is contingent upon the technology shift A_i and the gap term, ε_{ij}. As local county government's invest in policy, such policy could replace or complement household investments in health capital.

Mokyr's model could suggest that general innovation may impact the stock of health by impacting governmental policy spending Z_i and innovation and its best-practice (use), B_i and A_i. County level policy could in turn effect spending Z_i by way of tax incentives or local tax investment in innovation productive actors such as entrepreneurial resource organizations, maker's spaces, and community infrastructure investment.

[2] Mokyr's X_{ij}, which represents household inputs would identify as I within the Grossman model for health capital investments.

Additionally, innovation's potential impact on B_i and A_i does not require policy makers to understand how or why it works, or even consciously be aware that it is impacting health at all (Mokyr, 1993).

2.3 Innovation's Influence on Health Outcomes

More robust economies tend to showcase greater innovative ability (United Nations Development Report, 2009; World Economic Forum, 2011) and technological advancement stimulates better health outcomes (OECD, 2010). This creates an incentive to evaluate innovation's impact on health outcomes. Organizations including the World Health Organization (WHO), the World Intellectual Property Organization (WIPO) and the World Trade Organization (WTO) have stressed the need for a positive link between public health, global trade and intellectual property rights (WHO, WIPO and WTO, 2012). Further, the Organization for Economic Co-Operation and Development (OECD) suggest that innovation can assist with social challenges, and that such challenges could include the health challenges of a community (OECD, 2010). The WHO (2006) asserts that health outcomes can lead to social challenges being positively affected through innovative practices of various kinds, including new biomedical intervention and improved methods of prevention, diagnosis and treatment. However, authors have found that innovation adoption is not necessarily a predictive process from development to market (Geljins and Rosenberg, 1994). As a result, calls from the literature encourage policy makers to recognize the impact of innovation.

When focusing solely on the United States, few have studied the relationship even though there are recognized bodies suggesting that increase technological advancement can equate to robust economies (United Nations Development Report, 2009; World Economic Forum, 2011) and help to drive better health outcomes (OECD, 2010). Gill (2012, 2013) being the only to analyze the relationship at the regional census level.

Through a single factor analysis of variance and Kruskal-Wallis median comparison tests, Gill (2012) confirmed statistically significant differences in technological innovation indicators and public health indicators between the four U.S. Census regions. Power law regression analyses found statistically significant differences between technological innovation indicators and public health indicators for any one of the four U.S. Census regions. Further, partial least squares structural equation modeling found potential causal relations between technological innovation and health outcomes for all four of the U.S. Censes regions (Gill, 2012).

The exploratory analysis between measures of innovation and population health indicators drawn from each of the four regions were separated as a collection of states labeled Midwest, Northeast, South, and West. Gill's analysis included innovation indicators and public health indicators from the time period 2003 – 2007. The innovation indicators included articles per 1,000 capita, patents per 1,000 capita, the percentage of the workforce in science and engineering occupations, the value of R&D performed as percent of GDP and Venture capital per $1,000 of GDP. The public health indicators included health status, insurance coverage, obesity and overweight rates, preterm birth rate, suicide rate and tobacco use rate.

Gill's preliminary results suggests that there are differences between health outcomes and the prevalence of innovation within the four U.S. Census regions. While each of the regions ranked differently in technological innovation and health indicators, the author found that better innovation indicator scores were related to better health outcomes per census region (Gill, 2012; 2013). While encouraging, a U.S. census region is comprised of multiple states whose similarities may simply rest in geography. In turn, this creates an opportunity for a more focused, granular study of innovation's effect on health outcomes. Score indicators show variances between urban, rural and frontier differences in innovative activity and health differences. Further, the opportunity to evaluate innovation's effect on health outcomes from a diverse sample of 3,139 counties versus a clustering of four U.S. Regions of state level data offers an opportunity for a more robust and thorough evaluation of the relationship.

As the smallest jurisdictional authority that maintains an ability to impact policy is at the county level (Allen, 2001), it stands to reason that the impact of innovation should be understood by all levels of policymakers, including at the county level. As such, extending exploratory research on innovation's effect on health outcomes at the county level would fill an important gap in the literature.

2.4 Practical Impacts of Innovation

The positive impact on health from innovations within the medical and pharmaceutical industries seem obvious[3]. However, since the rapid decline in mortalities as a result of infectious disease[4], there has been a shift in the focus of public health and health related research and development on deaths as a result of trauma and chronic

[3] There are varying ways innovations within this sphere impact health. For example, vaccines play a preventative role in communicable disease, screening innovation such as tuberculin tests; capacity to diagnose via an electrocardiogram; enhance treatment interventions through advancements in surgery and technology; and technology for rehabilitation i.e. hearing aids and incontinence aids. These innovations can span medicines, medical technology, biologics and pharmaceuticals (WHO, WIPS & WTO, 2013).
[4] Commonly referred to as the epidemiological transition.

conditions like diabetes, heart disease, and cancer (Rust, Satcher, Fryer, Levine, and Blumenthal, 2010; OECD, 2010). This transition has led to the need to evaluate non-medical factors that influence health (Shi and Johnson, 2013). The production of technologies across multiple sectors can lead to innovation that impact health outcomes and, in turn mortality rates.

For example, the proliferation of semiconductor portability and computer programming has brought on the profusion of mobile technology. Technology such as cell phones, tablets and mobile devices have expanded connectivity across populations and across a broad diversity of geographic locations. Mobiles offer capabilities of connectivity, division of labor, scale, replication, accountability, matching of buyers and sellers, communities of interest, education and training and can act as sensors (Sachs, 2008) for a plethora of different applications.

According to the Cellular Telecommunication Industry Association (CTIA) there were 273 million smartphones in active use in the Unites States in 2017 (CTIA, 2018). This creates an immense opportunity for innovations in mHealth and eHealth. Innovations in this space incorporate health call centers, mobile telemedicine, appointment reminders, community mobilization, patient records, informatics, patient monitoring, health surveys, surveillance, awareness raising and decision support systems toward addressing prevalent health issues. In addition to direct health applications, other innovations such as mobile money, crowdsourcing, spread of information through educational platforms, mobile software developed to effect behavior change, the dissemination of news and economic data for informed decision making and sales and auction platforms create connectivity to information and products that may indirectly impact health outcomes.

However, it is not simply the reality of mobile technologies for which there are potential impacts on health and health outcomes. Innovative activity within the development of existing products and industries such as transportation and automobiles are another example of innovation impacting health. Autonomous precision driven vehicles seek to replace human drivers while decreasing vehicular accident mortality rates. Current research and development in safety of recreational and sporting activity seeks to advance science toward protection of athletic participants. One such innovation is reflected in American football and helmet safety and safe tackling practices. These new practices impact the prevalence of Chronic Traumatic Encephalopathy (CTE) associated with repeated blows to the head.

Fire suppression activities and products reflect another innovative area that has contributed to health-related assistance in safety protection for fire fighters and inhabitants of affected facilities. Research, development and chemistry innovations have resulted in advancement of fire suppressive foams and textiles used for fire resistant Kevlar response suits.

New construction planning and practices seek to elicit better health outcomes around the environments in which we live, eat, work, play and pray. New advancements in urban planning, playground equipment and lighting solutions and methodologies seek to entice physical activity, which in turn affects chronic issues such as chronic obesity, hyper tension, heart disease and respiratory syndromes by decreasing motor vehicular traffic and increasing walkability and physical opportunities around population densities.

Advancements in renewable energy sources contribute to decreasing carbon emissions in areas such as solar, wind and hydroelectric energies. These energy sources may impact the prevalence of chronic respiratory issues that can lead to mortality.

Improvements in food security address access, availability and utilization. This again relates to built environments and urban planning. In the United States, many conversations are being had around food and good nutrition. A specific topic of interest is whether communities and individuals have adequate quantities of nutritious food available at affordable prices, and whether they are utilizing that access. The United Nations estimates by 2050 the world population will be around 9.8 billion people (UN, 2017). This means another, 2 – 2.5 billion people will be living on our planet. The Food and Agriculture Organization of the United Nations (FAO) predicts if that happens, the global need of food production will need to increase by 70% (FAO, 2009). Further, the amount of resources and effort required in the agriculture industry is exponential. Innovations such as new seed, new fertilizers, agricultural techniques developed at universities and from the private sector will potentially impact health. The amount of people involved in farming, transportation, processing, retail (farm to table) is quite large. Agriculture is also at the middle of many large-scale world issues such as lack of water, climate change, greenhouse gas emissions, hunger, poverty and nutrition.

As policy makers feel increased pressure to oversee the social, health and economic impacts of technological advancement (OECD, 2010), it would seem beneficial to have a greater understanding of the potential impact of general innovative activity to health.

2.5 Geographic Scope of Innovation's Influence on Health Outcomes

Literature suggests that the proliferation of technology diminishes the impact of physical proximity and that technology allows for the same level of interaction and productivity virtually. However, Dodge and Kitchin (2001) counter that the relationship between the physical and virtual is complex and creates "an experiential continuum" for the individual. While virtual proximity may well be able to replace physical proximity when it comes to standardized transactions, the context of transactions high in complexity, ambiguity and tacitness (Morgan, 2004), such as the act of innovation, would seem more challenging in a purely virtual environment. Brown and Duguid (2000) go on to say that "digital technologies may be adept at maintaining communities that are *already* formed; but they are not so good at *creating* them in the first place" [Emphasis Added]. Thus, while the cost of information transfer across geographical space has fallen, the marginal cost of information transfer still increases with distance (Treasury, 2004).

Dwyer-Lindgren et al. (2016) find that there are geographical differences among types of mortalities over time. Geography and regionality are also found to play a role in the development of innovation (Bjørn T. Asheim, Boschma, and Cooke, 2011; Bjørn T. Asheim and Gertler, 2009; Bjorn T. Asheim, Smith, and Oughton, 2011). Linking the two, Camagni (1985) argues that the ability of local economies to maintain competitiveness is contingent on a number of conditions individual to the territory. These conditions include the utilization and optimization of the existing stock of knowledge and technology which require investments in the tacit knowledge of the territory and its human capital resource; conditions that are individual to the territory and are not ubiquitous (Camagni, 1986). Thus, the geographic prevalence of innovation and its influence on health outcomes will be individual and unique to the territory or local economy. Whereas innovation's utility across jurisdictional boundaries will take time as distance increases the marginal cost of information transfer, due in part, to spatiality not being a neutral factor in influencing innovation (Camagni, 1985; Asheim and Gertler, 2009) and proximity being an influential factor in human capital resource differentiation (Cuadrado-Roura, 2017).

2.5.1 Territorial Diffusion Theory

Asheim and Gertler (2009) argue that geography plays a fundamental role in the innovation process and that spatiality is vitally important. The seminal work of Hagerstrand (1952) used Monte Carlo methods to simulate spatial patterns of the diffusion process. Coined the neighborhood effect, Hagerstrand states that "a person becomes more and more inclined to accept an innovation the more often he comes into contact with other persons who have already accepted it" (Hagerstrand, 1967: 264). Since then, scholars have attempted to address the simplification of innovation diffusion. That is, that basic interpersonal communication as a process, is too elementary for this day and age (Camagni, 1985). Camagni (1985) thus shifted the spatial element of analysis to economic distance rather than physical distance to better reflect differential economic characteristics. Camagni goes on to state that:

> "the introduction of the spatial dimension in the analysis of the innovation diffusion is not just a further dimension to an already complex problem, but it also plays a part in highlighting a number of fundamental genetic

aspects of actual diffusion processes." – Roberto Camagni (Capello, 2017: 39)

It is this idea of proximity and territory that plays an important role in innovation creation and diffusion (Cuadrado-Roura, 2017) as well as potentially heightening the large, between-county differences and varying geographic patterns of mortality (Dwyer-Lindgren et al., 2016, 2018; El Bcheraoui et al., 2018; Krumholz, Normand, and Wang, 2018; O'Connor, Sedghi, Dhodapkar, Kane, and Gross, 2018) that impact a local community's health capital or stock of health.

Territorial capital is a budding, promising conceptual model which seeks to discern territorial asset's impact on their local economy. Camagni (2017) suggests that territorial capital is at the root of regional performance, and that local assets are found within spheres of economy and economic geography. Hutton's (2004) work also found that location provided important aspects to the New Economy[5]. Further, Florida (2014) found that there were important validations when mapping venture capital investments by zip code and area codes in showcasing technological development and entrepreneurial activity which then impacts areas through local transit systems, suburb walkability and infrastructure. This illustrates a multi-dimensional trend toward local investment (Katz and Wagner, 2014). As the U.S. economy becomes more reliant on advancing knowledge and innovation, the advancement of technologies in pharmaceuticals, medical devices, motor vehicles and aerospace, in addition to advancements in software, data processing

[5] The New Economy is generally referred to as being novel, high-growth segments of industry such as technology and biotechnology intensifying the migration from a manufacturing-based economy to a more service-oriented economy.

and other technology, will be key (Muro, Fikri and Andes, 2014). Thus, the development of innovation and the location of development are vitally linked.

2.6 Known Influences on Health Outcomes

Innovations within the health care industry such as medications, medical technology, biologics and pharmaceuticals can impact health (WHO, WIPS and WTO, 2012). However, research has shown that other health care industry determinants can also impact health. Non-medical factors may affect both the average of health outcomes and the distribution of health outcomes within separate communities (Shi and Johnson, 2013). These determinants can include distal political, legal, institutional and cultural factors that can affect health, and more proximate elements of socioeconomic status, physical environment, living and working conditions, family and social network, lifestyle behavior and demographics (Shi and Johnson, 2013). This is in contrast to the more commonly assumed factors of access and use of health care services which often have less impact than factors such as where we live, the state of the environment, genetics, income and education level and the relationships held between family and friends (WHO, 2019).

Socioeconomic status (SES) is regularly included in the analysis of the determinants of health and mortality (Cutler, Lleras-Muney, and Vogl, 2011). Such SES variables can include income, education, occupation, race and ethnicity among other variables and can exhibit similar associations with health (Cutler, Lleras-Muney, and Vogl, 2011). Therefore, indicators of SES would seem paramount when evaluating the impact on health outcomes. For a more in-depth discussion of the SES variables included in the study see Chapter 3.

There have been calls for research institutions and universities to maintain focus on the health concerns of society (World Health Organization, 2006). Further, world recognized, health focused organizations like the WHO as well as WIPO and WTO are promoting technological innovation as a significant factor toward improving the health and wellbeing of mankind (Ridley, 2010; WHO, WIPO and WTO, 2012). Without access to technological innovation, there cannot be a true public health benefit.

2.7 County Level Mortality Rates as a Measure of Health Outcomes

This study proposes to expand upon Gill's exploration of innovation and health outcomes by evaluating the relationship at the lowest known ecological level for which available public data is present. Its uniqueness lies in the fact that only a small selection of studies have evaluated innovation's effect on indicators of health and have only evaluated the relationship from United States Census data at the regional level (Gill, 2013). This paper strives to expand such analysis to the county level, evaluating the innovative capacity of the individual county and its relationship to indicators of health of the county as represented by mortality. In doing so, results could provide insights on the impact innovation may have on county-level mortality indicators.

The relationship between innovation and county health outcomes is essential in the facilitation and promotion of strong local economies. A strong body of work allowing public health science to evaluate "street-level" health outcomes and determinants of health is leading health outcome research to become much more locally focused (The Lancet Public Health, 2017). Recent studies evaluating major-cause of death differences (Dwyer-Lindgren et al., 2016), cancer disparity (O'Connor et al., 2018), infectious disease mortality (El Bcheraoui et al., 2018) substance abuse and intentional harm (Dwyer-Lindgren et al., 2018), cardiovascular disease (Patel et al., 2016) and Medicaid population outcomes (Krumholz et al., 2018) at the county level have highlighted the growing importance of granular evaluations of mortality and health outcomes. Common throughout are large, between-county differences, with differentiating geographic patterns based on cause of mortality. Referenced as possible mechanisms for such vast differences among counties are varying economic and socioeconomic determinants (Dwyer-Lindgren et al., 2016, 2018; El Bcheraoui et al., 2018; Krumholz et al., 2018; O'Connor et al., 2018) with distinct calls to improve socio-economic circumstances (Patel et al., 2016) which is an outcome said to be impacted by innovation (OECD, 2010; WHO, WIPS and WTO, 2012; WHO, 2019)

Dwyer-Lindgren et al. (2016) posit that very little is known regarding geographic patterns of mortality and the inequalities that underly causes of death. Braverman (2014) argues that the greatest fundamental impact on health lies in socio-economic factors. Whereas such economic conditions are unique to individual local economies (Camagni, 1985), innovation's impact and economic utility will be diverse between counties (Camagni, 1985; Cuadrado-Roura, 2017).

Further, researchers advocate for addressing the challenges associated with prioritizing technological advancement and bringing them into practice (Wild and Langer, 2008) as well as developing a better understanding of the relationship between innovation and public health (Moniruzzaman and Andersson, 2008; Law, Noland and Evans, 2011; WHO, WIPO and WTO, 2012). Therefore, an understanding of the broad impact of innovation is essential. Hughes (2011) reasons that innovation goes beyond its developmental focus and initial industry delivery, and that there are times when non-healthcare related technology has had an impact on population health (Greenberg, 2006). As such, local policy should take a holistic approach toward innovation to seek efficiencies in leu of continual governmental austerity by investing in a broader range of innovations outside of healthcare (Varey, 2011). This work seeks to evaluate innovative economic activity's relationship on geographic patterns of mortality.

2.8 Chapter 2 Summary

The seminal work of Grossman (1972, 2000) established the production of health and consumption of health care at the individual level. However, Mokyr's (1993) extended theory of household health production allows for the evaluation of innovation's impact on local public goods and the diffusion of best practices allowing for evaluation at the county level. Literature also suggests that evaluating the impact of innovation on population health should be a goal toward more positive health effects for all (WHO, 2013; OECD, 2010; WHO WIPS, WTO, 2012). The potential of an innovation impacting the health of a community can span both medical, as well as non-medical innovations. The impact implications from advancements in general innovation and human capital response will diversify levels of territorial capital (Camagni, 1985; Cuadrado-Roura, 2017). Previous exploratory research evaluating the relationship between innovation and health outcomes has been conducted at the regional level (Gill, 2012; 2013). The body of public health literature is rallying around locally focused evaluations as vast differences in geographic mortality rates have been found (Dwyer-Lindgren et al., 2016). Calls for evaluation and a better understanding of innovation's link to public health, few prior studies of said relationship, and a call for locally focused health research provide support for the planned evaluation of the proposed study.

CHAPTER 3: METHODOLOGY

This work builds on previous literature by analyzing the relationship between innovation and health outcomes at the county-level as represented by the mortality rate per 100,000. The choice to use mortality as the greater proxy for health outcomes is 1) in line with previous research and 2) due to the limited availability of consistent county-level health measures. Data on mortality are obtained for all 3,139 counties and county-equivalents in the United States[6]. The working data set includes data for all variables from 2010 to 2014.

In the benchmark estimation equation (8), the mortality rate per 100,000 people in county i in year t is the dependent variable, while the key independent variable of interest is innovative activity in county i in year t:

$$Mortality_{it} = \beta_0 + \beta_1 Innov_{it} + \beta_2 X_{it} + \varepsilon_{it} + \mu_t \tag{8}$$

X represents a vector of control variables, μ_t controls for time variant fixed effects, and ε_{it} is the normally distributed error term. The empirical prediction is that greater innovative activity will have an inverse effect on mortality at the county level. As such:

H_1: Innovation will have a significantly negative effect on county-level mortality rates.

[6] Within the United States, 48 states utilize the term county. Louisiana and Alaska refer equivalents as parishes and boroughs respectively (Counties, n.d.). For the purposes of the paper, all counties and county equivalents will be referred to as counties.

3.1 Variables and Data

3.1.1 Dependent Variable: Mortalities, Per County

County-level mortality data obtained from the Institute of Health Metrics and Evaluation (IHME) database contains annual estimates of per county mortality rates per 100,000 people drawn from death registration data from the National Vital Statistics System (NVSS). The specific mortality dataset used is unique in that the data applied a garbage code (non-specific cause of death codes) redistribution method in addition to small area estimation methods to death registration data from the NVSS to estimate annual county-level mortality rate per 100,000 persons for the included 24 death indicators. Through this process mortality rates were scaled along multiple dimensions including population, age and sex.

Using the IHME dataset overcomes multiple shortcomings that are traditionally present when utilizing mortality data. In the United States, mortality data is protected under the Health Insurance Portability and Accountability Act (HIPAA) of 1996. As a result, all health information and data used for research is required to be de-identified. When working with mortality data at the population level, data can be censored as a result of small amounts of mortality rates in order to protect confidentiality. The IHME data set utilizes a small area effect regression strategy to estimate mortality rates at all levels, circumventing the potential censoring issue of previous mortality data sets. As mentioned previously, the IHME data set also uses a garbage code redistribution technique, which reclassifies the original intermediate or immediate cause of death code to reflect the underlying cause of death (e.g., cardiovascular disease) (Dwyer-Lindgren et al., 2016). This strategy creates a much more reliable and accurate mortality dataset whereas, types of mortality are more properly redistributed via the underlying cause of death and accurately estimates counties with populations within the lower percentiles.

The use of county-level mortality rates as a proxy for health outcomes mirrors the approach used by Studnickie et al. (2007) and Honore et al. (2011) as well as follows Dwyer-Lindgren et al. (2016, 2018) and El Bcheraoui et al. (2018). A strong body of literature has analyzed the relationship between poverty and types of mortality (Do, Wang, and Elliott, 2013; Fiscella and Franks, 1997; Hendryx, 2011; Messner, Raffalovich, and Sutton, 2010; Waitzman and Smith, 1998) as well as illustrating economic innovation's ability to lower poverty rates (Cooter, 2005). However, few studies have directly analyzed the relationship.

Data on all-cause mortality rates are available for the overall population, as well as for deaths related to communicable, maternal, neonatal, and nutritional diseases, HIV/AIDS and tuberculosis, diarrhea, lower respiratory, and other common infectious diseases, neglected topical diseases and malaria, maternal disorders, neonatal disorders, nutritional deficiencies, other communicable, maternal, neonatal, and nutritional diseases, non-communicable diseases, neoplasm, cardiovascular diseases, chronic respiratory diseases, cirrhosis and other chronic liver diseases, digestive diseases, neurological disorders, mental and substance use disorders, diabetes, urogenital, blood, and endocrine diseases, musculoskeletal disorders, other non-communicable diseases, injuries, transport injuries, unintentional injuries, self-harm and interpersonal violence, and forces of nature, war, and legal intervention.

The average number of actual deaths per county for the panel data set was 777.57 deaths, with a minimum number of deaths per count registering 0.37 and a maximum number of deaths registering 64,464.16 deaths. As the raw amount of deaths is strongly positively skewed, the use of mortality rate per 100,000 persons is used which better normalizes the data set. Further, to address a slight positive skew to the mortality rate per 100,000 data set, the logarithmic transformation was taken of the mortality rate and each individual type mortality rate to assist in normalizing the distribution of the dependent variable.

3.1.2 Independent Variable of Interest: Innovation

R&D expenditures, number of patent inventions, or an innovative output that could be measured directly have historically been the proliferated measures of technological change. Some past scholars have argued that while patent counts equate to an adequate indicator of technological creation, it lacks the ability to define potential economic value of those technologies (Hall et al., 2001). Griliches (1979) and Pakes and Griliches (1980) go on to state that "patents are a flawed measure (of innovative output) particularly since not all new innovations are patented and since patents differ greatly in their economic impact."

However, Acs, Anselin and Varga (2002) found when comparing actual patent count collected from the United States Patent and Trademark Office (USPTO) and the United States (U.S.) Small Business Association innovation county data at the U.S. metropolitan statistical area (MSA) level that the number of patents acts as a reliable proxy when measuring innovative activity. Thus, the number of patents per county was drawn from the USPTO, PatentsView database.

Further, previous research evaluating economic growth indicators on mortality have experimented with lagging to analyze time effect. Tapia Granados (2012) found a potential impact in economic indicators of growth as represented by GDP on age specific mortality rates in England and Wales. Tapia Granados lagged economic growth indicators at 0, 1, 2, 3 and 4 years finding that at 0 lags the economic growth indicator of GDP had the most statistically significant impact when mortality indicators were regressed on GDP with significance tapering off after short-lag effects. Tapia Granados illustrate that statistical significance of lagging economic growth indicators wanes after short-lag, whereas lag-zero showed the strongest relationship (Tapia Granados, 2012). In an effort to quantitatively prove the theoretical position of reverse causation of patent life on firm research and development expenditures Baraldi, Cantabene, and Perani (2014) lag patents by one and two years. However, their finding suggests that any lag effect found is impacted more by the type of industries than by time effect. Thus, to ensure capturing any temporal effects, patents will be zero lagged as well as adding one, two and three-year lags. Based on previous study, the expectation is that county-level indicators of innovation will be more negatively and significantly related to county-level mortality rates within year zero, than that of any year lag.

Since counties with larger populations are more likely to both yield more patents and have a greater mortality rate, it is important to look at these factors as per capita measures so to remove scale effects and truly isolate the relationship innovation has on mortality. This variable is continuous and positively skewed. As a result, the logarithm of patents per capita was taken to address the positive skew of the data. Being that roughly 71% (n = 11,095) of the observations within the panel data set were equal to 0 patents per capita, a constant was added before the logarithmic transformation of the independent variable.

3.1.3 Control Variables

Education:

Past literature has shown that the level of education can influence how healthy an individual is. Glied and Lleras-Muney (2008) found that as people pursue more education, the greater the advantage of preventing those diseases that see more health-related innovation.

They also find evidence that different levels of socio-economic status are, in part, a result from the association between education and innovation. Additionally, Yang et al. (2012) confirmed Link and Phelan’s (1995) argument that social conditions, at a county level are a fundamental determinant of health by finding that higher socioeconomic status equated to lower mortality rates per county. As such, education is separated from the measure of innovation to both confirm previous literature’s finding of the relationship of education on health outcomes, as well as to isolate the innovative prowess of the county separate from level of education.

The percentage of the population 25 years or older with a bachelor’s degree is included as a control variable. The motivation for education variable is twofold. First, confirmation of Glied and Lleras-Muney (2008) findings that greater concentrations of education, lead to more favorable health outcomes at the population level. Second, controlling for the impact of education and its role in innovation at the county level. The education indicator was collected from the United States Census Bureau's American Community Survey (ACS).

Inequality:

There have been other studies showcasing statistical relevance to the relationship between inequality and associated mortalities at the county level (Brodish, Massing, and Tryoler, 2000; Massing et al., 2004; Shi et al., 2005). A selection of literature has focused on how differing levels of inequality are related to mortality (McLaughling and Stokes, 2002; McLaughlin, Stokes, and Nonyama, 2001) while Yang et al. (2012) investigated the effect of inequality on varying levels of mortality. Studies have been able to provide insight on the relationship between inequality and mortality, finding inequality to influence mortality as mortality rates increase as well as not remaining constant over the distribution of mortality (James and Cossman, 2006; Cossman, Cossman, Cosby, and Reavis, 2008).

There are a number of commonly used measures that represent inequality including the variation coefficient, the Theil's index and the Gini index (Allison, 1978). Their impacts on health and mortality are readily recognized (Kawachi and Kennedy, 1997). For this study, the Gini index is used due to its availability. The U.S. Census defines the Gini Index as:

> "… a summary measure of income inequality. The Gini coefficient incorporates the detailed shares data into a single statistic, which summarizes the dispersion of income across the entire income distribution. The Gini coefficient ranges from 0,

> indicating perfect equality (where everyone receives an equal share), to 1, perfect inequality (where only one recipient or group of recipients receives all the income). The Gini is based on the difference between the Lorenz curve (the observed cumulative income distribution) and the notion of a perfectly equal income distribution" (U.S. Department of Commerce, 2016).

Data on inequality were collected from the United States Census Bureau's American Community Survey (ACS).

Socio-Economic Status

In addition to education, financial resources, race and ethnicity and how rural the environment is are not only associated with inequality but would intuitively have a relationship with health outcomes and thus mortality rates.

Measures of socio-economic status (SES) have been a regularity in the literature when evaluating determinants of health and mortality. Socio-economic variables vary but routinely include elements such as income, education, occupation, race, and ethnicity. Literature agrees that "a broader underlying dimension of social stratification or social ordering is the potent factor" (Adler et al. 1994: 15) impacting health outcomes and SES act as indicators of the underlying dimension. Yet Link and Phelan (1995) suggests that SES is comprised of multiple dimensions, not just a singular dimension, and thus impact health in multiple ways.

Sampson, Raudenbush, and Earls (1997) and Yang et al., (2012) operationalize a collection of variables from the U.S. Census to represent socio-economic status. Following suit, this study includes the percentage of the population that are unemployed and income per capita within the benchmark equation as indicators of socioeconomic status. Many public health researchers have suggested that the causal pathway of income SES runs from income to health (Cutler, Lleras-Muney and Vogl, 2011). Further, Wilkinson proclaims that income is "one of the most profound influences on mortality" (Wilkinson, 1990: 412). While not necessarily the only factor influencing mortality, income most certainly should be employed as a control of SES for the presented study. The log of income per capita is included to correct a positive skew of the original data.

Additional measures of socio-economic status included for robustness include the percentage of the population employed in management, business, science and art, the percentage of families with incomes over 75,000 dollars, the poverty rate, the percentage of persons receiving cash assistance and/or supplemental security income and the percentage of female-headed families with children. Included indicators all were taken from the United States Census Bureau's American Community Survey (ACS).

Race and Ethnicity:

As discussed previously, race and ethnicity differences are recognized to be of significance when evaluating SES strata and their influence on health. Unfortunately, there continues to be disparity between black-white population in the United States even after accounting for differences in education and income (Cutler, Lleras-Muney, and Vogl, 2011). Other explanations for such differences have included racial bias, difficulty in provider-client communication, residential segregation, and historical legacy (Howard et al., 2000).

To measure race and ethnicity, two groups drawn from the U.S. Census are included within the proposed study: County-level percentage of Hispanic and Latino and Black and African American. Following Yang et al. (2012), non-Hispanic white populations will be omitted to prevent collinearity issues. Data on race and ethnicity were collected from the from United States Census Bureau's American Community Survey (ACS).

Rurality:

The literature does not present an agreement on how best to measure how rural a county is (rurality). However, there have been approaches that have focused on multiple aspects of rurality that are established (Brodish et al., 2000; McLaughlin et al., 2001, 2007) and have been operationalized by Yang et al., (2012). What is discussed is that rural or sparsely populated areas impact health because of food access, school location, public transportation and social services (Macintyre, Ellaway and Cummins, 2002). Further, Brodish et al.'s (2000) stratified regression analyses on all 100 North Carolina counties found that all-cause mortality was significantly related to inequality, but the relationship depended upon how rural the county was.

For this work, the percentage of the population employed in agriculture, forestry and fishing will constitute the benchmark equation's measure of rurality. Additional measures of the rurality of a county considered for robustness consist of the percentage of workers commuting by public transportation, the percentage of workers traveling over an hour to work and the percentage of workers who work outside their county of residence.

Rural indicators all were taken from the United States Census Bureau's American Community Survey (ACS).

Due to the potentiality of unobserved variables that may evolve over time but are constant across entities, time fixed effects are utilized in order to control for the fact that every county repeats five times in the working data set. To do this, a year dummy variable was created and inserted into the regression equation. The model that includes time variant fixed effects eliminates bias from unobserved variable that change over time but remain constant across counties while also controlling for factors that differ across counties but are constant over the duration of the working data set.

3.2 Assumptions of The Linear Model

The classical linear regression model or ordinary least squares (OLS) model has several different conditions that should be met to ensure that there is confidence in the findings being generalizable.

The first assumption of the OLS model requires that the dependent variable *y* be a linear combination of the exploratory variables *X* and the error term ε, such as

$$y = X\beta + \varepsilon \tag{9}$$

as well as their combined effect being the best description of the explanatory variables sum.

$$y_{it} = \beta_0 + \beta_1 x_{it1} + \beta_2 x_{it2} + \cdots + \varepsilon_{it} \tag{10}$$

Where equation eight and nine illustrate a model that is both linear in parameters and its variables[7]. In order for the OLS model to estimate a relationship appropriately, the

[7] Note that equation three and four both illustrate the same model, just within a different notation.

specified model must be linear in its parameters. Whereas, if the dependent variable and independent variable are nonlinear, it will be impossible to estimate the β coefficient in a meaningful way.

This is not to say that the first assumption also requires the variables to be linear within the proposed model. The OLS model should produce meaningful estimations of the β coefficient. Using the OLS method allows for the estimation model that has linear parameters, even if variables within the estimation model are nonlinear. It is also an aspiration that every model estimated with the OLS model should attempt to contain all relevant explanatory variables. Should relevant variables be missing, it gives rise to omitted variable bias within the regression analysis.

A second assumption of the OLS model assumes for any of the included observations, the residual terms should be uncorrelated. More generally, the researcher is striving for each observation's error term to be independent or the assumption of independence. For the OLS model, violating the second assumption would provide non optimal estimates. To check for autocorrelation, a Durbin-Watson test can be run to test for serial correlation between errors. Also, models with more than one explanatory variable should ensure that there is no perfect linear relationship between two or more of said variables. The evaluation of a pairwise correlations can be consultant to ensure no perfect multicollinearity.

A third assumption of the OLS model expects the variance of the residual terms to be constant, or more commonly referred to as homoscedasticity. Violating the third assumption may invalidate the confidence intervals and significance tests of the regression analysis but can be overcome using weighted least squares regression where each case is weighted by a function of its variance (Field, 2013).

A fourth assumption is that the residuals of the OLS model are random and normally distributed with a mean of 0 (Field, 2013). That is that the difference between the model and observed data are most frequently zero or close to zero, and any difference much greater than zero are atypical (Field, 2013). This should not be confused with the expectation that all exploratory variables must be normally distributed. While lack of normality in small sample sizes may invalidate confidence intervals and significance testing, large sample sizes will adhere to the central limit theorem. However, bootstrapping confidence intervals will satisfy the fourth assumption.

CHAPTER 4: RESULTS

4.1 Descriptive Statistics

The mean values and standard deviations for all the variables (excluding sub mortalities) employed in the benchmark and robustness checks are presented in Table 1. Per county and year in the sample, the all-cause mortality rate[8] ranges from 323.29 to 1,660.67 with an average mortality rate of 870.11 per 100,000 amongst all U.S. counties in the sample period.

[Table 1]

Table 1: Descriptive Statistics (2010 - 2014)

	Obs.	Mean	Std. Dev.	Min	Max
All-Cause Mortality Rate Per 100,000	15,694	870.11	145.53	323.29	1,660.65
Patent Per Capita	15,694	0.0005	0.0054	0.0	0.2077
Income Per Capita	15,694	$23,338.86	$5,561.53	$8,200.00	$64,381
Inequality (Gini Index)	15,694	0.44	0.04	0.20	0.67
% Population Unemployed	15,694	8.37	3.68	0	30.90
% Population 25 Years or Older with a Bechelor Degree	15,694	12.86	5.37	0	42.2
% Population Employed in agriculture, forestry and fishing	15,694	6.94	7.49	0	58.90
% Population Hispanic or Latino	15,694	8.27	13.19	0	98.40
% Population Black or Aftican American	15,694	8.84	14.47	0	86.20
% Population that commutes via public transportation	15,694	0.95	2.97	0	61.50
% Population that Work Outside of County	15,694	29.64	17.78	0	86.10
% Population that has a 60 minute or greater commute to work	15,694	7.42	4.54	0	33.00
% Population Employed in management, business, science and art	15,694	30.51	6.45	6.20	69.2
% Families with a Household Income of $75,000 or more	15,694	28.91	13.49	3.90	177.90
% Families with a Female Head of Household	15,646	43.83	14.38	0	100
% Population Living Below Poverty Level	15,694	11.88	5.57	0	44.40
% Population Receive Cash / SSI Assistance	15,634	30.82	14.06	0	100
Population	15,694	98,260.56	316,962.90	41	9,974,203

The IHME via NVSS data provide several different sub-mortality rates that are included within the primary all-cause mortalities per county. This constitutes the dependent variable for the proposed study. The death[9] rate due to communicable,

[8] All results are reported as the number of deaths divided by the population of the county i for year t times 100,000 persons.

[9] For the purposes of this dissertation the term mortality(s) and death(s) are used interchangeably.

maternal, neonatal, and nutritional diseases, HIV/AIDS and Tuberculosis, Diarrhea, lower respiratory, and other common infectious diseases, neglected topical diseases and malaria, maternal disorders, neonatal disorders, nutritional deficiencies, other communicable, maternal, neonatal, and nutritional diseases, non-communicable diseases, neoplasm, cardiovascular diseases, chronic respiratory diseases, cirrhosis and other chronic liver diseases, digestive diseases, neurological disorders, mental and substance use disorders, diabetes, urogenital, blood, and endocrine diseases, musculoskeletal disorders, other non-communicable diseases, injuries, transport injuries, unintentional injuries, self-harm and interpersonal violence, and forces of nature, war, and legal intervention are also drawn from the IHME database. Table 2 shows mean values and standard deviations for each individual type of mortality rate by county and year in the sample panel of data.

[Table 2]

Table 2: Individual Mortality Rate per 100,000 Per County Descriptive Statistics (2010 - 2014)	Obs.	Mean	Std. Dev.	Min	Max
All-Cause Mortality	15,694	870.11	145.53	323.29	1,660.65
Communicable, maternal, neonatal, and nutritinal disease	15,694	41.53	12.41	15.14	144.04
HIV/AIDS and tuberculosis	15,694	1.61	2.07	0.22	67.78
Diarrhea, lower respiratory, and other common infectious Disease	15,694	33.09	10.10	8.61	90.83
Neglected tropical disease and malaria	15,694	0.08	0.06	0.02	0.78
Maternal disorders	15,694	0.37	0.15	0.10	1.59
Nutritional deficiencies	15,694	1.60	0.67	0.11	7.28
Other communicable, maternal, neonatal, and nutritional disease	15,694	1.25	0.31	0.68	7.15
Non-communicable disease	15,694	758.82	120.99	247.44	1449.21
Neoplasms	15,694	204.53	30.55	70.71	503.05
Cardiovascular disease	15,694	276.53	57.36	76.98	552.51
Chronic respiratory disease	15,694	62.84	16.06	14.27	160.97
Cirrhosis and other chronic liver disease	15,694	18.26	7.58	6.69	133.15
Digestive disease	15,694	16.24	2.41	7.90	31.10
Neurological disorders	15,694	95.01	21.42	22.23	212.10
Mental and substance use disorders	15,694	12.88	6.58	2.99	73.15
Diabetes, urogenital, blood, and endocrine disease	15,694	62.55	17.50	11.55	177.03
Musculoskeletal disorders	15,694	3.22	0.76	1.28	10.57
Other non-communicable disease	15,694	6.76	1.47	2.90	15.60
Injuries	15,694	69.49	18.59	24.20	238.75
Transport injuries	15,694	23.34	9.19	4.52	94.93
Unintentional injuries	15,694	24.18	5.25	7.62	76.29
Self-harm and interpersonal violence	15,694	21.66	6.98	7.34	85.93
Forces of nature, war, and legal intervention	15,694	0.31	0.71	0.01	39.39

Table 3 provides a brief summary of the key variables used in the empirical analysis, their transformations and sources.

[Table 3]

Table 3: Benchmark Equation Variable Descriptions

Variable (Name)	Measure	Transformation	Source
Mortality(s)	Mortality Rate per 100,000 per-county	Logged.	Institute of Health Metrics and Evaluation (IHME)
Innovation	Patent count per capita per-county	Constant of 1 added and then Logged.	United States Patent and Trademark Office PatentsView Database
Income	Household income per capita per-county	Logged.	United States Census Bureau American Community Survey
Inequality	Gini index per-county	None	United States Census Bureau American Community Survey
Socio-Economic Status	% of the population unemployed	None	United States Census Bureau American Community Survey
Education	% population 25 years or older with a bachelor degree	None	United States Census Bureau American Community Survey
Rurality	% population employed in agriculture, forestry and fishing	None	United States Census Bureau American Community Survey
Race and Ethnicity	% of Hispanic and Latino	None	United States Census Bureau American Community Survey
Race and Ethnicity	% of black and African American	None	United States Census Bureau American Community Survey

Note: Additional control variables include % of the population that commutes via public transportation; % of the population that are employed and commute out of their county of residence; %e of population that has a sixty minute commute or longer to work; % of the population that is employed in management, sciences and art; % of families with a household income of $75,000 a year or more; % of families with a female head of household; % of the population that lives below the poverty line; % of the population who receive cash and/or supplemental security income. All blanks left in to ensure mitigation of selection bias. All 0 values converted to 1 for natural log transformation.

The variables presented are included in the proposed model based on theory and precedence establish through prior study. All regressions include year fixed effects.

The working data set measures 3,139 counties or county equivalents, year over year from 2010 to 2014. Of those 3,139 counties, an average of 28.8% of counties are actively innovative as represented by a patent being assigned to that specific county in year t. From 2010 to 2014 there are 4,599 counties who have an average patent per capita rate of 0.0016. In terms of actual assigned patents, the average amount of patents for an actively innovative county over the period considered was 159.8 patents with the subset of innovative counties having a minimum of 1 patent in a year and a maximum of 9,107 patents.

[Figure 1]

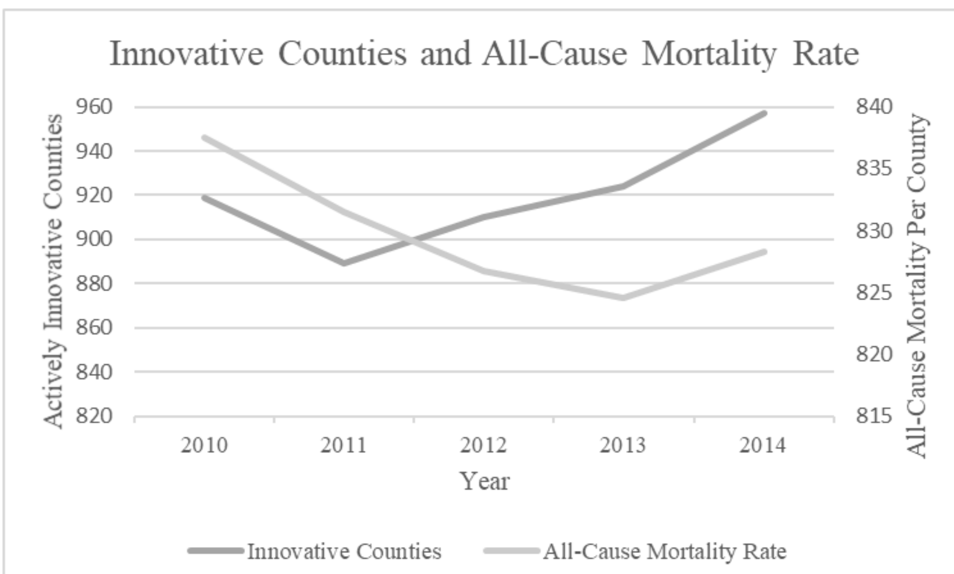


Figure 1 graphically depicts the number of counties that are actively innovating each year and the mortality rate concurrently over the duration of the data set. After a dip in actively innovating counties in 2011, there has been a steady increase in the number of innovative counties since then. With exception to the slight increase in the mortality rate from 2013 to 2014, Figure 1 shows the potential of the relationship between innovative activity and the mortality rate within those innovative counties.

When mapping the mortality rate per year, there is a general trend for deaths to be decreasing during the studied period. Figure 1 illustrates a general divergence between the number of counties who are actively innovating and the mortality rate within those innovating counties.

As such, a pairwise correlation seeks to further analyze the relationships among the proposed variables. The correlations for all variables (excluding sub mortalities) can be found in Table 4.

[Table 4]

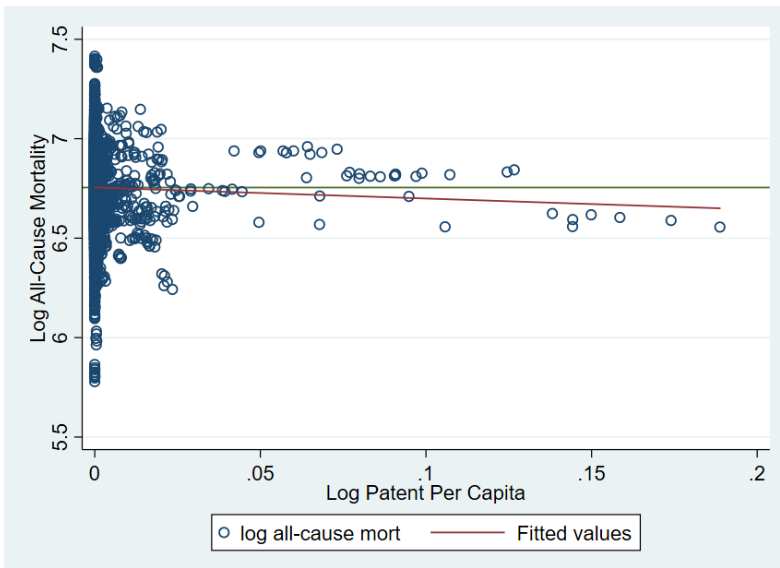
Table 4: Pairwise Correlation Table

	1	2	3	4	5	6	7	8	9
1. All-Cause Mortality per 100,000	---								
2. Patent Per Capita	-0.154***	---							
3. Income Per Capita	-0.617***	0.234***	---						
4. Inequality (Gini Index)	0.262***	0.093***	-0.086***	---					
5. % Population Unemployed	0.468***	0.004	-0.410***	0.280***	---				
6. % Population 25 Years or Older with a Bechelor Degree	-0.626***	0.163***	0.779***	0.012	-0.357***	---			
7. % Population Employed in Agriculture, Forestry and Fishing	-0.100***	-0.116***	-0.124***	-0.055***	-0.336***	-0.143***	---		
8. % Population Hispanic or Latino	-0.156***	0.078***	-0.043***	0.121***	0.002	0.023**	0.193***	---	
9. % Population Black or Aftican American	0.390***	0.015	-0.240***	0.372***	0.433***	-0.144***	-0.205***	-0.108***	---

Note: N = 15,694, ***, **, and * = 0.1%, 1%, and 5% significance levels, respectively.

Table 4 shows that patents per capita is significantly related with the all-cause mortality rate at a per county level, $r = -0.15$, $p < 0.001$. All benchmark controls were found to be significantly related to mortality as well. When analyzing the specific relationship between the patent amount and the mortality rate, we can see in Figure 2 a relationship that becomes progressively more negative, year over year.

[Figure 2]



The pattern of the data shown in Figure 2 confirms that a negative relationship exists between the death rate per county and patents per capita: so, the greater number of patents per capita, per county, the more likely that rate of mortality is to decrease. The scatter plot shows the line of best fit for the data. The mean is represented by the green line, showing the regression line to be noticeably different.

4.2 Benchmark Results

The goal of the empirical work is to estimate β_1 from equation one to measure the impact of county-level innovation on the all-cause mortality rate. The empirical model includes demographic and economic variables as controls. All empirical models include year fixed effects to control for year-specific influences driving differences in the mortality rate.

[Table 5]

Table 5: Benchmark Results: *Dependent Variable = Mortality Rate Per 100,000 Per County (2010-2014)*

	OLS (i)	OLS (ii)
Patents per capita	-0.557***	-0.557**
	(0.084)	(0.191)
Income Per Capita	-0.199***	-0.199***
	(0.009)	(0.046)
Inequality (Gini Index)	0.741***	0.741***
	(0.033)	(0.122)
% Population Unemployed	0.002***	0.002
	(0.000)	(0.002)
% Population 25 Years or Older with a Bechelor Degree	-0.013***	-0.013***
	(0.000)	(0.001)
% Population Employed in agriculture, forestry and fishing	-0.003***	-0.003*
	(0.000)	(0.001)
% Population Hispanic or Latino	-0.002***	-0.002***
	(0.000)	(0.000)
% Population Black or Aftican American	0.001***	0.001**
	(0.000)	(0.000)
R Squared	.585	.585
Year fixed effects	yes	yes
Standard Errors	Robust	Clustered
Obs.	15,694	15,694

Note: Standard errors are in parenthesis. ***, **, and * = 0.1%, 1%, and 5% significance levels, respectively. The natual log tranformation of all-cause mortality, patents per capita and income per capita were used in the regression computations.

Table 5 shows that county-level patenting activity per person, after controlling for recognized economic and socio-economic indicators effecting mortality, lowers the incidence rate of mortality per county year over year. Column i displays the benchmark regression and indicates that a one percent increase in patent per capita decreases the mortality rate by 0.56%. Column (ii) shows when clustering errors at the state level that the statistical strength of the relationship falls to the 1% level but still holds a strong elastic relationship between patent per capita and mortalities. The change in standard errors when clustering at the state level is representative of a state level effect that may have an impact on innovation at the local level. The estimates in Table 5 are therefore consistent with H1 that innovative activity, as represented by patenting activity, does impact all-cause mortality rates at the county level.

Let's briefly consider the impact of included control variables on mortality as demonstrated by column (ii). The log of income per capita has a negative and highly statistically significant effect on the death rate per county, with a one percent increase in income per capita decreasing mortality by 0.20%.

The effect of inequality[10] on rate of deaths per county has a statistically significant impact on mortality rates where a one unit increase in inequality equates to a 74% increase in mortality rates. As inequality is measured by the Gini coefficient which is a measure of 0 to 1. Zero being perfect equality and 1 being perfect inequality, a one unit increase in mortality would hypothetically equate to a shift to perfect inequality. Additionally, the percentage of the population that is unemployed holds a positive relationship with mortality, but was not statistically significant.

In line with previous research, the percentage of the population 25 years or older with a bachelor's degree was negative and highly statistically significant. This confirms that as populations become more educated their life expectancy increases, thus effecting a

[10] Inequality is represented by the Gini Index. The Gini Index is defined as a ratio between 0 and 1 where the numerator is the area between the Lorenz curve of the household income distribution and the uniform distribution line and the denominator is the area under the uniform distribution line. Thus, the smaller the Gini coefficient the more evenly distributed household income.

decrease in the mortality rate per county. This is illustrated by the mortality rate decreasing by a percent when the percentage of population 25 years or older with a bachelor's degree increases by one percentage point.

The coefficient for the percentage of the population that are employed in agriculture, forestry and fishing, the primary control variable to measure how rural a county is, was negative and statistically significant at the 5% level, indicating that the more rural the county (as represented by a unit increase in those employed in agriculture, forestry and fishing), the mortality rates tends to decrease by 0.26% year over year.

The demographic variables included in the benchmark equation included the percentage of Hispanic or Latino and Black or African American per county. The percentage of Hispanic or Latino population was found to be negative and highly statistically significant whereas a unit change in the percentage of population that is Hispanic or Latino decreases the rate of mortality by 0.18%. Separately, the percentage of black or African American population per county was positively related to mortality whereas, as the percentage of black or African American population increases, so does the rate of mortality by 0.14%.

The inclusion of the proposed control variables was developed based on theory and prior research. However, to ensure the validity of the model and proposed selection of variables, review of the akaike information criterion (AIC) was conducted. When regressing the all-cause mortality rate onto patents per capita, the initial AIC registered 20,863.60. As each individual control was added to the model, we find the AIC continues to decrease, inevitably ending with the full benchmark model AIC registering -25,131.25. Table 6 shows the AIC change per variable addition.

[Table 6]

Table 6: Akaike Information Criterion Benchmark Equation	AIC
Patents per capita	20,863.60
ln Income Per Capita	-19,914.56
Inequality (Gini Index)	-20,466.08
% Population Unemployed	-21,197.51
% Population 25 Years or Older with a Bechelor Degree	-23,275.27.
% Population Employed in agriculture, forestry and fishing	-23,973.75
% Population Hispanic or Latino	-24,740.31
% Population Black or Aftican American	-25,131.25

Note: Each additional explanatory variable was added in a stepwise progression while also controlling for year fixed effects and clustered standard errors. Whereas the final AIC metric -25,131.25 constitutes the full benchmark equation.

As additional explanatory variables are added to the model, the value of AIC continues to decrease. This communicates that the fit of the benchmark model improves as variables are added to the equation.

When evaluating for multicollinearity, first evaluating the correlation matrix of predictor variables, there are none that correlate very highly (correlations above .80 to .90 (Field, 2013)). An additional analysis would be to evaluate the variance inflation factor (VIF). VIF indicates whether an independent variable has a strong linear relationship with other Independent variables. Adhering to Bowerman and O'Connell (1990) recommendations, no VIF registered greater than 10 (the log of income per capita registered a VIF of 2.96 and the percentage of population 25 years or older with a bachelor's degree registered a VIF of 2.61 respectively). Additionally, the average VIF score for the benchmark model registered 1.70, suggesting the benchmark regression may be free of bias (Bowerman and O'Connell, 1990).

Heteroscedasticity

A Breusch-Pagan test showed heteroscedasticity may be an issue ($\chi^2 = 77.66, p \leq .05$) thus the null hypothesis assuming equal variance among the residuals is rejected. In violating the assumption of homoscedasticity, my interpretation of the confidence intervals and significance level comes into question as the standard errors are biased in the presence of heteroscedasticity. However, estimates of each β are still valid but sub-optimal (Field, 2013).

As equal variance among the residuals has been rejected, we have initially violated the assumption of homoscedasticity. This suggests that because $t = \frac{\beta}{s.e.}$ and because the standard errors are biased, it impacts the confidence interval, t-statistic and significance level of the analysis. An alternative method for reducing the potential effects of heteroscedasticity is to employ White-Huber standard errors, or robust standard errors, estimator of OLS estimates. Using robust standard errors, the regression model derives β in the same way by minimizing the sum of squared errors. The use of robust standard errors does not change the coefficient estimates, but because of the change to standard errors, the test statistics will give more accurate probability values. Robust standard errors relax the assumption that the errors are identically distributed.

Additionally, the use of clustered standard errors is useful as there is most likely different covariance structures within the data. There is a natural assumption that by analyzing all counties in the United States, there may be some unknown correlation between counties that reside in the same state. This suggests that there may be a state level influence effecting innovative activity at the county level. Clustered standard error estimates seek to converge to the true standard error as the number of clusters approaches infinity, not the number of observations (Nichols and Schaffer, 2007). Further, fifty clusters are similar enough to infinity for accurate inference (Kezdi, 2003). Thus, clustering standard errors at the state level should remediate violating the assumption of homoscedasticity by relaxing the assumption that the error terms are independent of each other.

These two remedial measures address issues of heteroscedasticity by controlling for robust and or clustered standard errors. In all, the results provided in Table 5 should reflect unbiased standard errors and connect levels of statistical significance.

4.3 Individual Mortalities

When regressing each individual type of mortality rate onto the patent per capita variable, several individual mortality types are significantly impacted by the patent per capita variable. As the mortality rate and patents per capita are in natural logarithmic form, the resulting estimates are elasticities at the death rate margin. Each empirical model includes economic and socioeconomic variables as controls in line with the benchmark equation. Standard errors clustered at the state level were employed for all the separate specifications. All empirical models include year fixed effects.

All the individual type of mortality rate coefficients presented in Table 7 are all negative and significant. Omitted from the table were individual mortality types that did not significantly respond to the patent per capita variable at the 5% level or stronger.[11] A 1% increase in patents per capita decreases the death rate attributed to neglected and tropical diseases (NTDs) and malaria by 2.77%; the mortality rate related to non-communicable diseases decreases by 0.46% ; cirrhosis and other chronic liver deaths due to these diseases decrease by 1.18% and the death rate due to mental and substance use disorders fall by 2.48%. These results suggest that a tool to be harnessed in addressing mortality at the county-level could be local policy incentives that foster innovative economic activity.

Hotez (2016) found that neglected tropical diseases not only occur in the settings of poverty, but also are a major cause of poverty among the bottom billion. Neglected tropical diseases reinforce poverty because of their long term and deleterious effects on child development, intelligence and cognition (Hotez, 2016). Hotez suggests that neglected tropical diseases are not rare diseases in the United States but rather prevalent in settings of poverty. Such diseases include the likes of toxocariasis, cysticercosis, chagas disease and toxoplasmosis. For example, in the case of toxocariasis, patient conditions include neurologic and psychiatric symptoms that include cognitive delays, epilepsy and ocular manifestations in children and pulmonary conditions that include diminished lung function asthma in adults (Hotez, 2016).

My analysis suggests that economic innovation could have an impact on neglected tropical disease mortality rates. This may be facilitated through innovations

[11] The specific mortalities that were not significant include communicable, maternal, neonatal, and nutritional diseases; HIV/Aids and tuberculosis; Diarrhea, lower respiratory, and other common infectious diseases; maternal disorders; neonatal disorders; nutritional deficiencies; other non-communicable, maternal, neonatal, and nutritional diseases; neoplasms; cardiovascular diseases; chronic respiratory diseases; digestive diseases; neurological disorders; diabetes, urogenital, blood, and endocrine diseases; unintentional injuries.

such as through physical commodities like footwear or through agriculture and animal control practices and recreational application through urban infrastructure and built environment. Medically, local research and development of treatment may also increase awareness of NTD's (Weng, Chen, and Wang, 2018) as well as its preventative impact (Santos-Gandelman & Machado-Silva, 2019), motivating constituents to both seek testing or treatment. Further, innovation may affect NTDs through the pathway of raising economic conditions such that the poverty level of the county is impacted in line with Hotez's (2016) statement that economic development and urbanization can strongly help to reduce the prevalence of NTDs.

Additionally, it is understood that that the clustering of economic activity and innovation can better facilitate face-to-face interaction as well as shortening interaction distances amongst actors (Feldman and Florida, 1994), these social interactions have been shown to change specific neuronal circuits that control cravings and relapse (Venniro et al., 2018) behaviors that are related to addiction. Innovations that seek to effect everyone's wellbeing, address socioeconomic factors that affect mental health, and empathetic discourse and ability can have an impact on mental health status (Nilekani, 2017). These can include leveraging e-health to digitally deliver mental health screenings in mass to better predict and prevent mental health issues and events as well as the issuance of self-help tools to better self-regulate (Nilekani, 2017).

Also, innovative activity has been shown to drive employment generation (North and Smallbone, 2000) which may impact abuse and mental health by providing more opportunity for higher work levels which can adversely impact abuse behavior (Zuvekas and Hill, 2000). The death rate because of cirrhosis and chronic liver disease through alcohol abuse and mortalities associated with a mental illness or substance abuse may decrease as result.

Additionally, a 1% increase in patents per capita decreased the musculoskeletal disorders death rate by 1.53% and other non-communicable disease rate decrease by 0.87%. The impact on the general injury mortality rate falls by 1.49% while the transportation injury mortality rate decreases by 2.22%; the self-harm and interpersonal violence rate decreases by 1.85%; and the mortality rate resulting from forces of nature, war, and legal intervention falls by 3.36%.

These results are interesting in that with the presence of economic innovation, the general injury mortality rate falls but the death rate of road injury or other transportation injuries decrease by another 0.73%. This may be attributable to the documented congruent clustering of economic activity and innovation (Feldman and Florida, 1994) in association with the movement for more walkable communities and its impact on health (Doyle, Kelly-Schwartz, Schlossberg, and Stockard, 2006). Potentially resulting in less motor vehicular use and as a result, transportation related mortality. Also, intriguing is the relative decrease in mortality because of self-harm and interpersonal violence and forces of nature, war, and legal intervention. While forces of nature are seemingly outside of human control, those counties that buoy innovative activity through policy directives may well be impacting mortalities that result from suicide, domestic violence and law enforcement activity.

An increasingly interconnected society through innovations in mobile and digital technologies, may stymie those desires to commit crime. Further, advancements in sensor technologies may be improving information about criminal behavior and predictive abilities of law enforcement before lethal force is required. From a population perspective, innovative activity may be increasing economic activity and decreasing material hardship through increasing employment, the standard of living (Blane, 1990) and expanse of social relationships and interaction (Holt-Lunstad, Smith, and Layton, 2010).

[Table 7]

Table 7: Results by Type of Mortality: *Dependent Variable = Individual Mortality Rate Per 100,000 Per County (2010-2014)*

	All-cause mortality (benchmark results)	Neglected tropical diseases and malaria	Non-communicable diseases	Cirrhosis and other chronic liver diseases	Mental and substance use disorders	Musculoskeletal disorders	Other non-communicable diseases	Injuries	Transport injuries	Self-harm and interpersonal violence	Forces of nature, war, and legal intervention
	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)
Patent Per Capita	-0.557**	-2.765**	-0.458*	-1.179*	-2.480**	-1.528**	-0.873***	-1.489***	-2.216***	-1.852***	-3.361***
	(0.191)	(0.857)	(0.176)	(0.464)	(0.837)	(0.559)	(0.245)	(0.340)	(0.458)	(0.480)	(0.886)
Adj. R Squared	0.585	0.433	0.55	0.429	0.322	0.119	0.640	0.503	0.597	0.305	0.653
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	15,694	15,694	15,694	15,694	15,694	15694	15694	15694	15694	15694	15694

Note: Clustered standard errors at the state level are in parenthesis. ***, **, and * = 0.1%, 1%, and 5% significance levels, respectively. The natual log tranformation of each mortality, patents per capita and income per capita were used in the regression computations. Each regression also includes inequality, the % of population unemployed, % of population 25 years or older with a bachelor degree, % of population employed in agriculture, forestry, fishing, hunting, and mining, % of population hispanic or latino and the % population black or african american.

4.4 Innovative Counties Only

Seeing differences in all-cause mortality rates per county, and of individual type of mortality rate response to the presence of innovation, a binary variable was created where if the county in year *t* was assigned a patent it was actively innovative in that year. Thus, a county was either innovative or not for year *t* (0 = non innovative and 1 = innovative). When regressing the all-cause mortality rate onto whether a county was innovative or not, the relationship was found to be non-significant. However, specific types of mortalities were found to be influenced by whether a county was innovative.

[Table 8]

Table 8: Results by Whether a County is Innovative: *Dependent Variable = Individual Mortality Rate 100,000 Per County (2010-2014)*

	Neglected tropical diseases and malaria	Nutritional deficiencies	Other communicable, maternal, neonatal, and nutritional diseases	Neurological disorders	Mental and substance use disorders	Other non-communicable diseases	Injuries	Transport injuries	Unintentional injury	Forces of nature, war, and legal intervention
	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)
County is innovative (0, 1)	-0.123**	-0.064*	-0.032**	0.045**	0.060*	-0.020*	-0.051**	-0.102***	-0.031*	-0.171***
	(0.044)	(0.025)	(0.012)	(0.015)	(0.028)	(0.010)	(0.016)	(0.024)	(0.015)	(0.048)
Adj. R Squared	0.440	0.247	0.511	0.156	0.324	0.641	0.508	0.607	0.384	0.658
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	15,694	15,694	15,694	15,694	15,694	15,694	15,694	15,694	15,694	15,694

Note: Clustered standard errors at the state level are in parenthesis. ***, **, and * = 0.1%, 1%, and 5% significance levels, respectively. The natual log tranformation of each mortality and income per capita were used in the regression computations .Each regression also includes inequality, the % of population unemployed, % of population 25 years or older with a bachelor degree, % of population employed in agriculture, forestry, fishing, hunting, and mining, % of population hispanic or latino and the % population black or african american.

From table 8, we can see that when a county is innovative, as represented by having a patent assigned to it in year *t*, the neglected tropical disease and malaria mortality rate decrease by 12%. This is extremely powerful if we take into account that the maximum mortality rate as a result of neglected tropical disease over the time series of data is 0.78 deaths per 100,000. Suggesting that the innovative county changes the potential of death as result of neglected tropical disease by .09 points. Further, if we consult literature, neglected tropical disease are most commonly associated within areas of poverty (Hotez, 2016). This may also be suggesting that an innovative county is having an impact on the poverty rates that are facilitating neglected tropical disease incidence as well.

Further, the nutritional deficiency mortality rate falls 6%, other communicable, maternal, neonatal, and nutritional disease death rate decreases by 3% and other non-communicable disease mortality rate decreases by 2%. The general injury mortality rate, the mortality rate related to transportation injuries and those deaths as a result of unintentional injuries all fall by 5%, 10% and 3% respectively. Mortality rates as a result of transportation injury may be associated with greater geographic clustering of innovative activity (Feldman and Florida, 1994) and in doing so may be directly impacting motor vehicular use and deaths associated with their use within innovative counties and geographic proximity.

Mortalities as a result of forces of nature, war, and legal intervention held the strongest statistical relationship where the death rate would decrease 17%. This is particularly interesting in that, when a county is innovative it may be having a positive outcome on those determinants of legal intervention through interactions with law enforcement. Physical innovations that enhance non-lethal equipment utilized by law enforcement as well as monitoring and accountability innovations may be captured within these results. Further, practice innovations such as the Domestic Violence Prevention Enhancement and Leadership Through Alliance (DELTA) program, universal school-based programs to prevent violence, and Business Improvement Districts to reduce violence may also be impacting legal intervention mortalities through prevention strategies. Though not measured, these results might also suggest that actively innovative counties, through economic opportunity, expand resources through the positive outcomes associated with innovation (including increased employment) (North and Smallbone, 2000). As more economic opportunity is available it may be decreasing relative deprivation within the county and thus decreasing those crimes that lead to lethal legal intervention (Kawachi, Kennedy, and Wilkinson, 1999)

Interestingly, the neurological disorder mortality rate is found to increase by 4% and the rate of mental and substance use disorders also increases by 6% when a county was innovative. This may be potentially teasing out a budding area of research around entrepreneurship and mental health. There are recent studies finding that a greater propensity of individuals who showcase entrepreneurial qualities tend to suffer from a neurological conditions (Wiklund, Hatak, Patzelt, and Shepherd, 2018; Wiklund, Patzelt, and Dimov, 2016). While this research suggests that these disorders could potentially be harnessed for productivity, research also shows a proclivity for self-medication (Derefinko and Pelham, 2013).

4.5 Quantile Regression Results

[Table 9]

Table 9: Quantile Benchmark Results: *Dependent Variable = All-Cause Mortality Rate Per 100,000 Per County (2010-2014)*

	q10	q20	q30	q40	q50	q60	q70	q80	q90
Patents Per Capita	-0.111*	-0.358*	-0.460**	-0.486***	-0.626***	-0.767***	-0.956***	-1.091***	-1.391***
	(0.045)	(0.141)	(0.158)	(0.151)	(0.100)	(0.079)	(0.085)	(0.115)	(0.239)
Income Per Capita	-0.188***	-0.189***	-0.206***	-0.203***	-0.206***	-0.200***	-0.190***	-0.208***	-0.217***
	(0.013)	(0.011)	(0.010)	(0.010)	(0.009)	(0.009)	(0.012)	(0.011)	(0.013)
Inequality (Gini Index)	0.653***	0.657***	0.749***	0.793***	0.808***	0.806***	0.821***	0.774***	0.808***
	(0.059)	(0.039)	(0.038)	(0.034)	(0.040)	(0.036)	(0.038)	(0.040)	(0.053)
% Population Unemployed	0.002***	0.002***	0.002***	0.001**	0.001**	0.002***	0.002***	0.002***	0.002**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
% Population 25 Years or Older with a Bechelor Degree	-0.014***	-0.013***	-0.012***	-0.013***	-0.013***	-0.013***	-0.013***	-0.012***	-0.012***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
% Population Employed in agriculture, forestry and fishing	-0.006***	-0.005***	-0.004***	-0.004***	-0.003***	-0.003***	-0.002***	-0.001**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Population Hispanic or Latino	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.001***	-0.001***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Population Black or Aftican American	0.001***	0.002***	0.002***	0.002***	0.002***	0.000***	0.002***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	15694	15694	15694	15694	15694	15694	15694	15694	15694

Note: Standard errors are in parenthesis. Bootstrapped with 1000 iterations. Year fixed effects are accounted for. ***, **, and * = 0.1%, 1%, and 5% significance levels, respectively. The natual log tranformation of all-cause mortality, patents per capita and income per capita were used in the regression computations.

The goal of conducting the quantile regression analysis is to estimate patent per capita's effect at different levels of the mortality rate per county. Previous research has shown that mortality rates in relation to inequality vary across the distribution of mortality (Yang, Chen, Shoff, and Matthews, 2012). Inequality is embedded within many aspects of society, including socio-economic conditions. Yang et al.'s (2012) analysis of the relationship between inequality and mortality suggests that auxiliary evaluation of independent covariates could provide further insight into this relationship. Innovation can increase economic activity, and through pathways such as employment and the standard of living, can impact socio-economic status as well. Intuitively, as population rates increase across counties, so then would the incidence of mortality. All else equal, the greater the population, the greater the incidence of mortality. Therein lies an expectation that evaluating innovation's effect across the mortality distribution will better illustrate the broad impact innovation has on mortality rates through economic pathways, not simply innovation specific influence on mortalities. Therefore, innovation should have greater negative impact at higher percentages of mortality rates as economic innovation should have broader impact.

Quantile regression can be well suited for empirical problems since it is able to provide estimates of effects of the independent variable at defined quantiles of the dependent variable's distribution. More simply, it offers the ability to evaluate explanatory effect at specific percentiles of the dependent variable. As discussed, evaluating innovation effect at differing quantiles of the mortality distribution will add further insight into the varying relationship between innovation and mortality. The quantile regressions include bootstrap standard errors based on 1000 repetitions.

The patent per capita coefficients presented in Table 9 are all negative and significant. The elasticities of each individual quantile both gain in magnitude and in significance illustrating a monotonic relationship between all-cause mortality rates and patents per capita. Intuitively, the impact of innovation by a county (as represented by patents per capita) has a greater impact on mortality as the mortality rate in a county increase.

This could suggest that counties with higher rates of mortality are specifically motivated on innovating to try and address mortality concerns. However, being that the innovation variable is a general metric of patents assigned, I do not generally believe this to be true as it would be indicative of more medical, health and pharmaceutical patents (which is discussed in a subsequent section). Instead, I believe that a policy environment at the county level that encourages economic innovative activity may be providing health benefits as an auxiliary effect by strengthening local economies through job creation, wage growth, social integration and the standard of living. That is, the act of innovation may have both a primary effect and a secondary effect on health outcomes Along with the primary impact the act of economic development and growth may also raise both the stock of community and individual resources that can be allocated to health and the standard and quality of life within the county. While it is not the main empirical approach of this dissertation to analyze these interpretations, preliminary interaction results are shown in the robustness section of this chapter.

Individual Mortalities

[Table 10]

Table 10: Quantile Results by Type of Mortality: *Dependent Variable = Individual Mortality Rate Per 100,000 Per County (2010-2014)*

	q10	q20	q30	q40	q50	q60	q70	q80	q90
Commmunicable, maternal, neonatal, and nutritonal disease									
Patents per capita	0.47**	-0.13	-0.55*	-0.82*	-0.56	-0.87	-0.79*	-1.31***	-1.93***
	(0.18)	(0.20)	(0.23)	(0.38)	(0.46)	(0.45)	(0.33)	(0.26)	(0.34)
HIV/AIDS and tuberculosis									
Patents per capita	-0.29	-0.28	-0.29	0.48	0.58	0.15	-0.25	0.30	3.16*
	(0.67)	(0.84)	(0.80)	(1.01)	(0.90)	(0.65)	(0.63)	(2.25)	(1.43)
Diarrhea, lower respiratory, and other common infectious diseases									
Patents per capita	0.44***	-0.19	-0.68	-1.02	-0.27	-0.55	-0.92	-1.18***	-1.80***
	(0.12)	(0.17)	(0.37)	(0.58)	(0.59)	(0.41)	(0.50)	(0.34)	(0.55)
Neglected tropical diseases and malaria									
Patents per capita	-1.33*	-1.93***	-2.48***	-3.01***	-2.53**	-3.05**	-2.33**	-3.37***	-4.43**
	(0.67)	(0.38)	(0.41)	(0.68)	(0.84)	(1.02)	(0.84)	(0.43)	(1.64)
Maternal disorders									
Patents per capita	-0.81	-1.49***	-1.50***	-1.45**	-1.75	0.76	1.00	0.44	-0.46
	(0.47)	(0.29)	(0.44)	(0.51)	(1.10)	(1.66)	(0.59)	(0.24)	(0.26)
Nutritional deficiencies									
Patents per capita	-0.67	-0.81	-1.03	-1.34*	-1.72**	-1.74*	-2.32	0.39	0.32
	(0.90)	(0.76)	(0.62)	(0.68)	(0.60)	(0.76)	(1.51)	(1.66)	(1.06)
Other communicable, maternal, neonatal, and nutritional diseases									
Patents per capita	0.18	-0.06	-0.10	-0.25	-0.38*	-0.56*	-0.58	0.14	-0.23
	(0.55)	(0.13)	(0.19)	(0.17)	(0.17)	(0.24)	(0.49)	(0.53)	(0.28)
Non-communicable disease									
Patents per capita	-0.05	-0.28***	-0.38***	-0.46***	-0.61***	-0.74***	-0.81***	-0.90***	-1.21***
	(0.06)	(0.08)	(0.12)	(0.09)	(0.09)	(0.09)	(0.11)	(0.12)	(0.28)
Neoplasms									
Patents per capita	0.14	-0.09	-0.16	-0.28	-0.28*	-0.36***	-0.44***	-0.47*	-0.64***
	(0.08)	(0.10)	(0.12)	(0.16)	(0.14)	(0.08)	(0.12)	(0.21)	(0.14)
Cardiovascular									
Patents per capita	0.18	0.04	-0.18	-0.26	-0.40*	-0.52***	-0.73***	-1.05***	-1.23***
	(0.22)	(0.21)	(0.20)	(0.20)	(0.17)	(0.15)	(0.14)	(0.20)	(0.20)
Chronic respiratory disease									
Patents per capita	-0.89	0.52	0.14	-0.15	-0.37**	-0.58	-0.65	-0.09	-0.18
	(0.81)	(0.83)	(0.36)	(0.23)	(0.14)	(0.32)	(0.61)	(0.51)	(0.47)
Cirrhosis and other chronic liver diseases									
Patents per capita	-0.61*	-1.03***	-1.39***	-1.61***	-1.54***	-1.24*	-1.48***	-1.88***	-2.42***
	(0.26)	(0.21)	(0.23)	(0.35)	(0.40)	(0.49)	(0.43)	(0.49)	(0.42)
Digestive disease									
Patents per capita	-0.40	-0.75	-0.10	0.44	0.32	0.25	0.05	-0.11	-0.35
	(0.23)	(0.43)	(0.45)	(0.46)	(0.32)	(0.19)	(0.17)	(0.17)	(0.22)
Neurological disorders									
Patents per capita	0.24	-0.51**	-0.95***	-1.23***	-1.10**	-0.86***	-1.23***	-1.55***	-1.82
	(0.24)	(0.17)	(0.20)	(0.34)	(0.39)	(0.25)	(0.15)	(0.13)	(1.36)
Mental and substance use disorders									
Patents per capita	-1.32**	-1.72***	-1.91***	-1.98***	-2.59***	-2.81***	-3.32***	-3.83***	-4.75***
	(0.50)	(0.41)	(0.52)	(0.49)	(0.51)	(0.50)	(0.43)	(0.48)	(0.55)
Diabetes, urogenital, blood, and endocrine diseases									
Patents per capita	-0.56	0.01	-0.15	-0.37*	-0.59***	-0.72**	-0.80***	-1.23***	-1.71***
	(0.46)	(0.43)	(0.22)	(0.16)	(0.16)	(0.26)	(0.22)	(0.18)	(0.17)
Musculoskeletal disorders									
Patents per capita	-1.21**	-1.49***	-1.93***	-1.72**	-1.06	-0.83	-1.00***	-1.36***	-1.87***
	(0.41)	(0.46)	(0.53)	(0.64)	(0.70)	(0.64)	(0.23)	(0.24)	(0.29)
Other non-communicable diseases									
Patents per capita	-0.28***	-0.56***	-0.74***	-0.93***	-1.06***	-1.12***	-1.06***	-0.97***	-1.36***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.18)	(0.22)	(0.19)	(0.19)
Injuries									
Patents per capita	-2.59	-1.07	-1.09***	-1.01***	-1.20***	-1.48***	-1.62***	-1.84***	-1.80***
	(1.75)	(0.68)	(0.24)	(0.17)	(0.14)	(0.09)	(0.24)	(0.44)	(0.27)
Transport injuries									
Patents per capita	-0.67	-1.28**	-1.31***	-1.54***	-1.87***	-2.28***	-2.51***	-2.55***	-2.90***
	(3.45)	(0.48)	(0.27)	(0.19)	(0.15)	(0.14)	(0.18)	(0.36)	(0.47)
Unintentional Injuries									
Patents per capita	-0.16	0.09	-0.10	-0.01	-0.14	-0.25	-0.52***	-0.85***	-1.24***
	(0.34)	(0.43)	(0.26)	(0.19)	(0.15)	(0.16)	(0.11)	(0.10)	(0.19)
Self-harm and interpersonal violence									
Patents per capita	-2.58	-1.41	-1.49***	-1.38***	-1.59***	-1.73***	-2.00***	-2.46**	-1.75*
	(1.64)	(0.95)	(0.38)	(0.34)	(0.21)	(0.17)	(0.27)	(0.91)	(0.74)
Forces of nature, war, and legal intervention									
Patents per capita	-0.26	-1.46***	-2.36***	-2.54**	-2.38***	-2.85***	-3.45***	-4.18***	-5.25***
	(0.17)	(0.28)	(0.67)	(0.90)	(0.72)	(0.55)	(0.41)	(0.47)	(0.53)
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	15,694	15,694	15,694	15,694	15,694	15,694	15,694	15,694	15,694

Note: Standard errors are in parenthesis. Bootstrapped with 1000 iterations. Year fixed effects are accounted for. ***, **, and * = 0.1%, 1%, and 5% significance levels, respectively. The natual log tranformation of each mortality and income per capita were used in the regression computations .Each regression also includes inequality, the % of population unemployed, % of population 25 years or older with a bachelor degree, % of population employed in agriculture, forestry, fishing, hunting, and mining, % of population hispanic or latino and the % population black or african american.

When conducting a quantile regression on each individual type of mortality rate, that is to say, when measuring the effect of patents per capita across the distribution of each individual mortality type per county, I find certain types of mortalities to be more broadly impacted by the presence of innovation than other types of mortalities. All quantile coefficients and standard errors for each type of mortality can be found in Table 10. I will call attention to a selection of results below.

There was a significant negative relationship across the entire distribution of neglected tropical diseases and malaria with the smallest at the 10th percentile and largest impact at the 90th percentile, suggesting a 1.33% decrease in the lowest quantile and a 4.34% decrease in the highest quantile respectively. Innovation in the physical commodities like footwear and increasingly affordable preventative commodities like insect repellant and pest control practice may be playing a part across the distribution of the NTD mortality rate. These results may also be illuminating greater impact in animal control activities in areas of higher populations as well as the potential impacts of business development districts that foster the clustering economic activity which leads communities to invest in urban infrastructure.

When impacting specific types of mortalities, patents per capita had one of the strongest impact in decreasing rates of mortality in relation to mental and substance use disorders. The relationship is highly and statistically significant while being monotonic in that as the percentiles of number of mortalities increase for mental and substance use disorders, so does the impact of the prevalence of innovation. Patents per capita decrease the mental and substance use disorder death rate by 1.32% in the 10th percentile while decreasing rates of mortality by 4.75% in the 90th percentile.

Transportation related injuries are statistically impacted by innovation beginning in the 20th percentile and holds a monotonic relationship through the 90th percentile, gaining strength as the percentile increases. This may be capturing potential innovations in both technology and practice as well as greater concentrations of response availability associated with greater population densities. Physical technologies such as autonomous vehicle, safety monitoring technology within vehicles, and advanced crash notification systems may be both preventing and hyphenating emergency response time, decreasing transportation mortality rates. Additionally, initiatives such as occupancy restraint advancements, child passenger restraint seats, helmet and safety equipment laws and injury control centers may also be indicative of the innovative activity impacting transportation mortality rates across the distribution. Further, local policy that incentivizes business and innovation clustering may impact transportation use, which in turn would effect transportation mortality rates.

Lastly, deaths as a result of forces of nature, war, and legal intervention are significantly impacted through most of the distribution. The relationship is monotonic with death rates decreasing throughout the distribution whereas, in the 20th percentiles innovation decreases the death rate by 1.46% to the 90th percentile where it decreases by 5.25%. This could be indicative of physical innovation's such as non-lethal intervention strategies for law enforcement that include long distance taser technology, different aerosol compounds developed to incapacitate suspects, as well as technology geared toward greater law enforcement accountability like body camera technology worn by individual law enforcement officials and tracking device and software for law enforcement deployment. Additionally, practice innovations like business improvement districts (BIDs) to reduce violence are proven as effective ways toward reducing rates of crime and violence in urban settings. When incentivizing and investing in business improvement districts, research has shown that communities can see up to a 32% decrease in police arrests over time (Kress, Noonan, Freire, Marr, & Olson, 2012).

4.6 Lagged analysis

In order to evaluate whether an assigned patents effect on the mortality rate at the county level lies within the innovation's assignment year, a selection of lagged patent per capita variables was tested. The inclusion of lagged innovation activity is motivated by attempting to isolate the timing effect of a patent's assignment on a counties mortality rate. Previous research by Tapia Granados (2012) illustrated that gross domestic product's impact on mortality rate in England was greatest at lag 0.

[Table 11]

Table 11: Results with Time Lag of Innovation: *Dependent Variable = Mortality Rate Per 1000,000 Per County (2010-2014)*

	OLS (i)	OLS (ii)	OLS (iii)	OLS (vi)
Patents per capita	-0.557**	-2.135*	-1.007	-2.029
	(0.191)	(0.926)	(0.582)	(1.197)
Patents per capita Lag 1		1.732	-0.549	1.781
		(1.066)	(1.010)	(1.749)
Patents per capita Lag 2			1.164	-0.999
			(0.944)	(1.471)
Patents per capita Lag 3				0.931
				(0.933)
R Squared	.585	.586	.585	.586
AIC	-25,230	-19,979	-14,789	-9,741
Controls	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Obs.	15,694	12,555	9416	6277

Note: Clustered error at the state level are in parenthesis. Year fixed effects are accounted for. ***, **, and * = 0.1%, 1%, and 5% significance levels, respectively. The natual log tranformation of all-cause mortality, patents per capita and income per capita were used in the regression computations. Each regression also includes inequality, the % of population unemployed, % of population 25 years or older with a bachelor degree, % of population employed in agriculture, forestry, fishing, hunting, and mining, % of population hispanic or latino and the % population black or african american.

Table 11 shows the benchmark equation with the inclusion of lagged variables to measure the temporal effects of patenting activity as a measure of innovation at the county level. One year, two year, and three-year lagged patent per capita variables were added to the initial model in addition to the patent per capita variable.

A likelihood ratio test was conducted to evaluate differing models. The initial model included the natural logged patent per capita variable between 2011-2014. The second model is comprised of the aforementioned patent per capita variable in addition to a one year lagged patent per capita variable. The likelihood ratio test registered $p = 0.56$ indicating that the results are consistent with the claim that the addition of a lagged variable does not substantially improve the models fit. Additionally, as indicated by the Akaike Information Criterion, the power of the model decreases as indicated by the AIC[12] measurement increasing with the addition of each additional lagged variable.

We can see that the addition of a one-year lag shows an increase in the impact innovation has on the all-cause mortality rate. As such, the benchmark equation suggests that a 1% increase in patents per capita leads to a 0.56% decrease in the mortality rate, with the addition of a one-year lag patent per capita variable increasing the magnitude of the patent per capita assigned in the same year's effect to 2.14%. With that said, while still statistically significant, the significance falls from 1% to 5%. Additionally, when comparing the standard clustered errors, the lag-zero shows that 95% of the observation should fall within plus or minus 0.38% of the fitted line versus that of the addition of a 1 year lag where 95% of the observations should fall within plus or minus 1.86% of the fitted line, effectively expanding the 95% prediction interval.

With the combination with the likelihood ratio test, AIC scorings, and evaluating the standard errors, there is confidence in the interpretation that the greatest impact the

[12] When evaluating the Akaike Information Criterion, it is preferable to have the smallest numerical AIC measurement.

patent per capita variable has on mortality rates seems to be within the same year as the patent assignment date within the individual county. This finding also aligns with the previous findings of greatest impact at lag-zero for GDP growth indicators regressed on to mortality (Tapia Granados (2012).

4.7 Robustness Tests

Substitute of different variables

To ensure robustness of results multiple alternative indicators were individually added within the benchmark equation. As illustrated by Table 12, the primary variable of interest in patents per capita retains significance when including alternative income, poverty, rural and education indicators.

[Table 12]

Table 12: Results with Additional Controls: *Dependent Variable = Mortality Rate Per 100,000 Per County (2010-2014)*

	OLS (i)	OLS (ii)	OLS (iii)	OLS (iv)	OLS (v)	OLS (vi)	OLS (vii)	OLS (viii)
Patents per capita	-0.581**	-0.567**	-0.475*	-0.542**	-0.558**	-0.545**	-0.552**	-0.558**
	(0.190)	(0.190)	(0.199)	(0.194)	(0.189)	(0.194)	(0.189)	(0.190)
Alternative Income Indicators								
Income per capita	-0.254***	-0.204***						
	(0.052)	(0.048)						
% Families with a Household Income of $75,000 or more	0.002*							
	(0.001)							
% Population Employed in management, business, science and art		0.001						
		(0.001)						
Alternative Poverty Indicators								
% Population Unemployed			-0.000	0.002	0.002			
			(0.002)	(0.002)	(0.002)			
% Population Living Below Poverty Level			0.009***					
			(0.002)					
% Population Receive Cash / SSI Assistance				0.001*				
				(0.000)				
% Families with a Female Head of Household					0.000*			
					(0.000)			
Alternative Rural Indicators								
% Population employed in agriculture, forestry and fishing						-0.003*	-0.003*	-0.003*
						(0.001)	(0.001)	(0.001)
% Population That Commutes via Public Transportation						-0.003***		
						(0.001)		
% Population that Work Outside of County							0.000	
							(0.000)	
% Population that has a 60 minute or greater commute to work								0.001
								(0.001)
R Squared	0.587	0.585	0.602	0.590	0.588	0.588	0.585	0.585
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	15,694	15,694	15,694	15,694	15,694	15,694	15,694	15,694

Note: Clustered standard errors at the state level are in parenthesis. ***, **, and * = 0.1%, 1%, and 5% significance levels, respectively. The natual log tranformation of all-cause mortality and patents per capita were used in the regression computations Unless substituted each regression also includes the natural log of income per capita, inequality, % of population unemployed, % of population 25 years or older with a bachelor degree, % of population employed in agriculture, forestry, fishing, hunting, and mining, % of population hispanic or latino and the % population black or african american.

When including the percentage of families with incomes over $75,000, a one unit increase in patents per capita decreases the all-cause mortality rate by 0.58%. When the percentage of population employed in business, science and art is included, a one unit increase in patent per capita decreases the mortality rate by 0.57%.

When alternative poverty indicators are included with the percent of population that is unemployed, again patent per capita persists in significantly influencing the mortality rate. The addition of the percentage of the population living below poverty, the percentage of the population per county receiving cash or supplemental security income assistance and the percentage of families with a female head of household, a one unit increase in patents per capita leads to a decrease in the mortality rate by 0.48%, 0.54% and 0.56% respectively. This suggests that the benchmark results are robust even with the addition of alternative control variables.

There was a minimal difference pertaining to the percentage of the population employed in agriculture, forestry, fishing, hunting, and mining with the addition of either the percentage of the population that commutes via public transportation or the percentage of the population that works outside of their county of residence. In both cases the mortality rate falls by 0.55% as a result of a one unit increase in patents per capita while mortality falls by 0.56% when including the percentage of the population that has a 60 minute or greater commute to work.

The adjusted R^2 for each alternative model ranged from describing 58% - 60% of the variance, illustrating consistency among each model and alternative measure inclusion. Each model included the initial benchmark equation set of controls unless otherwise stated. Each empirical model includes year fixed effects to control for national level time changes and clustered standard errors at the state level.

Pharmaceutical and medical patents

In order to better evaluate innovation's impact on mortalities, those patents whose cooperative patent classification codes related to medical or pharmaceutical use were parsed out and aggregated. Thus, a variable was created that compiled patent counts only for the subgroup of pharmaceutical and medical patents. Using this measure as an alternative innovation measure allows me to evaluate whether the impact of innovation on mortality is a result of medical and pharmaceutical innovation more so then general innovation. In order to define pharmaceutical and medical patents only, patent classifications were pulled from the United States Patenting and Trademark Office Cooperative Patent Classification system (USPTO, 2019) and selections were parsed out at the sub-section level. Table 13 shows a listing of the sub-classes of patents chosen and rationale for inclusion within the medical and pharmaceutical patent per capita variable. The sub-class selection is an expansion of (Eisinger, Tsatsaronis, Bundschus, Wieneke, and Schroeder, 2013) work towards automated patent categorization.

[Table 13]

Table 13: Medical & Pharmaceutical Sub-Class Patent Key Word Search and Descriptions

Sub Section Code	Key Word	Description
A23	Pharmaceutical	Food or Foodstuffs; Their Treatment, Not Covered By Other Classes
A61	Health, Medical, Pharmaceutical, Biological, Surgical	Medical or Veterinary Science; Hygiene
A62	Medical	Life-Saving; Firefighting
B01	Medical, Pharmaceutical	Physical or Chemical Processes or Apparatus in General
B02	Pharmaceutical	Crushing, Pulverising, or Disintegrating: preparatory Treatment of Grain for Milling
C08	Pharmaceutical	Organiz Macromolecular Compounds; Their Preperation or Chemical Working-up; Compositions Based Thereon
C10	Medical	Petroleum; Gase or Coke Industries; Technical Gases Containing Carbon Monoxide; Fuels; Lubricants; Peat
C12	Medical, Biological. Pharmaceutical, Surgical	Biochemistry; Beer; Spirits; Wine; Vinegar; Microbiology; Enzymology; Mutation or Genetic Engineering
C40	Medical, Biological	Combinatorial Chemistry
G16	Health, Medical, Surgical	Information and Communication Technology (ICT) Specially Adapted for Specific Application Fields
G21	Pharmaceutical	Nuclear Physics; Nuclear Engineering

As such, the average number of medical or pharmaceutical patents for those counties who had a patent in the provided subclasses assigned between the years 2010-2014 was 39.37 patents with the maximum number of patents assigned to an individual county for a year registering 9,107. Table 14 illustrates the comparison between the general indicator of innovation in patents per capita and the created medical and pharmaceutical patents per capita variable.

[Table 14]

Table 14: M&P Benchmark Results: *Dependent Variable = Mortality Rate Per 100,000 Per County (2010-2014)*

	OLS (i)	OLS (ii)
Medical & Pharmaceutical Patents Per Capita	-0.265***	
	(0.063)	
Non Medical & Pharmacuetical Patents Per Capita		-0.076***
		(0.020)
Income Per Capita	-0.246***	-0.246***
	(0.054)	(0.054)
Inequality (Gini Index)	0.412	0.412
	(0.216)	(0.216)
% Population Unemployed	-0.006	-0.006
	(0.004)	(0.004)
% Population 25 Years or Older with a Bechelor Degree	-0.010***	-0.010***
	(0.002)	(0.002)
% Population Employed in agriculture, forestry and fishing	-0.001	-0.001
	(0.002)	(0.002)
% Population Hispanic or Latino	-0.003***	-0.003***
	(0.001)	(0.001)
% Population Black or Aftican American	0.003***	0.003***
	(0.001)	(0.001)
R Squared	0.790	0.721
Year fixed effects	yes	yes
Obs.	644	644

Note: Note: Clustered error at the state level are in parenthesis. Year fixed effects are accounted for. ***, **, and * = 0.1%, 1%, and 5% significance levels, respectively. The natual log tranformation of all-cause mortality, income per capita, medical & pharmaceutical patents per capita and non medical & pharmaceutical patents per capita were used in the regression computations.

Column (i) shows the regression equation and the effect of medical and pharmaceutical patent assignment at the county level. Column (ii) shows the same equation when designated medical and pharmaceutical patents within the previously mentioned sub-classes are omitted from the sample of county-level patenting data. As shown in column (i), medical and pharmaceutical patent assignment at the county level holds a negative relationship with mortality, where a 1% increase in medical and pharmaceutical patenting assignment leads to a decrease in the mortality rate by 0.26% as compared to general innovation's 0.56%. Attempting to validate my hypothesis that general innovative activity does have an impact on county level mortality rates, medical and pharmaceutical patents were omitted from overall patenting assignment per county. As seen in column (ii), in the absence of medical and pharmaceutical patenting assignment, a 1% increase in non-medical and pharmaceutical patenting activity still results in a 0.07% decrease in the per county mortality rate. These findings demonstrate that non-medical and pharmaceutical innovative activity still influences mortality rates at the county level.

It should be noted that when controlling for medical and pharmaceutical patenting versus non-medical and pharmaceutical patenting that the sample size significantly fell from 15,694 of the panel data set, to 644 counties. The reasoning for such a decrease is uncertain, however a natural clustering of patent assignment may be evident within the data. Spatiality and potential clustering will be explored in the following pages.

To further evaluate the difference in impact, medical and pharmaceutical patent counts were regressed onto each individual type of mortality. These results can be found in Table 15.

[Table 15]

Table 15: M&P Results by Individual mortality: *Dependent Variable = Individual Mortality Rate Per 100,000 Per County (2010-2014)*

	Communicable, maternal, neonatal, and nutritional diseases	Diarrhea, lower respiratory, and other common infectious diseases	Neglected tropical diseases and malaria	Maternal Disorders	Nutritional deficiencies	Other communicable, maternal, neonatal, and nutrional diseases	Non-communicable diseases	Neoplasms	Cardiovascular disease	Chronic respiratory disaease	Mental and substance use disorders	Diabetes, urogenital, blood, and endocrine disease	Other non-communi cable disaease	Self-harm and interpersonal violence
	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS	(OLS)
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)	(xiii)	(xiv)
Medical & Pharmaceutical Patents Per Capita	0.536***	0.655***	0.672***	0.248***	-0.416**	-0.154**	-0.157***	-0.129***	-0.123*	-0.343**	-0.336*	-0.555***	-0.151***	-0.349***
	(0.091)	(0.105)	(0.141)	(0.066)	(0.130)	(0.057)	(0.046)	(0.032)	(0.056)	(0.118)	(0.135)	(0.058)	(0.038)	(0.085)
Adj. R Squared	0.453	0.341	0.432	0.575	0.243	0.508	0.555	0.557	0.525	0.365	0.321	0.505	0.640	0.304
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	644	644	644	644	644	644	644	644	644	644	644	644	644	644

Note: Clustered standard errors at the state level are in parenthesis. ***, **, and * = 0.1%, 1%, and 5% significance levels, respectively. The natual log tranformation of each mortality, income per capita and medical & pharmaceutical patents per capita were used in the regression computations. Each regression also includes inequality, the % of population unemployed, % of population 25 years or older with a bachelor degree, % of population employed in agriculture, forestry, fishing, hunting, and mining, % of population hispanic or latino and the % population black or african american.

At a per county level, medical and pharmaceutical patenting assignment shows an increase in communicable, maternal, neonatal, and nutritional diseases, Diarrhea, lower respiratory, and other common infectious diseases, neglected tropical disease and malaria, and maternal disorder rates by 0.54%, 0.66%, 0.67% and 0.25% respectively. These are interesting results as one would intuitively assume that communicable, maternal, neonatal and nutritional disorders, common infectious diseases, neglected tropical disease and maternal disorders would be most negatively impacted by medical innovation but instead a positive relationship is found. However, as Hotez (2016) suggests, neglected tropical diseases tend to be diseases of poverty. Further, fetal infant mortality, nutritional diseases and common infectious diseases tend to more greatly impact those populations who lack the economic resources for medical care (Ezzati et al., 2005; Gortmaker, 1979). What these results suggest is that new innovation may disproportionally benefit those who are employed or have more resources by way of income. More specifically, those who have insurance via employment may be able to better afford new medical and pharmaceutical innovation, and or those populations with higher incomes are able to afford new pharmaceutical innovations, while the cost of innovation in pharmaceuticals may be out of reach for those with lower incomes. Interaction results (see Appendix 1) would seem to corroborate this theory.[13]

The nutritional deficiency mortality rate decrease by 0.42% in the presence of medical innovation in addition to other communicable, maternal, neonatal, and nutritional

[13] Figures for interaction results are showcased in the appendix. The figures include the interaction of Medical and Pharmaceutical patenting with the percent of the population unemployed and the income per capita as it effects communicable, maternal, neonatal and nutritional disease mortality rates; diarrhea, lower respiratory and other common infectious disease mortality rates; neglected tropical disease and malaria mortality rates; and maternal disorder mortality rates.

disease, non-communicable diseases, neoplasms, cardiovascular disease and chronic respiratory disease mortality rates (0.15%, 0.16%, 0.13%, 0.12% and 0.34% respectively). The mental and substance use disorder mortality rate decreases by 0.34% with the assignment of medical and pharmaceutical patents per county. The strongest significant and negative relationship regarding medical and pharmaceutical patenting impact the mortality rate due to diabetes, urogenital, blood, and endocrine disease, decreasing the mortality rate by 0.55%. Additionally, the other non-communicable disease death rate decreases by 0.15% and self-harm and interpersonal violence death rate decreases by 0.35 %, both significant at the 0.1% level. Interestingly, in comparison to general innovation, mortalities as a result of injuries, and transportation injuries which were highly statistically significant in their relationship to general innovation, do not register significant with medical and pharmaceutical patenting. Further, when regressing medical and pharmaceutical patents onto percentiles of the all-cause mortality rate distribution, medical innovation was only statistically significant at the 40th, 50th and 90th percentiles. As a result, medical and pharmaceutical patents affected decreases in the mortality rate registering 0.10%, 0.16% and 0.31% respectively. Overall, this suggests that the effect of innovation being captured in the data are representative of not just the potentiality of medical and pharmaceutical innovation, but of all innovation and its impact on mortality at a per county level.

Preliminary Interaction Results

[Table 16]

Table 16: Results with Unemployment and Income Interactions: *Dependent Variable = Mortality Rate Per 100,000 Per County (2010-2014)*

	(benchmark results) (OLS) (i)	(OLS) (ii)	(OLS) (iii)
Patents per capita (centered)	-0.557**	-0.541***	-0.631***
	(0.191)	(0.159)	(0.186)
Income Per Capita (centered)	-0.199***	-0.199***	-0.199***
	(0.046)	(0.046)	(0.046)
Inequality (Gini Index)	0.741***	0.742***	0.742***
	(0.122)	(0.122)	(0.122)
% Population Unemployed (centered)	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)
% Population 25 Years or Older with a Bechelor Degree	-0.013***	-0.013***	-0.013***
	(0.001)	(0.001)	(0.001)
% Population Employed in agriculture, forestry and fishing	-0.003*	-0.003*	-0.003*
	(0.001)	(0.001)	(0.001)
% Population Hispanic or Latino	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)
% Population Black or Aftican American	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)
Patents per capita		0.175*	
x % unemployment		(0.079)	
Patents per capita			-2.015*
x Income per capita			(0.924)
Adj. R Squared	0.585	0.585	0.585
Controls	yes	yes	yes
Year fixed effects	yes	yes	yes
Obs.	15,694	15,694	15,694

Note: Clustered standard errors at the state level are in parenthesis. ***, **, and * = 0.1%, 1%, and 5% significance levels, respectively. The natual log tranformation of each mortality, patents per capita and income per capita were used in the regression computations. Each regression also includes inequality, the % of population unemployed, % of population 25 years or older with a bachelor degree, % of population employed in agriculture, forestry, fishing, hunting, and mining, % of population hispanic or latino and the % population black or african american.

As briefly discussed in previous results, there may be interacting effects of patenting assignment and other economic indicators that are impacting the relationship. Table 16 illustrates a preliminary analysis of two separate potential interactions. The effect of the percentage of the patent assignment per capita on mortality rates per 100,000 depends on the percentage of the population that is unemployed, and the effect of the percentage that are unemployed on mortality rates per 100,000 depends on the patent assignment per capita. When variables are centered, for a county with an average percentage of those unemployed (i.e. has a score of 0 on the centered percentage unemployed variable) the main effect of patenting per capita is the effect of patent per capita on a county that has an average percentage of its population that is unemployed.

Column (ii) in Table 16 suggests that at average levels of unemployment, patenting per capita still decreases all-cause mortality rates by 0.54%. However, as illustrated in Figure 3, this relationship shifts at differing levels of unemployment.

[Figure 3]

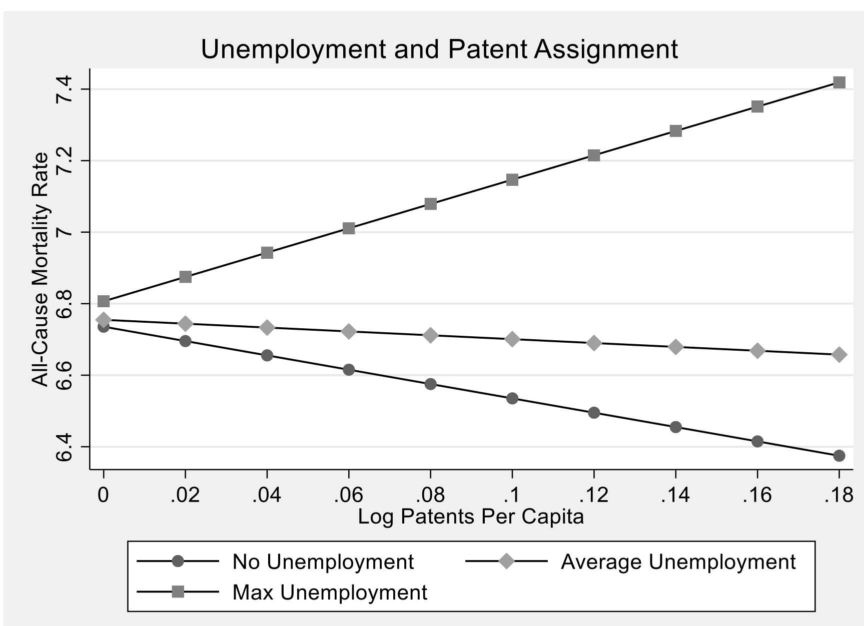
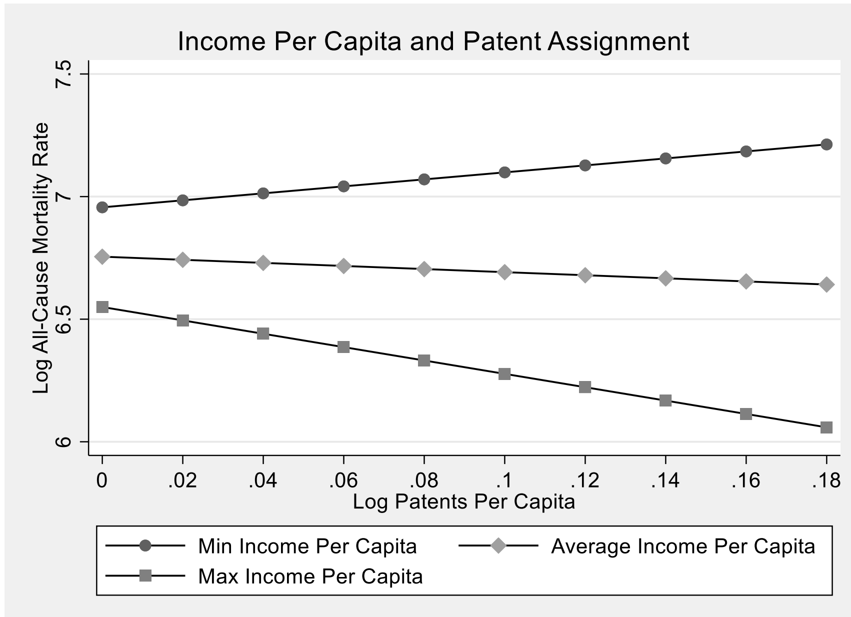


Figure 3 shows that when a county has no unemployment, patenting activity has a stronger impact toward decreasing the mortality rate than at the average unemployment level. For a county that has average unemployment, patent assignment within the county still decreases the overall mortality rate the more patenting assignment occurs. The results suggest a critical value of 3.17 is required before the interaction of patent per capita and the population of unemployed is able to positively impact the mortality rate. This is notable by the steep incline as a result of maximum unemployment within a county shown in Figure 3.

Additionally, the interaction between income per capita and patents per capita was analyzed. These results can be found in Table 16, column (iii). Generally, the results suggest that when the variables are centered, a county with an average income per capita has a mortality rate that decreases by 0.63%. However, as illustrated in Figure 4, this relationship also differs along the income per capita spectrum. Whereas at the minimum level of income per capita, patenting activity does not necessarily inversely impact the mortality rate. However, as income per capita increases, the relationship between patenting activity and the mortality rates gains in strength with a critical value registering 2.64, suggesting that the economic impact of patenting activity is also having an impact on the health outcomes at a per county level.

[Figure 4]



[Table 17]

Table 17: Results with M&P Interactions: *Dependent Varibale = Mortality Rate Per 100,000 Per County (2010-2014)*

	OLS (i)	OLS (ii)	OLS (iii)	OLS (iv)	OLS (v)	OLS (vi)
Medical & Pharmaceutical Patents Per Capita (centered)	-0.265***	-0.594	-0.243*			
	(0.063)	(0.316)	(0.119)			
Non Medical & Pharmacuetical Patents Per Capita (centered)				-0.076***	-0.037	-0.064*
				(0.020)	(0.063)	(0.023)
M&P Patents per capita		-0.053				
x % unemployed (centered)		(0.047)				
M&P Patents per capita			-0.173			
x income per capita (centered)			(0.767)			
Non M&P Patents per capita					0.002	
x % unemployed (centered)					(0.011)	
Non M&P Patents per capita						-0.132
x income per capita (centered)						(0.173)
R Squared	0.720	0.720	0.720	0.684	0.684	0.684
Year fixed effects	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes
Obs.	644	644	644	644	644	644

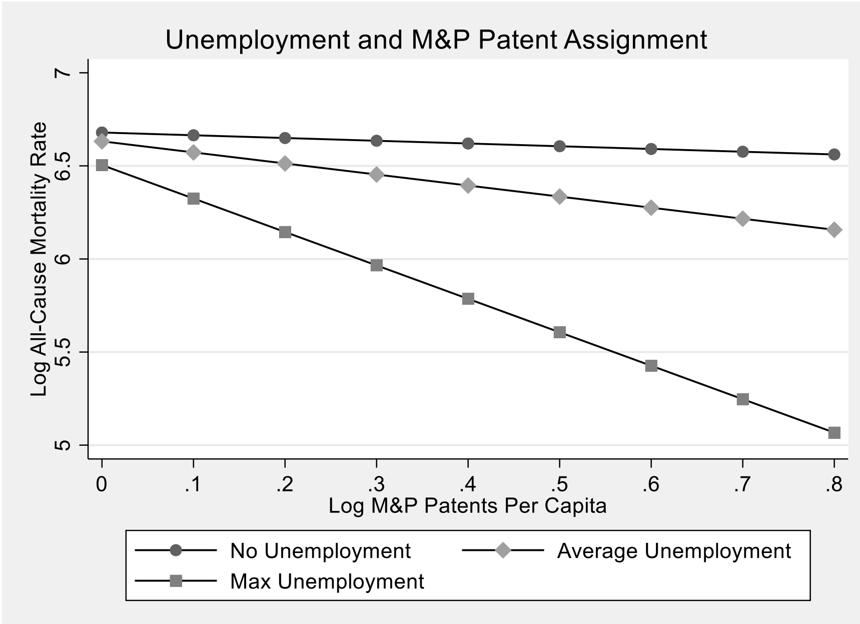
Note: Note: Clustered error at the state level are in parenthesis. Year fixed effects are accounted for. ***, **, and * = 0.1%, 1%, and 5% significance levels, respectively. The natual log tranformation of all-cause mortality, income per capita, medical & pharmaceutical patents per capita and non medical & pharmaceutical patents per capita were used in the regression computations. Each regression also includes inequality, the % of population unemployed, % of population 25 years or older with a bachelor degree, % of population employed in agriculture, forestry, fishing, hunting, and mining, % of population hispanic or latino and the % population black or african american.

Table 17 shows the benchmark results of medical and pharmaceutical patenting assignment (column (i)) and the effect of the interaction between medical and pharmaceutical patenting assignment and unemployment in addition to income per capita (Columns ii and iii) respectively, as well as the same interaction with non-medical and pharmaceutical patenting (columns iv-vi).

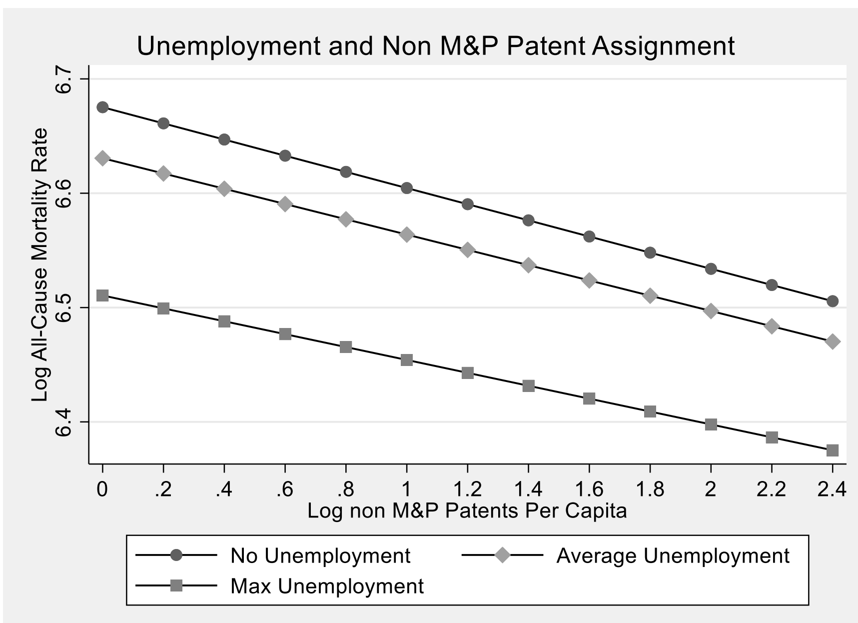
We can see that as compared to the benchmark equation, at average levels of unemployment, medical and pharmaceutical patenting decreases the mortality rate by 0.59%, although it should be noted the relationship is non-significant. Interestingly, at average levels of income per capita, medical and pharmaceutical patenting's impact on the mortality rate falls by two points. In contrast to general innovation, Table 17 suggests there is not much difference in non-medical and pharmaceutical patenting captured through the interaction of unemployment and income per capita impacting mortality rates, per county.

When analyzing the differences between Figure 5 and Figure 6, there is an interesting progression between the interaction of unemployment and medical and pharmaceutical patenting. Patenting has a greater positive impact on mortality rates as unemployment rates increase. Whereas non-medical and pharmaceutical patents maintain a relationship that results in decreasing mortality rates regardless of the unemployment rate.

[Figure 5]



[Figure 6]



[Figure 7]

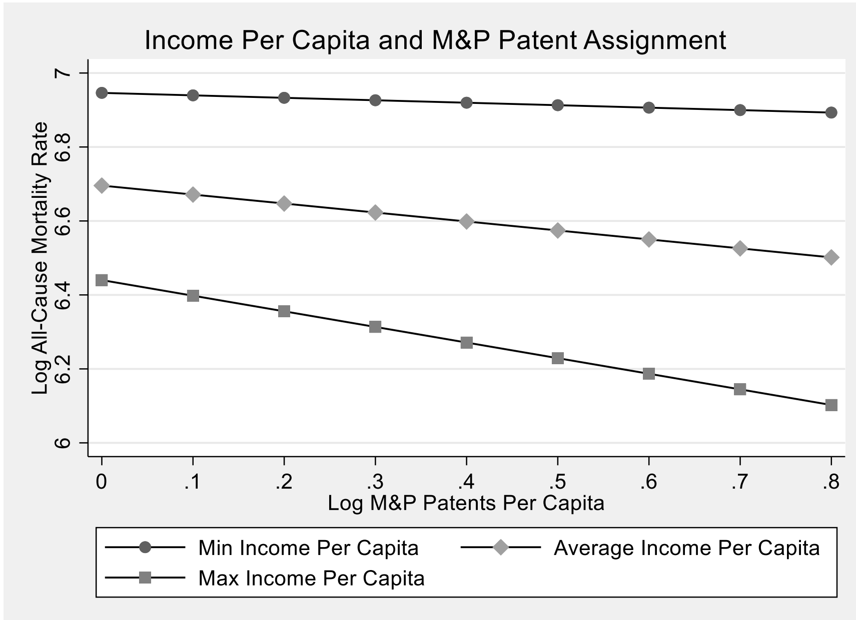
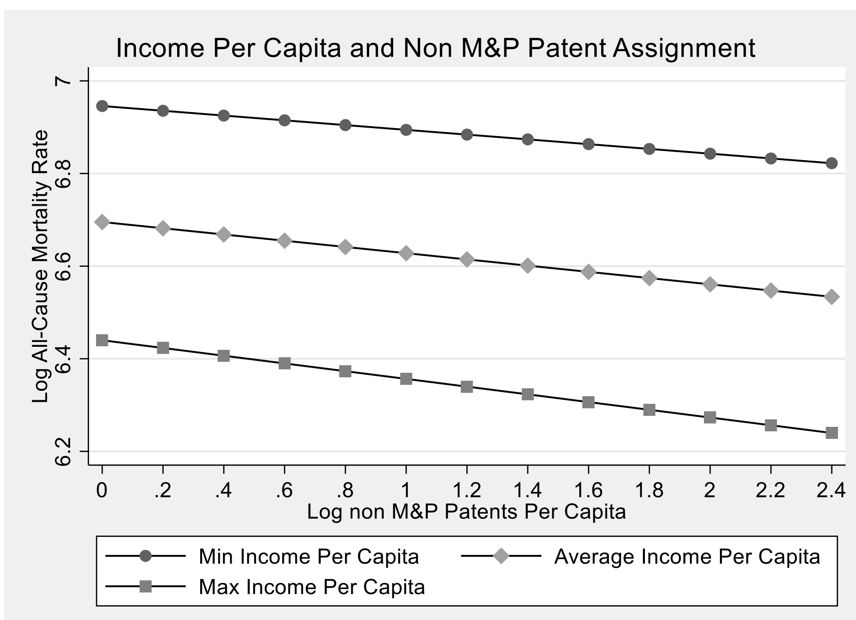


Figure 7 illustrates that as income per capita increases, the effect of medical and pharmaceutical patents increasingly decreases mortality rates, perhaps illustrating an ability to afford new medical interventions.

[Figure 8]



Preliminary Spatial Autocorrelation and Regression Analysis

In order to evaluate whether patenting assignment's effect on mortality rates is a phenomenon that is random, clustered, or dispersed across counties, a spatial autocorrelation, or Moran's I, was run. Moran's I is an inferential statistical method and should be interpreted in relation to the null hypothesis. In this case the null hypothesis states that the spatial distribution of patenting assignment per capita is a result of a random spatial process (Kondo, 2018). When analyzing the Moran's I statistic, I find that the Moran's I = 0.93 with a z score of 168.36 and $p = 0.00$. As such I can reject the null hypothesis. That is to say that the spatial distribution of patenting per capita in the data set is more spatially clustered than expected when assuming random spatial processes. This is indicated by the Moran's I being close to 1, suggesting that the mean values tend to cluster together (Kondo, 2018).

[Table 18]

Table 18: Spatial Autoregression Results: *Dependent Variable = Mortality Rate Per 100,000 Per County (2010-2014)*

	Random Effect Model (i)	Fixed Effect Model (ii)
Patents Per Capita (Direct Effect)	-0.15*	-0.16†
	(0.08)	(0.08)
Patents Per Capita (Indirect Effect)	-25.43***	-17.37***
	(5.31)	(5.29)
Year fixed effects	yes	yes
Controls	yes	yes
Obs.	9,417	9,417

Note: Note: Standard errors parenthesis. Year fixed effects are accounted for. ***, **, * and † = 0.1%, 1%, 5% and 10% significance levels, respectively. The natual log tranformation of all-cause mortality, income per capita, patents per capita were used in the regression computations. Each regression also includes inequality, the % of population unemployed, % of population 25 years or older with a bachelor degree, % of population employed in agriculture, forestry, fishing, hunting, and mining, % of population hispanic or latino and the % population black or african american.

As such a random-effects and fixed-effects spatial auto regression (SAR) model was run to analyze both the direct effect to the county and the indirect effect to the county as a result of spatial effects of patent assignment on all-cause mortality. Table 18 showcases those results, whereas column (i) is the random effect model and column (ii) is the fixed effect model. As such, the random effect parameter estimate for patent assignment suggests that a one percent increase in patent per capita results in a 0.15% decrease in the mortality rate. The indirect effect suggests that neighboring counties to patenting assignment activity see a one percent increase in patenting assignment decreases mortality rates by 25.43% of that county. The fixed-effects model suggests that a one percent increase in patenting activity within the county results in a 0.16% decrease in mortality rates while neighboring counties will see a 17.37% decrease in mortality rates. It is important to note that the direct fixed effect model was significant at the 10% level and provides greater support that both the direct and indirect effects have an impact on the mortality rate per county. This is indicative of the previous statistically significant results that do not account for spatial autocorrelation. These results show a strong impact in the indirect effect patenting assignment has on neighboring counties mortality rates per 100,000 persons. This is illustrated by the increase in effect being orders of magnitude larger than the direct impact innovation has on the mortality rate. However, the statistical significance of the indirect effect is still in support of innovation impacting mortality rates at a per county level.

Additionally, a Hausman Specification test was conducted to evaluate the consistency in estimator variables within a random-effects and fixed-effects spatial auto regression model. More specifically, a Hausman Specification test can be used with panel data to differentiate between a fixed effects model and random effects model. Generally, a random effects model is preferred under the null hypothesis as it provides higher efficiency. As a result, the Hausman test returns a χ^2 = 4,427.20 with a p = 0.00. This suggests that the null hypothesis should be rejected and that the fixed effects model is better than the random effects model when comparing the two models.

CHAPTER 5: CONCLUSION

5.1 Contributions

The intention of this dissertation is to examine the relationship between innovative economic activity (as captured by the number of patents assigned per county) and its impact on health outcomes at the county level. I show that the presence of innovation at a county level has an impactful role in decreasing mortality rates. By controlling for socioeconomic factors, I advance scholarly progress on the study of mortality and its relationship to innovation and provide evidence rooted in existing theory of health production.

By using a sample size of U.S. counties over several years, I am able to test my results across both medically motivated innovation and non-medical innovation sub-groups. I find that the results hold even in the absence of medical innovation at a county level and offers an opportunity to explore effects of innovation on mortality rates. Additional robustness analyses shows consistency in results when substituting alternative measures of socioeconomic status at the county level. My results also suggest a need to further consider interacting effects when testing for innovation's impact on county-level mortality rates.

As introduced previously, the United States' national healthcare expenditure topped $3.3 trillion in 2016. Unfortunately, U.S. employers take on a lion's share of that cost (Stewart et al., 2003). This cost impact inevitably trickles down to the individual county-level. In an effort to ease ballooning health care costs, a focus on health outcomes and innovative economic activity may be a lens from which to ease health spending pressures. Controlling health care costs, increasing innovation and bolstering the general health of human capital at a local level would be a pursuit worth embarking on toward bolstering local, regional and state economies.

In chapter 4, I examined variation in county-level rates for all-cause and individual type mortality rates between 2010 – 2014. I found that counties with more patenting activity had lower mortality rates and the effect gains strength in counties with higher concentration of mortalities (i.e. more populated counties). Interestingly, the effect of general innovation's impact on separate types of mortalities is not ubiquitous. The impact on mortality rates seems to also rely on the level of patenting activity per county, not whether a county is simply innovatively active or not.

When examining patenting activity excluding medical and pharmaceutical innovative activity, all-cause mortality rates decrease, although not at the same clip as medical and pharmaceutical innovative activity. Additionally, further analysis regarding potential time delays of the influence of patent assignment showed that the strongest impact on mortality rates falls within the same year of patent assignment. This suggests that the year of patent assignment has the greatest impact on health outcomes more so than subsequent years post patent assignment.

These findings support the argument that innovative activity at the county level has an impact on the mortality rates of the county. Although there is variability in the type of mortality and its response to all innovative activity, the findings provide a foundation from which future research on the relationship between innovative economic activity and health outcomes can build.

The findings of this paper may be offering a different lens from which to evaluate the theoretical prose of innovation economics (Schumpeter, 1942) or more recently

Romer's theory of endogenous growth. This research finds that mortality rates do decrease in the presence of innovation. While I did not set out to directly test for it, further study could better tease out the relationship to economic growth being a positive outcome of improved mortality. That is health outcomes or mortality may be a secondary, or indirect causal pathway by which innovation may impact economic growth by bolstering the local health stock of human capital.

These results also may be illuminating a greater shift in the impact on health outcomes as a result of our evolving economy in the Unites States. Just as in the early 1900's as people of agrarian pursuits transitioned into factories, economic prosperity shifted via indicators such as quality of housing. In turn, this showed a decrease in the rates of mortality as a result of such a transition. Where the American economy continues to transition from manual labor into a knowledge bound economy, the results may be beginning to tease out a new epidemiological transition as a result of the shifting economy. Such that demands for things like increases in urbanization with good planning may continue to positively impact population health

However, urbanization and growth should not outstrip physical and socioeconomic infrastructure such that they outpace sanitary planning, health in built environment and social service offerings. An example of such may be the direction change within the maternal disorder mortality rate and, more specifically, the direction change within the 60-80th percentiles. Mortality concentration increases may suggest that in higher population counties issues of maternal health for underserved populations within more urbanized areas may be lagging.

From a policy perspective, the results of this study provide support to existing research such as Rigby and Hatch (2016) that make the case for health to be a focus in more broad economic policy development. This work seeks to help communicate the health implications in broad economic policy by offering evidence of the effect for local, state and federal economic policy making. However, health is not necessarily on the radar for most economic policy makers (Rigby and Hatch, 2016). Additionally, economic policy making must also overcome a policy making environment that is much more ideologically polarized than in years past (Robert Wood Johnson Foundation, 2009). With that said, the results provide greater support for health to be a part of the broader conversation around economic development within local communities and back a health-in-all policy type approach to economic policy making.

5.2 Limitations

This study is not without its limitations. The sample is a U.S. county-level analysis only. For additional external validity, a similar analysis could be carried out in other geographic substrata such as at the Metropolitan Statistical Area (MSA) or at the Census Enumeration Track level to have a more granular analysis of the relationship between innovative activity and mortality. This analysis is limited to the jurisdictional boundary of the U.S. county and creates a blind spot for specific localities within the county such as metropolitan population that may share a county with a rural population.

As mentioned previously in the literature review, there are other ways to measure innovation as well. While patent counts are a valid metric in measuring innovation (Acs, Amselin and Varga, 2002), additional indicators of innovation could be tested to see if these results hold. This is true for the measurement of health as well. While mortalities are used in this analysis and is an accepted measure of health outcomes, other variables of health status and outcomes could be used. Perhaps leveraging the existing work of the annual County Health Rankings[14] work that measures vital health factors, including high school graduation rates, obesity, smoking, unemployment, access to healthy foods, the quality of air and water, income inequality, and teen births in nearly every county in America (Remington, Catlin, and Gennuso, 2015). Or perhaps an alternative health outcome measures such as self-reported health status (SRHS) could act as an alternative health metric.

While I include known socioeconomic control variables and mortality influencers, there could be others that might help explain the influence of innovation on mortality rates. I use a standard ordinary least squares regression in this analysis while exploring time effects and the type of innovation to minimize potential endogeneity of the results, but the same approach could be used with other health outcome measures as the dependent variable. While attempts were made to minimize potential endogeneity as best as possible by considering potential confounders, there is still a possibility that endogeneity is not fully eliminated. Further, the exploration of the interactions and mediating effects of socioeconomic variables role in innovation effect on mortality could continue to parse out more subtle touch points of the relationship to health outcomes.

Great care must also be taken in interpretation as the ecological approach suggests that the findings should not be generalized to the individual-level (Piantadosi, Byar, and Green, 1988). Literature refers to this as the ecological fallacy. Further, changing the spatial scale and unit of analysis may also lead to different conclusions (Openshaw,

---

[14] The county health rankings and roadmaps is a national project conducted through the collaboration of the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute.

1984). Referred to as the modifiable real unit problem, studies that utilize aggregate data tend to share these issues.

Also, the inequality measure utilized stresses the income per household per county. This could be confounded by other social subsidies that are offered to disadvantaged populations. Income inequality is just one aspect of inequality. It is not clear that the selection of socio-economic indicators included capture the entirety of inequality and further study is suggested to elucidate the broad spectrum that exists regarding inequality.

5.3 Extensions

As mentioned previously, a similar analysis could be applied to a sample of smaller geographic areas to ensure the external validity of the results. Such comparison could offer a more intricate geographic comparison to show differences in how innovative activity impacts health outcomes at an even lower ecological level. As mentioned in the literature review previously, there are other potential metrics that can be used to measure innovation as well. While patent counts are shown to be an appropriate measure of innovation (Acs, Amselin and Varga, 2002), further research could leverage additional measurements of innovation to see if the results will still hold. One could see where innovation data at the census track level could bring forward differences of impact to the city sector or neighborhood level of analysis.

Further, literature has shown that there is some relationship between measures of social capital and mortality. However, a measure of social capital was not included for this study but may prove to be a variable of consideration toward future research. Future research could also tease out policy intervention’s impact on health by evaluating the local county policy environment around economic development and tax incentive policy toward entrepreneurial work and its relationship to health indicators. Additional research using more focused research design could help to better understand the mechanisms for which innovation impacts health and establish causal impact.

Also, while control measures of rurality of a county were included in the study, patenting activity in highly agrarian communities may not be the best indicator of innovative economic activity. Future research could evaluate a separate economic measure of activity in rural and frontier settings such as indebtedness to further tease out health implications of economic activity in such communities.

Lastly, while preliminary interaction results were shown based on the percentage of the population that was unemployed and the income per capita, there is an opportunity to study in more detail the relationships of variables impact on health outcomes. Such an analysis would better define both the direct and indirect effects of innovation in a more broad economic sense.

APPENDIX

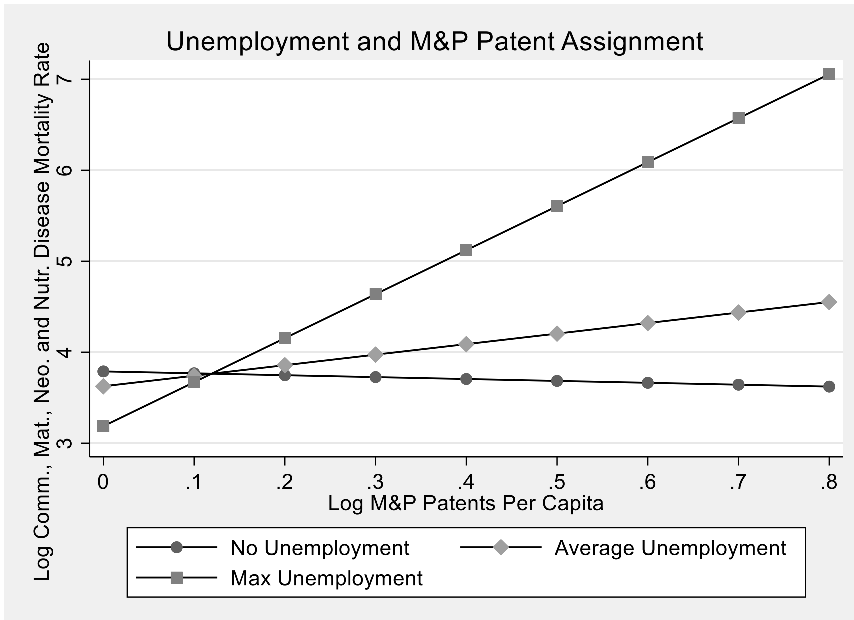
Appendix Item 1 – Interaction table and figures

Table 19: Results with M&P Interactions: *Dependent Variable = Individual Mortality Rate Per 100,000 Per County (2010-2014)*

	Communicable, maternal, neonatal and nutritional diseases	Communicable, maternal, neonatal and nutritional diseases	Diarrhea, lower respiratory, and other common infectious diseases	Diarrhea, lower respiratory, and other common infectious diseases	Neglected tropical diseases and malaria	Neglected tropical diseases and malaria	Maternal disorders	Maternal disorders
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Medical & Pharmaceutical Patents Per Capita (centered)	1.16	0.74	1.25	0.73	4.61	2.06*	0.33	0.49
	(0.80)	(0.53)	(0.94)	(0.57)	(2.56)	(0.99)	(1.39)	(0.70)
M&P Patents per capita	0.16		0.19		0.55		0.05	
x % unemployed (centered)	(0.12)		(0.15)		(0.36)		(0.22)	
M&P Patents per capita		-4.58		-4.87		-6.52		-3.52
x income per capita (centered)		(3.96)		(4.20)		(5.41)		(5.20)
R Squared	0.51	0.51	0.36	0.36	0.31	0.31	0.59	0.59
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	644	644	644	644	644	644	644	644

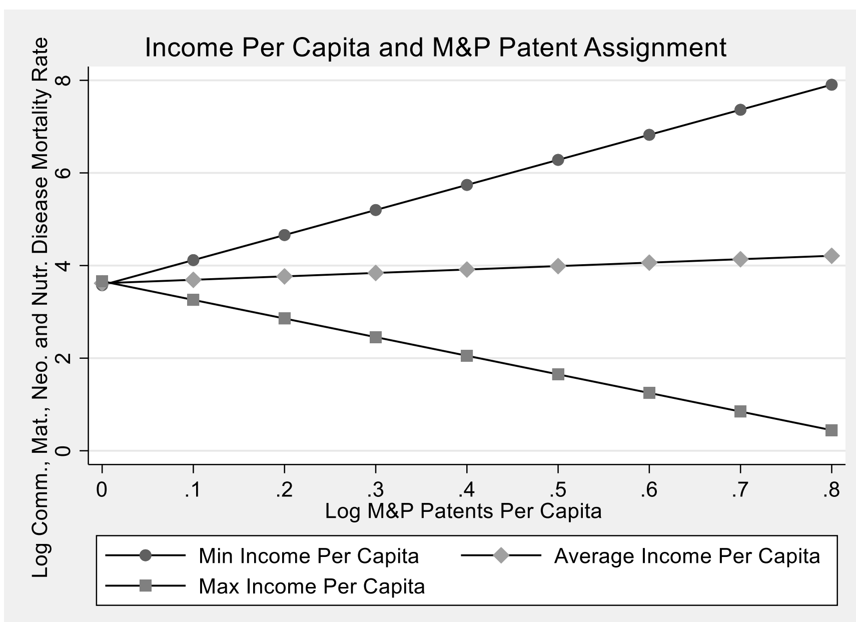
Note: Note: Clustered error at the state level are in parenthesis. Year fixed effects are accounted for. ***, **, and * = 0.1%, 1%, and 5% significance levels, respectively. The natual log tranformation of all-cause mortality, income per capita, medical & pharmaceutical patents per capita and non medical & pharmaceutical patents per capita were used in the regression computations. Each regression also includes inequality, the % of population unemployed, % of population 25 years or older with a bachelor degree, % of population employed in agriculture, forestry, fishing, hunting, and mining, % of population hispanic or latino and the % population black or african american.

(i)



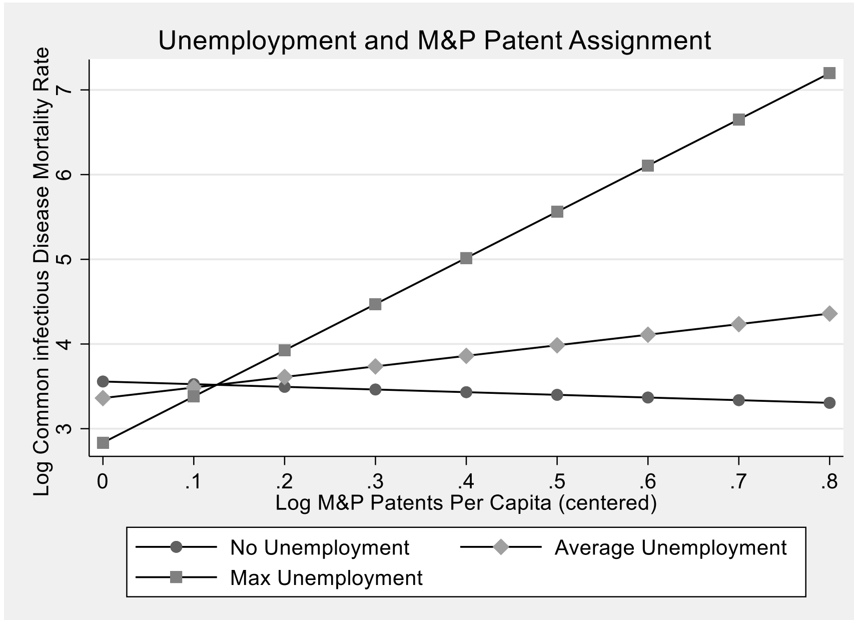
Unemployment and M&P Patent Assignment
Log Comm., Mat., Neo. and Nutr. Disease Mortality Rate
3
4
5
6
7
0
.1
.2
.3
.4
.5
.6
.7
.8
Log M&P Patents Per Capita
No Unemployment
Average Unemployment
Max Unemployment

(ii)



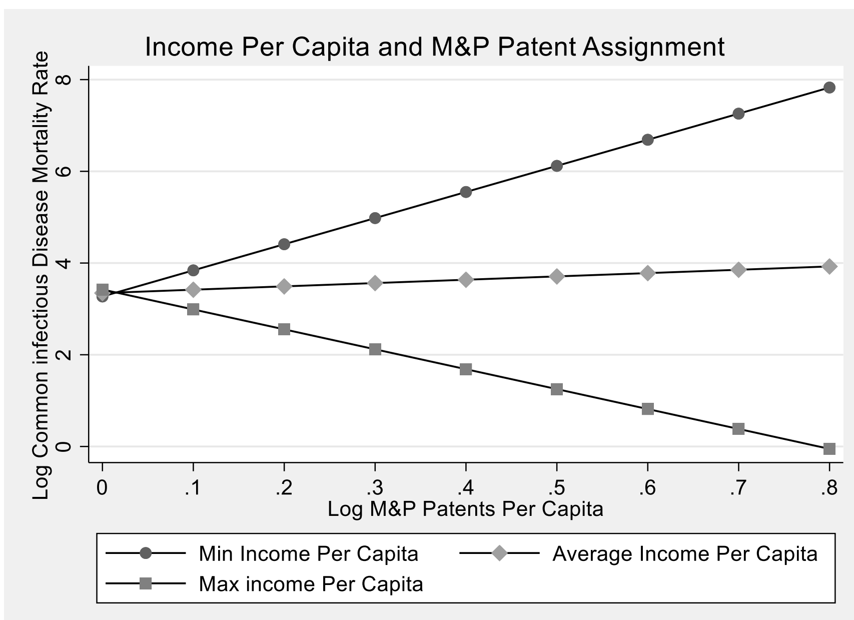
Income Per Capita and M&P Patent Assignment
Log Comm., Mat., Neo. and Nutr. Disease Mortality Rate
0
2
4
6
8
0
.1
.2
.3
.4
.5
.6
.7
.8
Log M&P Patents Per Capita
Min Income Per Capita
Average Income Per Capita
Max Income Per Capita

(iii)



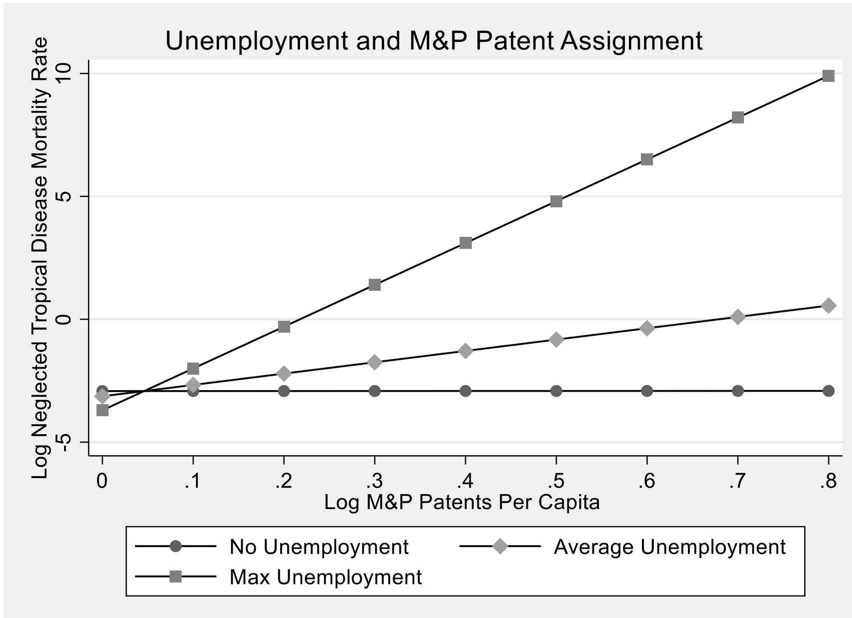
Unemployment and M&P Patent Assignment
Log Common infectious Disease Mortality Rate
3
4
5
6
7
0
.1
.2
.3
.4
.5
.6
.7
.8
Log M&P Patents Per Capita (centered)
No Unemployment
Average Unemployment
Max Unemployment

(iv)

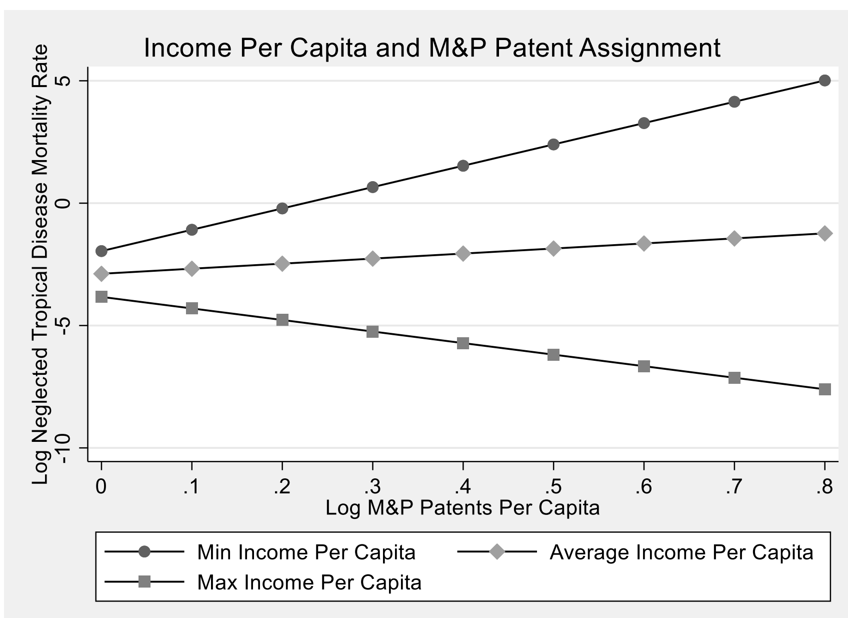


Income Per Capita and M&P Patent Assignment
Log Common infectious Disease Mortality Rate
0
2
4
6
8
0
.1
.2
.3
.4
.5
.6
.7
.8
Log M&P Patents Per Capita
Min Income Per Capita
Average Income Per Capita
Max income Per Capita

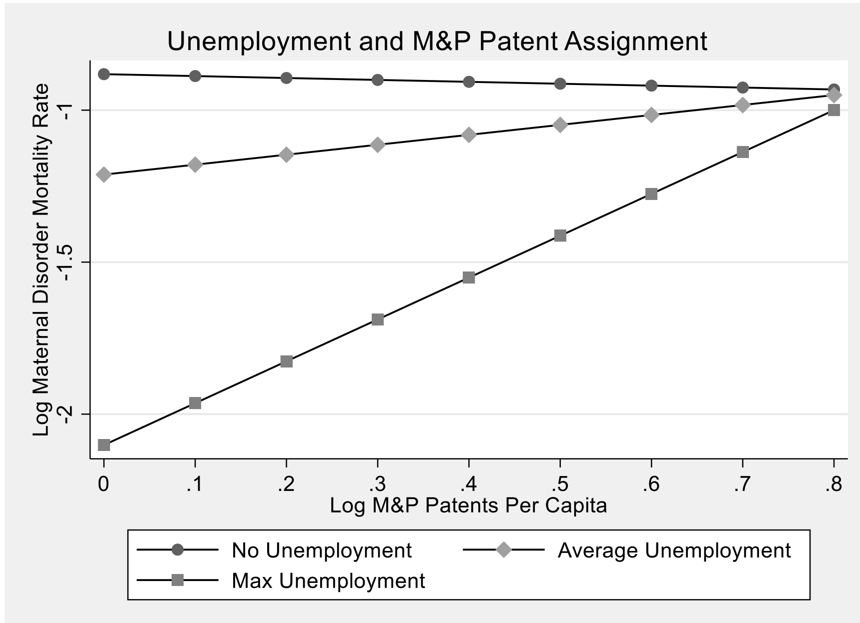
(v)


Unemployment and M&P Patent Assignment
Log Neglected Tropical Disease Mortality Rate
-5
0
5
10
0
.1
.2
.3
.4
.5
.6
.7
.8
Log M&P Patents Per Capita
No Unemployment
Average Unemployment
Max Unemployment

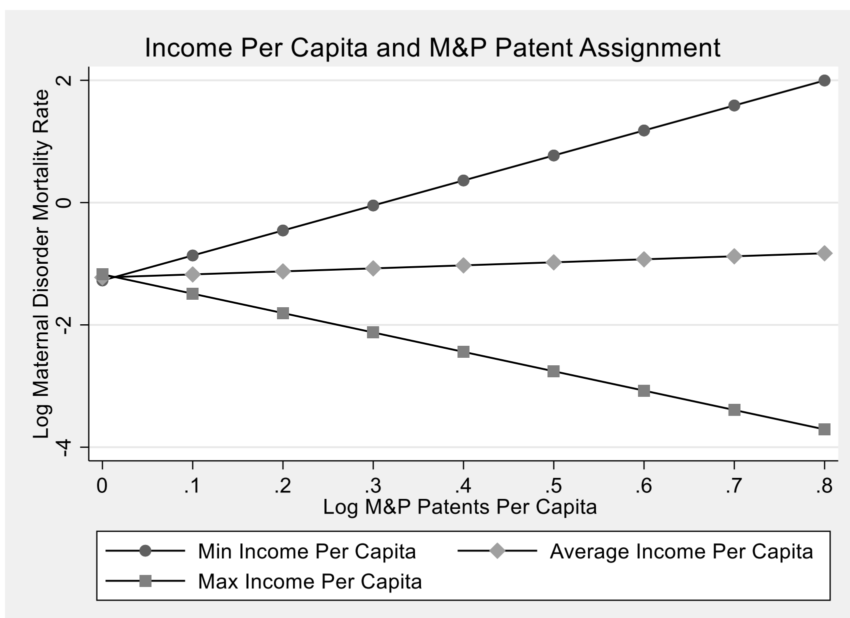
(vi)


Income Per Capita and M&P Patent Assignment
Log Neglected Tropical Disease Mortality Rate
-10
-5
0
5
0
.1
.2
.3
.4
.5
.6
.7
.8
Log M&P Patents Per Capita
Min Income Per Capita
Average Income Per Capita
Max Income Per Capita

(vii)


Unemployment and M&P Patent Assignment
Log Maternal Disorder Mortality Rate
-1
-1.5
-2
0
.1
.2
.3
.4
.5
.6
.7
.8
Log M&P Patents Per Capita
No Unemployment
Average Unemployment
Max Unemployment

(viii)


Income Per Capita and M&P Patent Assignment
Log Maternal Disorder Mortality Rate
2
0
-2
-4
0
.1
.2
.3
.4
.5
.6
.7
.8
Log M&P Patents Per Capita
Min Income Per Capita
Average Income Per Capita
Max Income Per Capita

REFERENCES

Acs, Z. J., Anselin, L., & Varga, A. (2002). Patents and innovation counts as measures of regional production of new knowledge. Research Policy, 31(7), 1069-1085.

Adams, S. M., Mahoney, M. C., Hyland, A., Cummings, M., Davis, W., & Song, L. (2006). Early evidence on the effectiveness of clean indoor air legislation in New York State. American Journal of Public Health, 96, 296-298.

Adler, N. E., Boyce, T., Chesney, M. A., Cohen, S., Folkman, S., Kahn, R. L., and Syme, S. L. (1994). Socioeconomic Status and Health: The Challenge of the Gradient. American Psychologist, 49(1): 15-24.

Allen, D. W. (2001). Social class, race, and toxic releases in American counties, 1995. The Social Science Journal, 38(1), 13-25.

Allison, P. D. (1978). Measure of inequality. American Sociological Review, 43(6), 865-880.

Asheim, Bjørn T., & Gertler, M. S. (2009). The Geography of Innovation: Regional Innovation Systems. *The Oxford Handbook of Innovation*, (June).

Asheim, Bjørn T., Boschma, R., & Cooke, P. (2011). Constructing Regional advantage: Platform policies based on related variety and differentiated knowledge bases. *Regional Studies*, *45*(7), 893–904.

Asheim, Bjorn T., Smith, H. L., & Oughton, C. (2011). Regional Innovation Systems: Theory, empirics and policy. *Regional Studies*, *45*(7), 875–891.

Baraldi, A. L., Cantabene, C., & Perani, G. (2014). Reverse causality in the R&D-patents relationship: An interpretation of the innovation persistence. *Economics of Innovation and New Technology*, *23*(3), 304–326.

Bishai, D., Alfonso, y. N., Brady, E., Leider, J. P., Sensenig, A., & Resnick, B. (2016). *Putting Public health Capital in the Grossman Model: Theory and tests of links between government public health spending and mortality*.

Blane, D. (1990). Real Wages, the Economic Cycle, and Mortality in England and Wales, 1870–1914. *International Journal of Health Services*, *20*(1), 43–52.

Bowerman, B. L., & O'Connell, R. T. (1990). *Linear statistical models: An applid approach* (2nd ed.). Belmont, CA: Duxbury.

Brodish, P. H., Massing, M. & Tyroler, H. A. (2000). Income inequality and all-cause mortality in the 100 counties of North Carolina. Southern Medical Journal. 93(4), 386-391.

Brown, J. S., & Duguid, P. (2017). The Social Life of Information: Updated, with a New Preface. Harvard Business Review Press.

Camagni, R. (1985). Spatial diffusion of pervasive process innovation. *Papers in Regional Science*, *58*(1), 83–95.

Capello, R. (2017). Seminal Studies in Regional and Urban Economics. Springer.

Cellular Telecommunications Industry Association (CTIA) (2018). Industry Data. https://www.ctia.org/the-wireless-industry/infographics-library?topic=35, accessed November 11, 2018.

Chernozhukov, V., & Hong, H. (2002). Three-Step Censored Quantile Regression and Extramarital Affairs. Journal of the American Statistical Association, 97(459)

Cohen, A. B., & Hanft, R. S. (2004). Technology in American health care: Policy directions for effective evaluation and management. University of Michigan Press.

Cooter, R. (2005). Innovation, information, and the poverty of nations. *Fla. St. UL Rev.*, *33*, 373.

Cossman, R. E., Cossman, J. S., Cosby, A. G. & Reavis, R. M. (2008). Reconsidering the rural urban continuum in rural health research: A test of stable relationships using mortality as a health measure. Population Research and Policy Review, 27(4), 459-476.

Counties, N. A. of. (n.d.). Overview of County Government. Retrieved from https://web.archive.org/web/20130417063950/http://www.naco.org/Counties/Pages/Overview.aspx

Cuadrado-Roura, J. R. (2017). From the Role of Space in Knowledge Creation to Scenario Building Through Territorial Capital. In *Seminal Studies in Regional and Urban Economics* (pp. 37–47). Springer.

Cutler, D. M., Lleras-Muney, A., & Vogl, T. (2011). Socioeconomic status and health: dimensions and mechanisms. In The Oxford Handbook of Health Economics. (pp. 126-163). Oxford University Press.

Derefinko, K. J., & Pelham Jr, W. E. (2013). ADHD and substance use. In *The oxford handbook of substance use and substance use disorders*.

Do, D. P., Wang, L., & Elliott, M. R. (2013). Investigating the relationship between neighborhood poverty and mortality risk: A marginal structural modeling approach. *Social Science & Medicine*, *91*, 58–66.

Dodge, M., & Kitchin, R. (2003). Mapping cyberspace. Routledge.

Doyle, S., Kelly-Schwartz, A., Schlossberg, M., & Stockard, J. (2006). Active Community Environments and Health: The Relationship of Walkable and Safe Communities to Individual Health. *Journal of the American Planning Association*, *72*(1), 19–31.

Dwyer-Lindgren, L., Bertozzi-Villa, A., Stubbs, R. W., Morozoff, C., Kutz, M. J., Huynh, C., … Murray, C. J. L. (2016). US county-level trends in mortality rates for major causes of death, 1980-2014. *JAMA - Journal of the American Medical Association*, *316*(22), 2385–2401.

Dwyer-Lindgren, L., Bertozzi-Villa, A., Stubbs, R. W., Morozoff, C., Shirude, S., Unützer, J., … Murray, C. J. L. (2018). Trends and patterns of geographic variation in mortality from substance use disorders and intentional injuries among us counties, 1980-2014. *JAMA - Journal of the American Medical Association*, *319*(10), 1013–1023.

Eisinger, D., Tsatsaronis, G., Bundschus, M., Wieneke, U., & Schroeder, M. (2013). Automated Patent Categorization and Guided Patent Search using IPC as Inspired by MeSH and PubMed. *Journal of Biomedical Semantics*, *4*(1), S3.

El Bcheraoui, C., Mokdad, A. H., Dwyer-Lindgren, L., Bertozzi-Villa, A., WStubbs, R., Morozoff, C., … Murray, C. J. L. (2018). Trends and patterns of differences in infectious disease mortality among US Counties, 1980-2014. *JAMA - Journal of the American Medical Association*, *319*(12), 1248–1260.

Ezzati, M., Vander Hoorn, S., Lawes, C. M. M., Leach, R., James, W. P. T., Lopez, A. D., … Murray, C. J. L. (2005). Rethinking the “Diseases of Affluence” Paradigm: Global Patterns of Nutritional Risks in Relation to Economic Development. *PLOS Medicine*, *2*(5), e133. Retrieved from https://doi.org/10.1371/journal.pmed.0020133

Feldman, M., & Florida, R. (1994). The Geopgraphic Sources of Innovation: Technological Infrastructure and product innovation in the United States. *Annals of the Assication of American Geographers*, *84*(2), 210–229.

Field, A. (2013). *Discovering Statistics Using IBM SPSS Statistics* (4th ed.). Sage Publications Ltd.

Fiscella, K., & Franks, P. (1997). Poverty or income inequality as predictor of mortality: longitudinal cohort study. *BMJ*, *314*(7096), 1724.

Florida, R. L. (2014). Startup City: The Urban Shift in Venture Capital and High Technology. Martin Prosperity Intstitute.

Food and Drug Organization of the United Nations. (2009). 2050: A third more mouths to feed. http://www.fao.org/news/story/en/item/35571/icode/

Gelijns, A., & Rosenberg, N. (1994). The dynamics of technological change in medicine. *Health Affairs*, 13(3), 28-46.

Gill, P.S. (2012). Technological Innovation and Public Health: A descriptive exploratory investigation of the relationship between technological innovation indicators in the Unites States from 2003 – 2007. *Global Journal of Medical Research*, 12 (6), 63-81

Gill, P. S. (2013). Technological innovation and its effect on public health in the United States. Journal of Multidisciplinary Healthcare, 6, 31-40.

Glied, S., & Lleras-Muney, A. (2008). Technological innovation and inequality in health. Demography, 45(3), 741-761.

https://www.nlm.nih.gov/nichsr/hta101/HTA_101_FINAL_02-02-15.pdf

Gortmaker, S. L. (1979). Poverty and Infant Mortality in the United States. *American Sociological Review*, *44*(2), 280–297.

Greenberg, M. R. (2006). The Diffusion of Public Health Innovations. American Journal of Public Health, 96(2), 209.

Griliches, Z. (1979). Issues in Assessing the Contribution of Research and Development to Productivity Growth. The Bell Journal of Economics, 10(1), 92-116.

Grossman, M. (1972). On the concept of health capital and the demand for health. *Journal of Political Economy*, *80*(2), 223–255.

Grossman, M. (2000). The human capital model. In *Handbook of health economics* (Vol. 1, pp. 347–408). Elsevier.

Hagerstrand, T. (1952). The propagation of innovation waves. *Lund Studies of Geography*, *B*(4), 355–357.

Hagerstrand, T. (1967). *Innovation diffusion as a spatial process*. University of Chicago Press.

Hall, B, Jaffe, A., Trajtenberg, M. (2001). The NBER patent citations data file: lessons, insights and methodological tools. WP 8498 National Bureau of Economic Research.

Hendryx, M. (2011). Poverty and Mortality Disparities in Central Appalachia: Mountaintop Mining and Environmental Justice. *Journal of Health Disparities Research and Practice*, *4*(3), 44–53. Retrieved from http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Poverty+and+Mortality+Disparities+in+Central+Appalachia:+Mountaintop+Mining+and+Environmental+Justice#0

Holt-Lunstad, J., Smith, T. B., & Layton, J. B. (2010). Social Relationships and Mortality Risk: A Meta-analytic Review. *PLOS Medicine*, *7*(7), e1000316. Retrieved from https://doi.org/10.1371/journal.pmed.1000316

Honoré, P. A., Fos, P. J., Wang, X., & Moonesinghe, R. (2011). The effects on population health status of using dedicated property taxes to fund local public health agencies. BMC public health, 11(1), 471.

Hotez, P. J. (2016). *Blue Marble Health: An innovative plan to fight diseases of the poor amid wealth*. Johns Hopkins University Press.

Howard, G., Anderson, R. T., Russell, G., Howard, V. J., and Burke, G. L. (2000). Race, Socioeconomic Status, and Cause-Specific Mortality. *Annals of Epidemiology*, 10(4): 214-223.

Hughes, L. (2011). Innovation and the new landscape for public health. Perspectives in Public Health, 131(3), 114-115.

Hutton, T. A. (2004). The new economy of the inner city. *Cities*, 21(2), 89-108.

Institute for Health Metrics and Evaluation (IHME) (2016). United States Mortality Rates by County 1980-2014. Seattle, United States: Institute for Health Metrics and Evaluation.

Jacobson, L. (2000). The family as producer of health – an extended Grossman model. *Journal of Health Economics*. 19(5), 611-37.

James, W. L. & Cossman, J. S. (2006). Does regional variation affect ecological mortality research? An examination of mortality, income inequality and health infrastructure in the Mississippi Delta. Population Research and Policy Review, 25(2), 175-195.

Kawachi, I. & Kennedy, B. P. (1997). The relationship of income inequality to mortality: Does the choice of indicator matter? Social Science & Medicine, 45(7), 1121-1127.

Kawachi, I., Kennedy, B. P., & Wilkinson, R. G. (1999). Crime: social disorganization and relative deprivation. *Social Science & Medicine*, *48*(6), 719–731.

Katz, B., & Wagner, J. (2014). The rise of innovation districts: A new geography of innovation in America. Washington: Brookings Institution.

Kezdi, G. (2003). Robust standard error estimation in fixed-effects panel models. Available at SSRN 596988.

Kolesnikova, N. A., & Shimek, L. M. (2008). Community colleges: Not so junior anymore. *The Regional Economist*, (Oct), 6-11.

Kondo, K. (2018). Testing for global spatial autocorrelation in Stata. Available: http://fmwww.bc.edu/RePEc/bocode/m/moransi.pdf

Kress, H. C., Noonan, R., Freire, K., Marr, A., & Olson, A. (2012). Top 20 violence and injury practice innovations since 1992. *Journal of Safety Research*, *43*(4), 257–263.

Krumholz, H. M., Normand, S. L. T., & Wang, Y. (2018). Geographical health priority areas for older Americans. *Health Affairs*, *37*(1), 104–110.

Law, T. H., Noland, R. B., & Evans, A. W. (2011). The sources of the Kuznets relationship between road fatalities and economic growth. Journal of Transport Geography, 19(2), 355-365.

Link, B. G., & Phelan, J. (1995). Social conditions as fundamental causes of disease. Journal of health and social behavior, 80-94.

Macintyre, Ellaway, & Cummins. (2002). Place effects on health: How can we conceptualise, operationalise and measure them? *Social Science & Medicine*, *55*(1), 125-139.

Massing, M. W., Rosamond, W. D., Wing, S. B., Suchindran, C. M., Kaplan, B. H. & Tyroler, H. A. (2004). Income, income inequality, and cardiovascular disease mortality: Relations among county populations of the United States, 1985 to 1994. Southern Medical Journal, 97(5), 475-484.

McLaughlin, D. K. & Stokes, C. S. (2002). Income inequality and mortlity in US counties: Does minority racial concentration matter? American Journal of Public Health, 92(1), 99-104.

McLaughlin, D. K., Stokes, C. S. & Nonoyama, A. (2001). Residence and income inequality: Effects on mortality among US counties. Rural Sociology, 66(4), 579-598.

Messner, S. F., Raffalovich, L. E., & Sutton, G. M. (2010). Poverty, Infant Mortality, and Homicide Rates in Cross-National Perspective: Assessments of criterion and contruct validity*. *Criminology*, *48*(2), 509–537.

Mokyr, J. (1993). Technological progress and the decline of European mortality. (includes bibliography) (Recent Findings on Living Standards, Work Levels, Health, and Mortality: an International Comparison)(Papers and Proceedings of the American Economic Association Annual. *American Economic Review*, *83*(2), 324.

Moniruzzaman, S., & Andersson, R. (2008). Economic development as a determinant of injury mortality–A longitudinal approach. Social Science & Medicine, 66(8), 1699-1708.

Morgan, K. (2004). The exaggerated death of geography: Learning, proximity and territorial innovation systems. *Journal of Economic Geography*, *4*(1), 3–21.

Muro, M., Fikri, K., & Andes, S. (2014). Powering Advanced Industries: State by State. Washington: Brookings Institution.

National Center for Health Statistics. (2017). Health, United States, 2016: With Chartbook on Long-term Trends in Health. Hyattsville, MD.

Nichols, A., & Schaffer, M. (2007). Clustered errors in Stata. In Paper presented at the United Kingdom Stata Users' Group meeting.

Nilekani, R. (2017). *The Emerging Pardigm in Mental Health*.

North, D., & Smallbone, D. (2000). Innovative Activity in SMEs and Rural Economic Development: Some Evidence from England. *European Planning Studies*, *8*(1), 87–106

O'Connor, J. M., Sedghi, T., Dhodapkar, M., Kane, M. J., & Gross, C. P. (2018). Factors Associated With Cancer Disparities Among Low-, Medium-, and High-Income US Counties. *JAMA Network Open*, *1*(6), e183146.

Organization for Economic Co-Operation and Development (OECD). (2010). Measuring Innovation: A new perspective.

Organization for Economic Co-Operation and Development (OECD). (2010). Addressing global and social challenges through innovation. The OECD Innovation Strategy, 165-188

Office, U. S. P. and T. (2019). USPTO Cooperative Patent Classification Resource. Retrieved from https://www.uspto.gov/web/patents/classification/cpc/html/cpc.html

Openshaw, S. (1984). The Modifiable Areal Unit Problem. Norwich, UK: Geo Books.

Pakes, A., Griliches, Z., 1980. Patents and R&D at the firm level: a first report. Economics Letters, 5, 377–381.

Patel, M. S., Asch, D. A., Rosin, R., Small, D. S., Bellamy, S. L., Heuer, J., Sproat, S., Hyson, C., Haff, N., Lee, S. M. and Wesby, L. (2016). Framing financial incentives to increase physical activity among overweight and obese adults: a randomized, controlled trial. *Annals of internal medicine*, 164(6), pp.385-394.

Piantadosi, S., Bryar, D.P., & Green, S.B. (1988). The Ecological Fallacy. American Journal of Epidemiology. 127(5). 893.

Remington, P. L., Catlin, B. B., & Gennuso, K. P. (2015). The County Health Rankings: rationale and methods. *Population Health Metrics*, *13*, 11.

Ridley, R. (2010). Science, technology, innovation and health. TDR News, (85), 2.

Rigby, E. and Hatch, M. E. (2016). Incorporating Economic Policy Into a 'Health-In-All-Policies' Agenda. *Health Affairs*, 35(11), 2044-2052.

Robert Wood Johnson Foundation. (2009). Robert Wood Johnson Foundation Commission to Build a Healthier America. Beyond Health care: new directions to a healthier America. Princeton, NJ

Rust, G., Satcher, D., Fryer, G. E., Levine, R. S., & Blumenthal, D. S. (2010). Triangulating on success: innovation, public health, medical care, and cause-specific US mortality rates over a half century (1950–2000). *American Journal of Public Health*, 100(S1), S95-S104.

Sachs, J. (2008). Common wealth: Economics for a crowded planet. Penguin.

Sampson, R. J., Raudenbush, S. W. & Earls, F. (1997). Neighborhoods and violet crime: a multilevel study of collective efficacy. *Science*, 277(5328), 918-924

Santos-Gandelman, J., & Machado-Silva, A. (2019). Drug development for cryptococcosis treatment: what can patents tell us? *Memorias Do Instituto Oswaldo Cruz*, *114*, e180391–e180391.

Schumpteter, J. A. (1942). Capitalism, Socialism and Democracy, 3rd ed. New York, Harper & Row.

Shi, L., & Johnson, J. A. (2013). Novick & Morrow's Public Health Administration. Jones & Bartlett Publishers.

Shi, L., Macinko, J., Starfield, B., Politzer, R., Wulu, J. and Xu, J. (2005). Primary care, social inequities, and all-cause heart disease, and cancer mortality in US Counties, 1990. American Journal of Public Health. 95(4), 674-680.

Stewart, W. F., Ricci, J. A., Chee, E., Morganstein, D., & Lipton, R. (2003). Lost productive time and cost due to common pain conditions in the US workforce. Journal of the American Medical Association, 290(18), 2443-2454.

Studnicki, J., Gipson, L. S., Berndt, D. J., Fisher, J. W., Callandar, M., Pracht, E., & Langland-Orban, B. (2007). Special healthcare taxing districts: association with population health status. American Journal of Preventive Medicine, 32(2), 116-123.

Tapia Granados, J. A. (2012). Economic growth and health progress in England and Wales: 160 years of a changing relation. *Social Science and Medicine*, *74*(5), 688–695.

The Lancet Public Health. (2017). Public health is local. *The Lancet Public Health*, *2*(9), e387.

Treasury, H. M. (2004). Devolving Decision Making 2-Meeting the Regional Economic Challenge: Increasing Regional and Local Flexibility. HM Treasury, London.

United Nations Development Report. (2009). Human Development Report 2009. Overcoming Barriers: Human Mobility and Development. Retrieved from http://hdr.undp.org/sites/default/files/reports/269/hdr_2009_en_complete.pdf.

United Nations, Department of Economic and Social Affairs, Population Division (2017). World Population Prospects: The 2017 Revision, Key Findings and Advance Tables. ESA/P/WP/248.

United States Department of Commerce. (2016). United States Census Bureau. Gini Index. Retrieved from https://www.census.gov/topics/income-poverty/income-inequality/about/metrics/gini-index.html

Varey, P. (2011). Spend to save: Synergy and innovation in public health. Perspectives in Public Health, 131(3), 112-114.

Venniro, M., Zhang, M., Caprioli, D., Hoots, J. K., Golden, S. A., Heins, C., Morales, M., Epstein, D., & Shaham, Y. (2018). Volitional social interaction prevents drug addiction in rat models. *Nature Neuroscience*, *21*(11), 1520–1529.

Waitzman, N. J., & Smith, K. R. (1998). Phantom of the area: poverty-area residence and mortality in the United States. *American Journal of Public Health*, *88*(6), 973–976.

Weng, H.-B., Chen, H.-X., & Wang, M.-W. (2018). Innovation in neglected tropical disease drug discovery and development. *Infectious Diseases of Poverty*, *7*(1), 67.

Wiklund, J., Hatak, I., Patzelt, H., & Shepherd, D. A. (2018). Mental disorders in the entrepreneurship context: when being different can be an advantage. *Academy of Management Perspectives*, *32*(2), 182–206.

Wiklund, J., Patzelt, H., & Dimov, D. (2016). Entrepreneurship and psychological disorders: How ADHD can be productively harnessed. *Journal of Business Venturing Insights*, *6*, 14–20.

Wild, C., & Langer, T. (2008). Emerging health technologies: informing and supporting health policy early. Health Policy, 87(2), 160-171.

Wilkinson, R. G. (1990). Income Distribution and Mortality: A 'Natural' Experiment. *Sociology of Health and Illness*, 12: 391-412.

World Economic Forum. The Global Competitiveness Report 2010-2011. Geneva: World Economic Forum. 2011

World Health Organization (WHO). (2006). Public health, innovation and intellectual property rights. Report to the Commission on Intellectual Property Rights, Innovation and Public Health. World Health Organization.

World Health Organization (WHO). (2019). Health Impact Assessment (HIA). Retrieved from https://www.who.int/hia/tools/process/en/index1.html.

World Health Organization (WHO), World Intellectual Property Organization (WIPO) & World Trade Organization (WTO). (2012). Promoting access to medical technologies and innovation: intersections between public health, intellectual property and trade. Book Now Ltd., London.

Yang, T.-C., Chen, V. Y.-J., Shoff, C., & Matthews, S. (2012). Using quantile regression to examine the effects of inequality across the mortality distribution in the U.S. counties. *Social Science and Medicine*, *74*(12), 1900–1910.

Zuvekas, S. H., & Hill, S. C. (2000). Income and employment among homeless people: the role of mental health, health and substance abuse. *The Journal of Mental Health Policy and Economics*, *3*(3), 153–163.