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Disrupting disruption

An empirical analysis of patent activities in the aftermath of Hurricane Katrina.

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Abstract

It is well established that innovation is one of the key factors to fight climate change. This thesis explores the reverse relationship between climate change and innovation by investigating the implication of a natural disaster on patent numbers. In August 2005, one of the most devastating natural disasters in U.S. history, Hurricane Katrina, struck the continent causing costly damages and more than 1500 fatalities. This paper uses patent data on county level covering the years from 2002 to 2008 to investigate the effect of Hurricane Katrina and the subsequent hurricanes Rita and Wilma on patent activities in the impacted areas. The patent data have been acquired from PatentsView, while data concerning the hurricanes are retrieved from The Federal Emergency Management Agency (FEMA). Previous studies suggest that natural disasters and climate change have an impact on patent levels which is mainly positive. To the best of my knowledge, there are no similar studies of the relationship between hurricanes and patents using data on county level. The econometric analysis is conducted by performing a difference-in-difference regression with fixed effects on the aggregated inventor patent share per 100.000 inhabitants. Patents related to all technologies, climate-change related technologies only, and construction related technologies only were assessed. The results show no significant evidence for a relationship between the hurricanes and patent numbers. Given that the used model is well specified and factors pushing the effects towards zero are absent, this study implies a non-existing or weak relationship between the hurricanes and average patent levels in impacted areas.

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1 Introduction

The world needs innovation to disrupt human-induced climate change while sustaining economic growth. However, the consequences of climate change, such as natural disasters, can both motivate and disrupt innovative efforts and technological opportunities. In this thesis, I investigate the impact of climate change on innovation.

Innovation has been one of the cornerstones to the development of life as we know it today. Several million years ago, ancestors of homo sapiens came up with the idea to use sharp flakes of stones as knives and began to use fire for warmth, protection, and cooking. About 15.000 to 20.000 years ago, humans started doing agriculture instead of getting their food by foraging. Innovations still relevant to this day, such as sailing ships, windmills, and printing, dates back to before 1500 CE (Gregersen, n.d.). The industrial revolution (1750 - 1900) marked a world-changing era of innovations forming modern civilization by enabling mechanized manufacturing and large-scale industry. Existing industries became more productive and efficient as a result of new machines, new power sources, and new ways of arranging work (The Editors of Encyclopaedia Britannica, 2021).

The technological advances from the industrial revolution have not only been positive. This new way of living also formed the basis for one of the worst crises and most important political concerns of our time, climate change. Mainly due to human activities, the concentration of carbon dioxide in the atmosphere has increased about 40% over the industrial era, which is one of the main reasons for the development of the climate crisis (U.S. Global Change Research Program, 2018). Despite being one of the sources for today's climate challenges, innovation has solved many problems through history and is a crucial part of the solution to the climate crisis. It is well established by professionals that technological development is one of the critical steps towards reducing the human-induced emissions of greenhouse gases sufficiently while continuing to have economic growth (U.S. Global Change Research Program, 2018; IPCC, 2014; Gross et al., 2018; WIPO, n.d.; Rubin, 2013; ICC, 2015; UNFCC, 2021).

Climate change is a topic receiving more and more attention from scientists, politicians, corporations, and individuals. In the past couple of years, increasing numbers of efforts have been made to fight climate change. Through the Paris Agreement, which was adopted in 2015, 189 countries committed to reduce their emissions and cooperate to adapt to the impacts of climate change. The goal is to limit the global temperature increase to below 2 degrees Celsius compared to pre-industrial levels (United Nations, n.d.). To contribute towards the goal, Denmark recently became the first major-oil producing country in the world to start phasing out fossil fuel extraction (Ambrose, 2020).

On the corporate side, sustainability has become an essential part of most firms' business strategies, and some even have executives with a dedicated role in managing environmental-related activities. According to a report from KPMG 80% of companies worldwide reported on sustainability in 2020 compared to 18% in 2002 (KPMG, 2020). Furthermore, climate activism are more visible than before and engages thousands of individuals and communities. In 2019 the biggest climate demonstration in history with several million participants in 185 different countries was held (Laville and Watts, 2019). The previously mentioned activities is a part of an increasing number of efforts with the purpose of ensuring sustainable development. However, to reach the below two-degree climate goal, drastic changes are needed.

One of the many consequences of climate change is extreme weather. According to scientists: "climate change leads to changes in the frequency, intensity, spatial extent, duration, and timing of weather and climate extremes, and can result in unprecedented extremes" (IPCC, 2018, p.123). Natural disasters cause severe damages to the impacted areas, which paradoxically could slow down innovative processes in the affected communities. On the contrary, it is also plausible that disasters could motivate local innovation. In this thesis, I seek to understand how inventors are affected when a natural disaster strikes their community. In other words, I investigate the reverse relationship between innovation and the consequences of climate change.

During the 2005 Atlantic Hurricane Season, three of the most damaging hurricanes in the U.S. history occurred. Using the events of the hurricanes to construct a natural experiment together with using patents as a proxy for innovation, I seek to answer the following research question:

To what extent did the hurricanes Katrina, Wilma and Rita affect the number of patents in the impacted areas?

I have employed a difference-in-difference model with fixed effects to investigate the research question. First, I analyze all U.S. patents. Then, I study climate-change-related patents only. Lastly, I look at patents related to construction. My findings show no evidence for a change in patent shares due to the hurricanes.

This study contributes to the literature on the economic impacts of extreme weather. Innovation and climate disasters are two opposite externalities to society. How the former affects the latter is important from a corporate and policy perspective. Innovation enhances firms' knowledge and performance. Hence, the impact of extreme weather on innovation can indirectly affect the daily operations and long-term goals of a firm. Managers can learn from external shocks that increase innovation to encourage it even in the absence of the event. Additionally, circumstances that mitigate innovation are essential to identify in order to manage and prevent the potential loss of performance. From a policy perspective, innovation in the aftermath of extreme weather is important to understand for economic recovery as well as development and to gain insight into the consequences of climate change.

The next section of this thesis provides background information on innovation, patents, and the 2005 Atlantic Hurricane Season, in addition to introduce relevant literature. Following, the data basis of the analysis is presented. Next, I describe the used methodology before presenting the results of the analysis. After this, a discussion of the findings is conducted. Finally, I summarize the findings in a conclusion.

2 Background

The following sections elaborate on the main topics of this thesis. First, I briefly present background information on innovation before patenting is discussed. Then, the 2005 Atlantic Hurricane season is presented. Lastly, I introduce relevant literature for this study.

2.1 Innovation

In the mid 20th century, the concept and value of innovation were brought to attention by the Austrian economist Joseph Schumpeter. He emphasized the importance of what he called "creative destruction," which he described as a "...process of industrial mutation that continuously revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one" (Schumpeter, 2010, p. 73). His work has formed the basis for economic theory of innovation.

Innovation can be defined as a new idea or method that improves a product, process, or service (Cambridge dictionary, n.d.; WIPO, n.d.). New ideas and technological change are widely recognized as the main driver for economic growth and development (Romer, 1990; Schumpeter, 2010; Freeman, 1991). Additionally, there seems to be a consensus that innovation has a positive impact on the performance of firms (Lengnick-Hall, 1992; Artz et al., 2010; Belderbos et al., 2004; Calantone et al., 2002).

To encourage innovation, there exist laws that protect human creations and give inventors ownership of their inventions which is referred to as intellectual property rights. The protection enables people to earn recognition or financial benefit from what they invent (WIPO, n.d.). According to the United States Trademark and Patent Office (USPTO), industries in the United States and Europe that intensively use intellectual property rights account for approximately 40% of GDP and 30% of jobs (USPTO, 2020).

In this thesis, I use patents as a proxy for innovation. The following section describes patents in further detail.

2.2 Patents

Patents are a form of intellectual property protection that prohibits people from copying the patent holder's invention for a limited time period. More specifically, the patent owner has the right to exclude others from making, using, offering for sale, or selling in the invention. The protection is territorial, meaning that patent grants only are effective within the country where the patent was granted. In the United States, patents are granted through USPTO. A new patent granted by USPTO normally has a term of 20 years from the patent application's filing date. The owner of a patent also has the right to sell or mortgage it (USPTO, n.d.). Patents are usually owned by firms, but they can also be owned by governments or individuals.

There are three types of patents: (i) Utility patents, (ii) design patents, and (iii) plant patents. As the names indicate, design patents are related to unique and new appearances of an item, and plant patents are related to inventions and discovery of distinct and new varieties of plants. In this thesis, I only focus on utility patents. USPTO specifics the following criteria for utility patents: "Utility patents may be granted to anyone who invents or discovers any new and useful process, machine, article of manufacture, or composition of matter, or any new and useful improvement thereof" (USPTO, n.d.). Between 2002 and 2008, USPTO received 2,763,004 utility patent applications, and approximately 40% were granted (USPTO, 2021).

2.2.1 The rational behind the patent system

From a macroeconomic perspective, no firm would undertake the costs or risks of discovering new inventions if there was no assurance that the development costs related to the invention were covered. The patent system gives the innovator temporary monopoly power to ensure that profit exceeds the costs to incentivize innovation. In exchange, the innovator must make the knowledge underlying for the discovery public to ensure that knowledge is shared and flourish new inventions (Jones, 2014).

There exist several theories about the economic costs and benefits of patents. Nelson and Mazzoleni (1997) have highlighted some of them. On the beneficial side, the anticipation of receiving patents can facilitate inventors to work on different and non-competing inventions and by that provide more useful innovation. Furthermore, having a patent enables the patent holder to get development financing from the capital markets. Additionally, patenting makes it easier to sell inventions as the buyer will not be able to copy the inventions themselves. The public disclosure of patents makes the invention available for uses that the inventor did not know about or was not in a position to implement.

On the contrary, the monopoly position of the patent holder causes some theoretical concerns as well. Foremost, the use of the invention becomes restricted, which is a cost for society. In addition, depending on the extent to which the patent controls later improvements and variations in the initial invention, it can mitigate second-generation inventions until the duration of the patent has expired. Another perspective emphasizes that patents can lead to inefficient use of resources if inventors perceive competition as only the one who achieves the invention first will benefit from it. The perceived competition can also deter inventors from engaging due to fear of losing.

2.2.2 Patents as a measure for innovation

Measuring innovation is complex, and patent data are not a perfect measure. Not all inventions are patented, and those that are do not always become innovations (Archibugi and Planta 1996). Furthermore, patents differ greatly in their economic impact (Pakes and Griliches, 1980). Despite this, many researchers use patent data as a proxy for innovation in the absence of economy-wide data on the quantity of innovations (Moser, 2013).

A few studies investigating the reliability of patent data as a proxy for regional innovative activity have been conducted. The findings suggest that patent data provides a reasonably reliable measure of innovative activity on industry level and metropolitan statistic area level. Additionally, there is some evidence that patents and innovations behave similarly at the state level (Acs and Audretsch, 1989; Acs et al., 1992; Acs et al., 2002).

2.3 2005 Atlantic Hurricane Season

In August 2005, the United States was struck by one of the most devastating natural disasters ever experienced on the continent, Hurricane Katrina. In addition to the 1833 lives that were lost, the disaster is estimated to have cost the nation more than $100 billion dollars, making it one of the costliest and deadliest hurricanes in the history of the United States. The following months after Hurricane Katrina, two other devastating hurricanes struck the country, Hurricane Rita and Hurricane Wilma, costing more than $50 billion dollars and causing over 150 fatalities (Beven II et al., 2007).

The three hurricanes were a part of the Atlantic Hurricane Season, which is the time period where hurricanes usually form in the Atlantic Ocean. It usually stretches from June through November (National hurricane center and central pacific hurricane center, n.d.). In other words, 2005 was not the first time the areas hit by the three hurricanes experienced a natural disaster. However, the costs of the three hurricanes was substantially higher than any other disasters ever happened in the United States. Figure 2.1 presents the total cost of all billion-dollar disasters occurring in the United States between 1980 and 2015. The numbers are CPI-adjusted. Hurricane Katrina, Hurricane Rita, and Hurricane Wilma account for 97% of the costs in 2005.

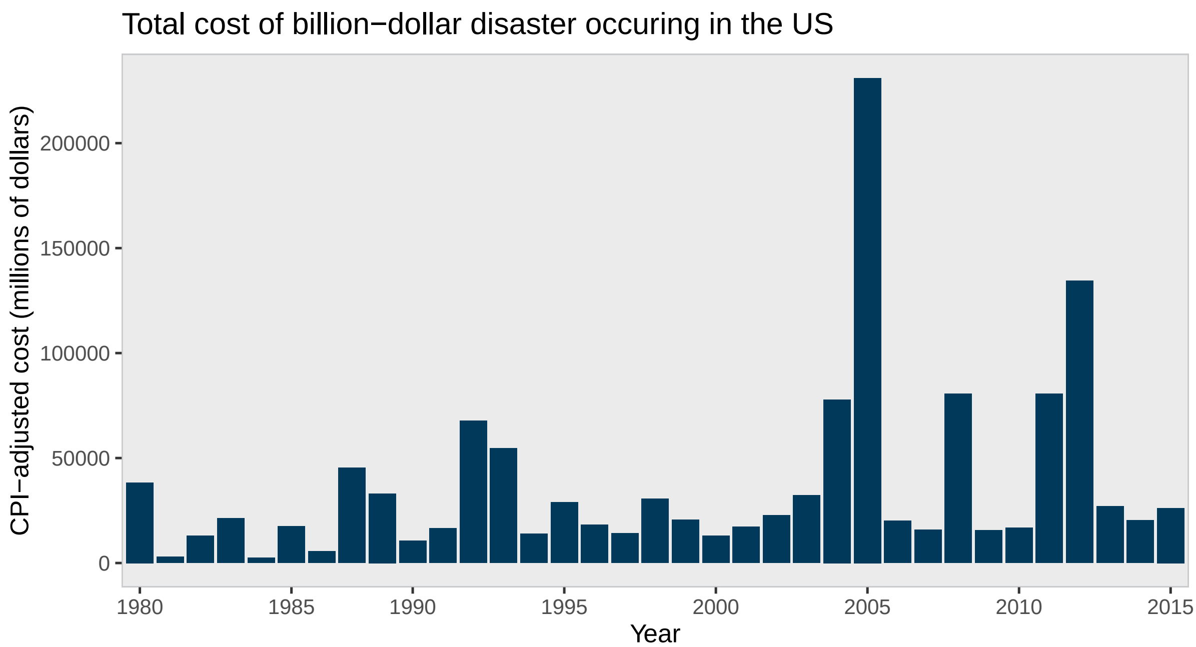

Figure 2.1: Total cost of all billion-dollar disasters occurring in the United States between 1980 and 2015. The numbers are CPI-adjusted. Data source: HurricanesCosts

2.4 Previous literature

A few previous studies have sought to identify the effect of climate change and natural disasters on innovation. Using global climate-change-related patents, Su and Moaniba (2017) have studied how environmental innovation responds to climate change indicators such as carbon dioxide and other greenhouse gas emissions. They find that increasing levels of carbon dioxide emissions from gas and liquid fuels influence the number of climate-related patents positively. In contrast, increases in carbon dioxide emissions from solid fuel consumption and other greenhouse gas emissions negatively influence the number of climate-related patents.

Miao and Popp (2014) investigate if natural disasters can spur technical innovations which potentially reduce the risk of future hazards. In particular, they study the impact of floods, droughts, and earthquakes on the patent counts of their corresponding technologies. Analyzing data from 28 countries for 25 years, they find that all three types of natural disasters increase the number of patents related to risk-mitigating innovations.

Other studies investigate the post-disaster effects on entrepreneurial activity. Monllor and Altay (2016) found that natural disasters have a significant and positive impact on entrepreneurial opportunity perceptions and actions but not on perceptions of self-efficacy, fear of failure, and entrepreneurial intentions. On the other hand, Brück et al. (2011) suggest that natural disasters tend to impact entrepreneurial activity negatively.

Innovation is a comprehensive process. Gross et al. (2018) emphasize that climate change is an urgent problem and investigates how long it takes individual technologies to emerge from research, find market opportunities and make a tangible impact on emissions reductions. This paper uses historical evidence from the development and deployment of a range of energy supply and energy end-use technologies, they find that: "invention of new technology to widespread commercialisation is a multi-decadal process". Among their investigated technologies, the time horizon ranged from 20 years to 69 years, with a median of 32 years.

Apart from studies concerning climate change, previous studies have investigated the impacts of the 2005 Atlantic Hurricane Season. Using a similar approach as this paper, Schüwer et al. (2018) studied how hurricane Katrina, Rita and Wilma affected banking given the structure of the banks. The authors find that individual banks in the disaster areas increase their risk-based capital ratios after the hurricanes in contrast to those that are part of a bank holding company. Additionally, their findings suggest that the structure of the banking system impacts economic development in the aftermath of the disasters and suggest that the economic growth in total personal income and employment after the disasters is better for counties with a higher share of independent banks and relatively high average bank capital ratios.

Deryugina et al. (2014) have studied the long-term economic impact on Hurricane Katrina victims in New Orleans. Their evidence shows that the hurricane had a short-term and long-term effect on the number of inhabitants. More than a third of those displaced due to the disaster had not returned to the city eight years after the disaster. Furthermore, despite the immediate negative economic experiences of the storm victims, they do not suffer earning losses in the long run. Deryugina et al. explain this with a strengthening of the labor market in New Orleans, as well as many victims moving to stronger labor markets. Additionally, they find that unemployment and non-employment spiked right after the storm, but only a few years later, labor market outcomes were recovered.

In summary, the literature suggests that a relationship between climate-change and innovation exists, mainly leading to more innovation. However, the long time horizon for inventions to be commercialized and deployed questions immediate effects on innovation after natural disasters. Furthermore, previous studies investigating Hurricane Katrina find that the disaster had an economic impact on the affected areas.

3 Data

This paper uses panel data on county level with a time span from 2002 to 2008. The analyzed data set is based on patent data from PatentsView, disaster data from the United States' Federal Emergency Management Agency (FEMA), county characteristics from various governmental resources. The following sections describe the database for the thesis in further detail.

3.1 Patent data

Data on patents have been retrieved from PatentsView. PatentsView is supported by USPTO and provides several web-based tools and databases that can be used to collect information on intellectual property (PatentsView, n.d.). The extracted data consists of all utility patents granted in the United States applied for between 01.01.2002 and 31.12.2008. Additionally, I have created two subsets containing patents related to climate-change technologies and constructions only. To identify the subsets, I have taken advantage of the Cooperative Patent Classification (CPC) system, which is a scheme classifying patents in different technology areas. In particular, I have used subsection Y02 and section E, which are defined as "Technologies or applications for mitigation or adaption against climate change" and "Fixed constructions" (USPTO, n.d.). The data set has been used to calculate an aggregated inventor patent share for each county, which forms the basis of the dependent variable used in the analysis.

For simplicity reasons, counties with substantial changes in borders during the period are removed from the sample for all regression. The exclusion involves 14 counties (United States Census Bureau, n.d.). Furthermore, I only look at counties belonging to the 50 areas defined as states. Lastly, counties with less than 5000 inhabitants are excluded.

The full sample consists of 706 178 granted patents and 567 579 unique inventors. On average, there are 2.7 inventors per patent. Figure 3.1 present the number of patents applied for in the United States between 2002 and 2008 with at least one U.S. inventor. Mark that the graph only includes patents that have become granted. In general, the number of patent applications decreased from 2002 to 2004 and was at the lowest in the period from 2004 to 2006 before it spiked in 2007.

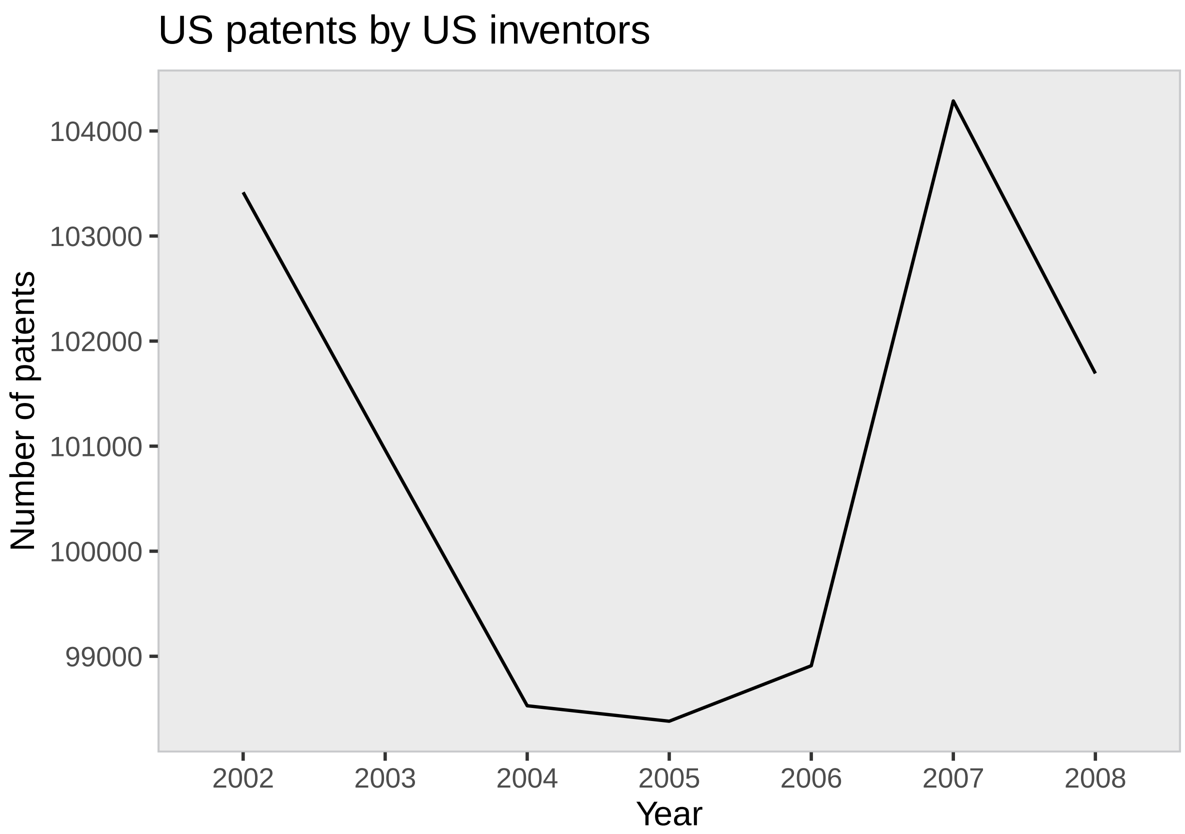

Figure 3.1: Number of U.S. granted patents applied for between 2002 and 2008 with at least one U.S inventor. *Data source:* FEMA.

3.2 Disaster data

I have utilized disaster declaration data from Federal Emergency Management Agency (FEMA) to identify if and to what extent a county was affected by Hurricane Katrina, Hurricane Wilma, and Hurricane Rita that struck the United States in 2005. FEMA is an agency of the United States Department of Homeland Security. Their mission is to "...support citizens and emergency personnel to build, sustain, and improve the nation's capability to prepare for, protect against, respond to, recover from, and mitigate all hazard" (USA.gov, nd).

When a disaster strikes in the United States, the local government of the impacted area can request federal support if the damages exceed the capabilities of their resources. A disaster declaration will be created if the President approves the request. The disaster can either be declared an emergency or a major disaster. The latter is declared when the damages are so severe that additional and more long-term federal support is needed.

In terms of federal support, the impacted area can receive individual assistance, public assistance, and hazard mitigation assistance. The level of support is higher for all types of assistance when a major disaster is declared (FEMA, 2020). Individual assistance is financial and direct services to eligible individuals and households (FEMA, 2020a). The purpose of public assistance is to increase the communities' ability to respond to and recover from a disaster. The grants can be received by local governments and certain types of private non-profits (FEMA, 2020c). Hazard mitigation assistance is funding provided to communities for actions taken to prevent or reduce long-term risk to life and property from natural hazards (FEMA, 2020).

Data on declared disasters are publicly available at FEMA's database, OpenFEMA (FEMA, 2020b). Through the database, I have accessed information concerning the type of provided assistance to counties during the hurricanes. The data lays the foundation for the assignment of counties to the treatment group, which is described in section 4.3.

3.3 County characteristics

To obtain information about county characteristics, I have utilized several sources. First, I used data from the United States Census Bureau to find data on population and the number of establishments. Secondly, numbers on unemployment have been collected from the U.S. Bureau of Economic Analysis. Lastly, I have collected measures for GDP and personal income from the U.S. Bureau of Labour Statistics. The data have been used to assess the balance between the treatment and control groups and perform a propensity score matching procedure. This will be further discussed in section 4.

4 Methodology

This master thesis aims to identify how innovation is affected by natural disasters. In particular, I use the event of the three related hurricanes Katrina, Rita, and Wilma as a natural experiment to investigate changes in the number of patent shares in the aftermath of the shock. The analysis has been conducted using a difference-in-difference regression with time-fixed effects and county-fixed effects in order to get a causal estimate. I start by assessing the overall patent shares before I separately analyze patents related to climate-change and construction only. The following sections describe the applied methodology.

4.1 The difference-in-difference method

To identify the hurricanes' effect on patent number in the affected counties, I must consider what the number of patents would have been in the absence of the event. The difference-in-difference approach allows me to do this using a control group as a proxy for the counterfactual outcome.

Difference-in-difference models are commonly used to measure the effect of public policies and other sudden changes in the economic environment on an affected group. The method estimates the effect of an exogenous shock by comparing the difference in outcome over time of the affected group (the treatment group) to an unaffected group (the control group). The comparison of changes over time adjusts for permanent differences between the treatment and control group and thereby reduces the chances of the result being biased due to group-specific variables that affect the outcome.

The results of the difference-in-difference model yields the average effect of being in the treatment group (Angrist and Pischke, 2014). In other words, using the difference-in-difference approach, I estimate the average change in the number of patents caused by the hurricanes for counties in the treatment group. As an illustrative example, Figure 4.1 visualize the intuition behind the model. The solid golden line represents the treatment group, the counterfactual outcome is represented by the dashed golden line, and the blue line represents the control groups. The graph shows that the treatment effect is the difference in patent numbers between the treatment and control groups after the hurricanes minus the difference in patent numbers of the two groups before the hurricanes.

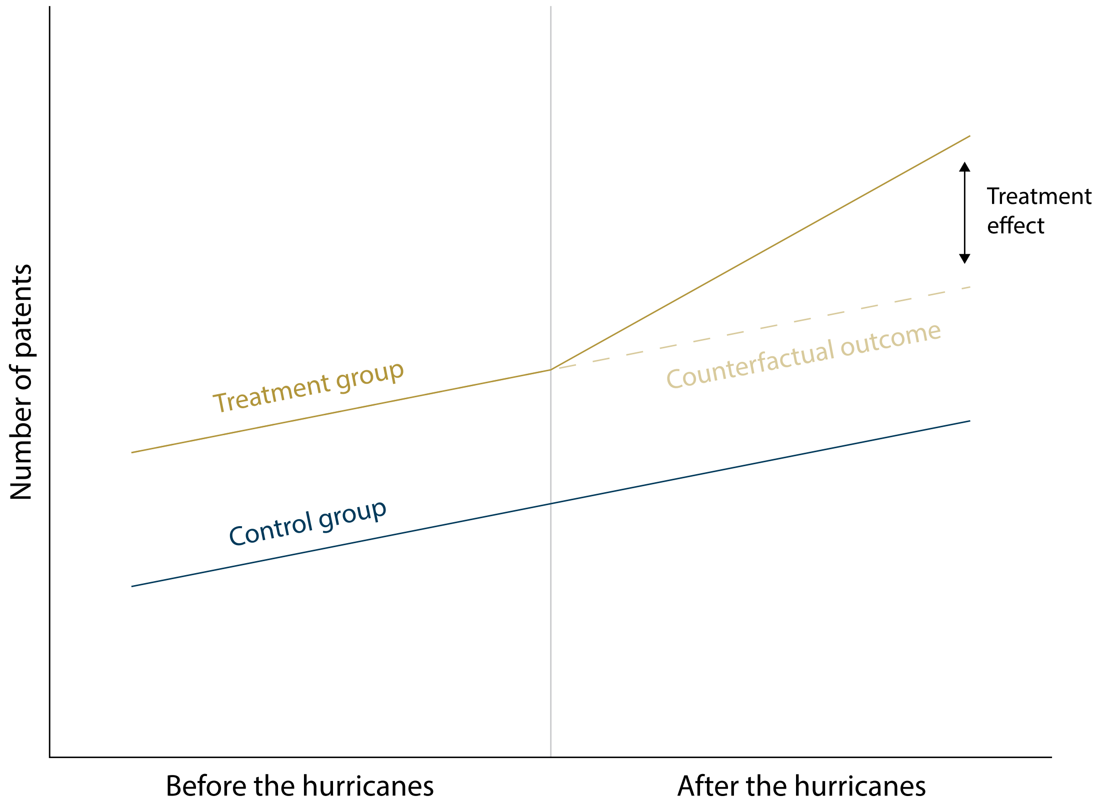

Figure 4.1: An illustration of the difference-in-difference model. Inspired by Angrist and Pischke (2014)

The difference-in-difference model relies on the assumption that no time-varying difference exists between the treatment group and control group (Angrist and Pischke, 2014). Hence, it is crucial that the trend over time would have been the same for the two groups in the absence of the shock. Meaning that the affected and unaffected counties would have experienced the same average change in patent numbers if the hurricanes never occurred. Potential threats to the identification strategy is elaborated on in section 4.4.

4.1.1 Inclusion of fixed effects

When analyzing panel data, it is common to include group- and time-fixed effects in the model. By including county-fixed effects, I capture the unobserved time-invariant systematic differences between counties. Similarly, the time-fixed effects capture yearly external factors that are equal for all counties (Wooldridge, 2014).

4.2 Baseline model

I have estimated equation 4.1 for three years before and after 2005. The dependent variable, PAT_{kt}, is the aggregated inventor patent share per 100.000 inhabitants for county k at time period t. The fixed effects are implemented using dummy variables, where α_k represents the unobserved time-invariant county effects, and δ_t represents the unobserved county-invariant time effects. T_k is a treatment indicator which is 1 for all counties k that were hit by the hurricanes, while $Post_t$ is a dummy that equals 1 for all observations in the years after the hurricanes. The estimate of interest is β_3 which captures the interaction of the two previously explained variables. In other words, it represents the effect of being an affected county in the post-hurricane period. The last term, ϵ_{kt}, represents the error term.

$$PAT_{k_t} = \beta_0 + \alpha_k + \delta_t + \beta_3(T_k \times Post_t) + \epsilon_{kt} \tag{4.1}$$

4.2.1 Inventor patent share (PAT_{kt})

I use patents as a proxy for the level of innovation in the counties, whereby I attribute a patent to a county if the inventor lives in the county. Patents usually have several inventors. To account for the number of inventors per patent, an inventor share has been calculated for all inventors. The inventor share is calculated by dividing one by the number of inventors for each patent. After this, the shares have been aggregated on county level. Furthermore, the share has been adjusted relative to the population of the county to increase comparability since population can differ between counties and over time. As a result, the final measure is the inventor patent share per 100.000 inhabitants. Equation 4.2 presents the calculation where PAT_{kt} is the inventor patent share per 100.000 inhabitants for county k in time t, N_{ij} is the total number of inventors for patent j of inventor i, and POP_{kt} is the population of county k in time t.

$$PAT_{kt} = \frac{\sum_{i=1}^{I} \sum_{j=1}^{J} \frac{1}{N_{ij}}}{POP_{kt}} \tag{4.2}$$

4.2.2 Dependent variables

The analysis includes three different dependent variables, all representing patent numbers but for different compositions of technologies. The first measures the patent numbers of all patents to capture the overall effect on innovation. Furthermore, the second dependent variable only consists of climate-change related patents and is included to see if the hurricanes impact patents involving technologies that seek to mitigate the sources of natural disasters. Lastly, the third dependent variable includes construction related patents only as hurricanes cause damage to buildings and infrastructure. Thus, it is plausible that the disasters increase the interest in new technologies related to construction.

4.3 Treatment and control groups

The counties in the sample have been assigned to the treatment and control group based on the level of federal support received due to the disasters. Nearly all counties in the United States received federal support when the hurricanes struck. However, only 132 were declared a major disaster and were eligible for both individual and public support. Hence, these can be considered substantially more impacted by the hurricanes than other counties and have consequently been assigned to the treatment group. Counties that were declared a major disaster but did not receive both individual and public support are removed from the sample to obtain a more clear differentiation between the treatment and control groups. The exclusion involves 260 counties, giving a control group which consists of the 2384 counties that did not have a declared major disaster in the event of the hurricanes.

4.3.1 Subsamples

I have investigated four subsamples in addition to the full sample which contains counties in all the 50 states. All the counties in the treatment group are located in the U.S Gulf States (Texas, Louisiana, Mississippi, Alabama, and Florida). Hence, the first subsample (Subsample 1) includes counties in the Gulf States and neighboring states to obtain a sample consisting of counties with similar geographical traits. The second subsample (Subsample 2) comprises counties in Alabama and Florida as they were the only states with counties present in both the treatment and control groups. The third and fourth subsample (Subsample 3 and Subsample 4) consists of a treatment group and control group, which have been constructed using propensity score matching on the full sample and the first subsample. This process is described further in section 4.3.2.

All the subsamples have the same counties in the treatment group apart from Subsample 2, which only includes 24 of the treated counties. Subsample 1 and Subsample 2 have 475 and 85 counties in the control group, while the control groups of Subsample 3 and Subsample 4 have the same number of counties as the initial treatment group (132 counties).

4.3.2 Propensity score matching

Propensity score matching can be used to construct control groups that are well balanced to the treatment group in terms of confounding factors (Inacio et al., 2015). Differences affecting the trend or composition of the treatment and control groups over time are a concern when implementing difference-in-difference methods. Hence, it is preferable to find a comparison group that has relatively similar characteristics as the treatment group (Stuart et al., 2014).

I have constructed two control groups through propensity score matching: (i) One where the counties in the treatment group are matched with all counties in the sample, and (ii) one matching counties in the Gulf States or neighboring states only. To capture the general economic environment, the counties have been matched based on measures for 2004 of GDP per capita and personal income per capita. Furthermore, I have included measures from 2004 of the unemployment rate and the number of large firms per 100.000 inhabitants to capture the business environment. Table 4.1 presents an overview with descriptions of the used covariates.

The conducted matching procedure has applied logistic regression to find the propensity score of each county by estimating the probability of being in the treatment group given the described covariates. After this, each county in the treatment group is matched to the untreated county with the most similar propensity score to form the control group. Matching was performed in R using the MatchIt package (Greifer, 2020).

Table 4.1: Description of covariates used for propensity score matching. All measures are from 2004 (i.e., the year before the hurricanes hit).

Variable name	**Description**
GDP per capita	The value of the final goods and services produced in the county divided by population. *Source:* U.S. Bureau of Economic Analysis.
Personal per capita	Income received by people living in the county including wages, proprietors' income, dividends, interest, rents, and government benefits divided by population. *Source:* U.S. Bureau of Economic Analysis.
Unemployment rate	The proportion of unemployed people among the labor force in the county. *Source:* U.S. Bureau of Labour Statistics.
Number of large firms per 100 000 inhabitant	The number of firms with more than 500 employees divided by population multiplied with 100 000. *Source:* United States Census Bureau (nda).

4.4 Threats to the identification

The validity of the difference-in-difference estimate relies on several aspects. First, the treatment status must be exogenously determined and unexpected. Secondly, the pre-trends of the outcome variable are assumed to be parallel. Third, the compared groups should share similar characteristics. Lastly, other exogenous shocks affecting the outcome variable for only one group can confound the results.

4.4.1 Treatment status

For the treatment and control groups to be comparable, it is important that the probability of the treatment status is not possible to affect and that the timing of the event can not be predicted (Angrist and Pischke, 2014). The probability of being hit by a hurricane is difficult to affect directly. Reducing greenhouse emissions locally will not have a direct impact on where and how hurricanes hit. The treatment status can therefore be considered exogenous. The ability to predict the event is more debatable. Since the treated counties in this study are placed in areas that regularly experience tropical cyclones, one could argue that hurricanes can be expected. However, as shown in section 2.3, the impact of the three hurricanes used in this study was more remarkable than previous hurricanes. Hence, I suggest that the impact of the three hurricanes was unexpected.

4.4.2 Parallel trends

For the estimate of the difference-in-difference model to be unbiased, it is crucial that the only difference between the control and treatment group that changes over time is the treatment (Angrist and Pischke, 2014). By comparing the trends of the treatment and control groups before the hurricanes struck (2005), one can evaluate if the assumption is plausible to hold.

To assess the pre-trends, I have included data for two additional years (2000 - 2001). Figure 4.2 presents the trends for average patent share per 100.000 inhabitants of the full sample. The vertical dashed line marks the time of the hurricanes (2005). Panel A shows all patents, panel B presents climate-change related patents, and panel C exhibit construction related patents. All the pre-trends follow each other for all three panels. The average patent share is higher for the control group for all patents (A) and climate-change related patents (B). In contrast, the treatment groups have the highest average patents share for construction related patents (C). A change in levels appears to be present for the climate-change (B) related and construction (C) related patents but is less visible for all patents (A). The trends of the subsamples are presented in Appendix A2.1 - A5.1. For the subsamples the pre-trends are more questionable and results must thereby be interpreted with caution. Overall, I consider the parallel trend assumption to be viable.

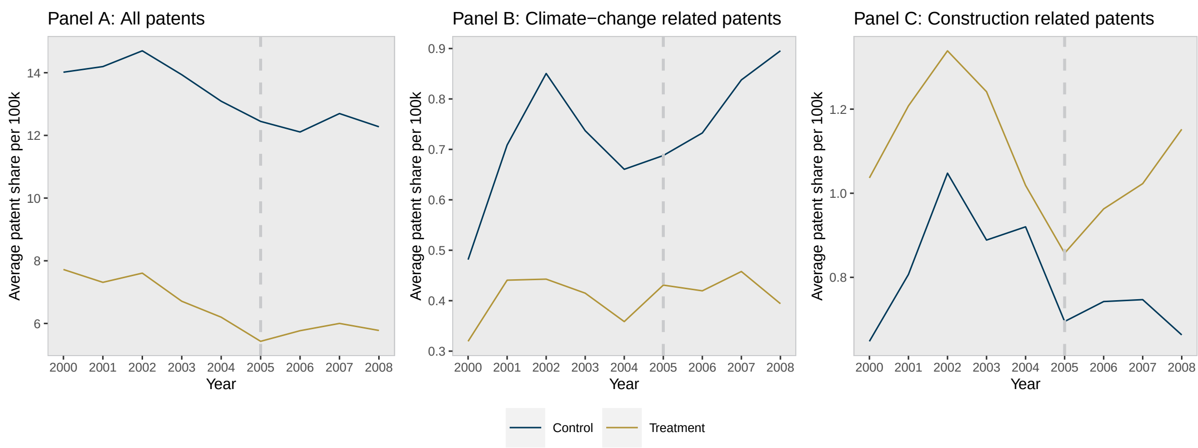

Figure 4.2: Trends in average patent share per 100.000 inhabitant of the full sample for all patents (panel A), climate-change related patents (panel B), and construction related patents (panel C) *Data source:* FEMA.

4.4.3 Confounding shocks

Even if the parallel trend assumption holds other events that are happening simultaneously or in the aftermath of the hurricanes, it is a concern for the analysis if they affect the groups differently and impact the patents numbers. When confounding shocks are present, they can overshadow the treatment effect (Angrist and Pischke, 2014). Disasters occur in the United States every year, and many counties have received federal support through the 2000s. Table 4.2 presents the percentage of counties in the treatment and control groups that experienced one or several other major disasters between 2002 - 2008. Both the treatment groups and control groups have experienced other major disasters in the time period. For the validity of the analysis, it is essential that these have not affected the patent numbers in each group differently. As presented in 2.3 the three hurricanes of 2005 investigated in this analysis were concerned with substantially more costs than any other disasters between 1980 and 2015. Therefore, I suggest that the other major disasters are not comparable shocks and thereby do not reduce the validity of the methodology. However, it is important to keep this in mind when interpreting the results.

Table 4.2: Percentage of counties having experienced another major disaster than the hurricanes between 2002 and 2008.

		Full sample	*Subsample 1*	*Subsample 3*	*Subsample 4*	*Subsample 3*	
Year	Treatment	Control	Control	Control	Control	Treatment	Control
2002	52%	28%	26%	23%	25%	25%	22%
2003	30%	33%	35%	36%	41%	25%	40%
2004	71%	44%	48%	52%	44%	100%	100%
2005	55%	20%	24%	17%	17%	50%	49%
2006	8%	15%	5%	14%	7%	0%	1%
2007	5%	22%	19%	12%	14%	0%	12%
2008	70%	35%	38%	32%	37%	50%	32%

De facto changes in patenting by inventors are also a concern that can affect the patent numbers. Additionally, other events related to inventors, such as if a large firm files an extraordinary number of patent applications in a given year, affect the analysis. Apart from this, changes in patent law, policy changes, and macroeconomic shocks are also potential confounding factors. However, they often happen on a higher level than on the county level. If the examples mentioned above affect the patent numbers equally in the treatment and control groups, the effect will be adjusted for when performing the difference-in-difference regression. In other words, the events only impact the analysis when the effect is inconsistent between the treatment and control group.

4.4.4 Characteristics of the treatment and control group

The treatment and control groups should share similar characteristics for the analysis to yield a causal effect. Table 4.3 on the next page presents characteristics of the groups from the year before the hurricanes (2004) for the full sample and Subsample 1, 3, and 4. The first column (1) presents the mean for each characteristic of the treatment group. Column (1) - (3) shows the difference between the treatment and control groups mean for each sample. The numbers in parenthesis are the normalized difference between the groups, according to Imbens and Wooldridge (2008). Groups are regarded sufficiently equal if normalized differences are largely in the range of +/-0.25. Personal income per capita appears unbalanced for the full sample's control group, while GDP per capita appears unbalanced for the control group of Subsample 1. The unemployment rate appears unbalanced for both the control group of the full sample and Subsample 1. All measures are balanced for the subsamples based on propensity score matching (Subsample 4 and Subsample 5). Appendix A1.1 presents the difference between the treatment group and control of Subsample 2. Similar to Subsample 1, there exist unbalances for the unemployment rate and GDP per capita.

4.5 External validity

The external validity of my analysis relies on the ability to apply the findings to another context, in such a different place, time, or natural disaster. It can be difficult to generalize the findings of this study to a location outside of the United States as the institutional settings are likely to be quite different. Regarding the time aspect, one could assume that new technologies related to hurricanes or the evolution of climate-change and global warming would lead to different effects if measuring the same type of event in the future. Lastly, conducting a similar study using another type of natural disaster can be applicable as the consequences of the disasters to the community might be similar. However, this is not necessarily the case for all events.

Table 4.3: Comparison of characteristics in 2004 between the treatment and control groups. Column (2) - (5) present the difference in means between the control group and the treatment group. Numbers in parenthesis are the normalized difference. A normalized difference of +/- 0.25 indicates that the characteristics is similar for the groups

	(1) Treatment Mean	Full sample (2) Control (1) - (2)	Subsample 1 (3) Control (1) - (3)	Subsample 3 (4) Control (1) - (4)	Subsample 4 (5) Control (1) - (5)
Economic characteristics					
Population	147520.985	44663.123 (0.085)	81490.097 (0.185)	77013.508 (0.174)	58638.546 (0.128)
GDP per capita	29221.857	-144.266 (-0.005)	5069.130 (0.251)	2163.333 (0.106)	1211.878 (0.053)
Personal income per capita	25471.263	-2590.211 (-0.274)	613.490 (0.076)	-255.267 (-0.028)	309.359 (0.036)
Unemployment Rate (%)	6.745	1.048 (0.426)	1.114 (0.487)	-0.114 (0.561)	-0.032 (-0.013)
Large firms per 100k	3.720	-0.377 (-0.024)	0.200 (0.037)	0.071 (0.014)	-0.115 (-0.020)
All patents					
Inventors	44.326	-8.658 (-0.022)	29.520 (0.139)	16.978 (0.072)	21.349 (0.097)
Patent share per 100k	628.515	-699.229 (-0.236)	-93.754 (-0.045)	-230.659 (-0.142)	-70.568 (-0.044)
Counties with zero patents (%)	32.576	8.247 (0.130)	-0.477 (-0.007)	3.788 (0.058)	-3.788 (-0.056)
Construction-related patents					
Inventors	9.045	7.394 (0.126)	8.070 (0.138)	7.719 (0.132)	7.765 (0.133)
Patent share per 100k	102.667	8.806 (0.019)	11.494 (0.016)	-1.242 (-0.003)	43.447 (0.133)
Counties with zero patents (%)	65.909	0.137 (0.002)	-9.459 (-0.147)	1.515 (0.022)	-7.576 (-0.117)
Climate-change-related patents					
Inventors	3.523	0.053 (0.002)	2.592 (0.146)	1.447 (0.075)	2.303 (0.128)
Patent share per 100k	36.417	-30.645 (-0.137)	-5.594 (-0.027)	-7.356 (-0.037)	9.273 (0.072)
Counties with zero patents (%)	71.970	-0.136 (-0.002)	-4.501 (-0.163)	-8.333 (-0.138)	-11.363 (-0.194)

5 Analysis

In this section, I present the results from the empirical analysis. When using an econometric model, the null hypothesis is that there exists no effect, while the alternative hypothesis states a significant relationship. Thereby, I assess the following hypotheses:

H_0 = *Hurricane Katrina, Hurricane Rita and Hurricane Wilma have no effect on patents shares in the areas they struck.*

H_A = *There exists a significant relationship between being affected by Hurricane Katrina, Hurricane Rita and Hurricane Wilma with the level of patent shares in the impacted area.*

5.1 Baseline results

To perform the analysis, I have used the baseline model described in section 4.2. Table 5.1 presents the results from the difference-in-difference regression for all patents. Column (1) shows the full sample consisting of counties in all states, while column (2) presents the subsample with Gulf Coast states and neighbouring states, column (3) exhibits the subsample with Alabama and Florida and column (4) and column (5) display the subsamples based on the propensity score matching of the full sample and the first subsample respectively. The estimate of interest is the interaction term, $T_k \times Post_t$. The interaction term is not significant for any of the groups. Thus, the regressions show no evidence for a systematic change in inventor patent shares of the affected counties in the aftermath of the three hurricanes. In other words, I can not reject the null hypothesis. My results are consistent for all the dependent variables. Appendix A6.1 - A7.1 present the results for climate-change related patents and construction related patents.

Table 5.1: Estimates from differences-in-differences regressions for all patents.

	All patents				
	Full sample	Subsample 1	Subsample 2	Subsample 3	Subsample 4
	(1)	(2)	(3)	(4)	(5)
Treatment	7.067	7.090	1.434	−4.854	7.106
	(4.594)	(3.007)	(2.232)	(2.393)	(2.223)
	p = 0.124	p = 0.019**	p = 0.521	p = 0.043**	p = 0.002***
Post	−1.281	−1.226	−0.415	−0.948	−1.188
	(0.134)	(0.197)	(0.342)	(0.297)	(0.276)
	p = 0.000***	p = 0.000***	p = 0.226	p = 0.002***	p = 0.00002***
Treatment×*Post*	0.601	0.547	0.220	0.268	0.509
	(0.586)	(0.422)	(0.730)	(0.420)	(0.390)
	p = 0.305	p = 0.196	p = 0.764	p = 0.523	p = 0.193
Constant	1.610	1.587	1.239	11.285	1.571
	(3.244)	(2.124)	(1.569)	(1.692)	(1.572)
	p = 0.620	p = 0.456	p = 0.430	p = 0.000***	p = 0.318
Time-FE	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
Observations	17,612	4,249	763	1,848	1,848
Adjusted R^2	0.904	0.852	0.845	0.863	0.865
Note:				*p<0.1; **p<0.05; ***p<0.01	

5.2 Extended version of the baseline model

To investigate if there exists any effect for each of the years after the hurricanes, I have modified the baseline model (4.1) to the following:

$$PAT_{kt} = \beta_0 + \alpha_k + \delta_t + \beta_3(T_k \times Year_t) + \epsilon_{kt} \tag{5.1}$$

In equation 5.1 the variable, $Post_t$, from 4.1 have been replaced with a matrix of dummies for each year, $Year_t$, where 2005 is the reference level. Table 5.2 presents the regression results for all patents. As before, column (1), (2), (3), (4), and (5) show the full sample and the four subsamples. If an effect exists the interaction terms of the regression is expected to be significant for the years after the hurricanes (2006 - 2008), while non-significant for the years before (2002 - 2004). As seen in the table, this is not the nature of the presented results. For Subsample 1 the interaction term for 2008 are significant at a 10% level which can indicate some effects. However, the evidence is not very strong as this is the only significant estimate. Overall, the results do not provide any evidence for the alternative hypothesis. The interaction terms of the pre-period is also non-significant. This is consistent with the assumption of parallel trends and provide support for the validity of the difference-in-difference model. The regression tables of climate-change related patents and construction related patents can be found in Appendix A8.1 - A9.1. In similarity with the other results, there is no evidence for significant treatment effects for any of the dependent variables.

Table 5.2: Estimates from differences-in-differences regressions for all patents exhibiting the interaction term of all years

	All patents				
	Full sample	Subsample 1	Subsample 2	Subsample 3	Subsample 4
	(1)	(2)	(3)	(4)	(5)
Treatment	7.188	6.777	0.449	−5.259	7.118
	(4.625)	(3.033)	(2.376)	(2.426)	(2.243)
	p = 0.121	p = 0.026**	p = 0.851	p = 0.031**	p = 0.002***
Treatment×2002	−0.201	0.605	0.971	0.679	0.253
	(1.081)	(0.778)	(1.349)	(0.773)	(0.714)
	p = 0.853	p = 0.438	p = 0.472	p = 0.380	p = 0.724
Treatment×2003	−0.282	0.602	1.672	0.551	−0.033
	(1.081)	(0.778)	(1.349)	(0.773)	(0.714)
	p = 0.795	p = 0.440	p = 0.216	p = 0.476	p = 0.964
Treatment×2004	−0.001	0.045	1.300	0.393	−0.268
	(1.081)	(0.778)	(1.349)	(0.773)	(0.714)
	p = 1.000	p = 0.955	p = 0.336	p = 0.611	p = 0.708
Treatment×2006	0.649	0.578	0.757	0.668	−0.257
	(1.081)	(0.778)	(1.349)	(0.773)	(0.714)
	p = 0.549	p = 0.458	p = 0.576	p = 0.388	p = 0.720
Treatment×2007	0.292	0.648	2.072	0.354	0.659
	(1.081)	(0.778)	(1.349)	(0.773)	(0.714)
	p = 0.788	p = 0.406	p = 0.126	p = 0.647	p = 0.357
Treatment×2008	0.500	1.353	0.788	1.000	1.088
	(1.081)	(0.778)	(1.349)	(0.773)	(0.714)
	p = 0.645	p = 0.083*	p = 0.560	p = 0.196	p = 0.128
Constant	0.459	0.870	0.708	10.660	0.529
	(3.236)	(2.128)	(1.614)	(1.715)	(1.586)
	p = 0.888	p = 0.683	p = 0.662	p = 0.000***	p = 0.739
Time-FE	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
Observations	17,612	4,249	763	1,848	1,848
Adjusted R^2	0.905	0.853	0.846	0.864	0.868
Note:					*p<0.1; **p<0.05; ***p<0.01

6 Discussion

As presented in section 5, I do not find any significant results in the analysis. There are mainly three potential reasons for the zero effects: (i) The hurricanes had no impact on the inventor patent shares in the affected counties, (ii) the effect of hurricanes moves in opposite directions, (iii) the model is unable to capture the effect.

The most straightforward explanation for the zero effect is that the hurricanes did not impact the patent numbers in the affected counties. It can take several decades from an invention is discovered until it reaches the market. The time-consuming process of innovation argues for a non-existent positive effect on the number of patents in the years following the hurricanes. Additionally, even if the disaster increased the motivation to innovate among inhabitants in the affected areas, they might lack the knowledge and capabilities needed. Furthermore, the United States has institutions dedicated to emergency response. Hence, one could expect the counties' resilience to be sufficient and argue for non-existing negative effects. Even though it is plausible that real zero effects exist, it is non-viable to conclude that the hurricanes did not affect the patent numbers.

Contradicting effects of the hurricanes are another potential reason for the non-significant results. If there exist outcomes moving in opposite directions, they can counterbalance each other leading to no statistically observable effects. An example of this will be if more people start to innovate due to unemployment while recovery efforts reduce the local government's prioritization of innovation in the community at the same time. Identical consequences occur if the hurricanes lead to changes in the composition of patents rather than the amount, which means that the hurricanes affect patents related to different technologies in opposite directions. However, I do not find any significant results when investigating patents related to climate change and construction. These findings suggest that specific types of patents are not affected as well. Furthermore, the difference-in-difference estimate is an average for all counties in the treatment group. Meaning that the hurricanes might influence the inventor patent share for some counties, while not for the average county, resulting in a zero effect. By dividing the full sample into subsamples, one can control for this to some extent as the treatment group is compared to different compositions of counties in each subsample. However, the analysis consistently showed no significant estimates for any of the subsamples.

The results from the analysis depend on the applied research design, which can suffer from weaknesses mitigating the possibilities of identifying an effect. Hence, non-significant estimates can occur if the applied methodology does not capture the effects sufficiently. The lack of significant findings in this study can be related to problems associated with treatment intensity and spillover effects, confounding shocks, and the measurement of patents.

The applied treatment group consists of the counties that received the highest amounts of federal support. In section 4.3, I argue for the validity of the approach. However, as highlighted in the same section, nearly all counties received some sort of federal support during the 2005 hurricane season. Furthermore, it is also plausible that there exist spillover effects. One could imagine that inventors in unaffected counties perceived the hurricanes as a national crisis and responded to the disasters. In addition, inhabitants might relocate after the disasters leading to movements of people between the treatment and control group. However, since innovation does not entirely rely on individuals but also institutions and firms, a relocation effect of patent numbers is questionable. Overall, the difference in treatment intensity between the two groups might not be sufficient to capture an effect. In this case, the estimate will be biased towards zero, also known as attenuation bias.

Parallel exogenous events, such as policy changes or macroeconomic shocks that affect the treatment and control groups differently, can confound the results if they impact the number of patents. The most apparent exogenous events are other disasters happening in the same period. In section 4.4, I argue for the hurricanes of the experiment to have substantially more influence on the counties due to their relatively high amount of costs and thereby suggest other disasters to not result in confounding effects. However, the impact on patents does not necessarily take the severity of a disaster into account. To my knowledge, no other exogenous events exist with implications for the validity of the analysis.

Using a similar research design as this study, Schüwer et al. (2018) finds that the structure of the banking system had an effect on economic development following Hurricane Katrina, Hurricane Rita, and Hurricane Wilma. These authors assign counties to the treatment group with the same rationale as this study. Their ability to find evidence for another outcome variable can argue for the validity of the research design to capture effects.

Given that the research design is sufficient, the study should have identified an effect if it was large enough. Nonetheless, it is also plausible that the methodology does not capture the effect simply because it is too small. Minimal effects are impossible to distinguish from a null effect. A small effect indicates a weak relationship between the hurricanes and patent number. However, the effect can still be important from a policy or corporate perspective.

Patent counts as the dependent variable can be misleading since one invention can be related to numerous patents. For instance, a smartphone is made by combining several patented technologies. Ideally, when comparing two groups, the proportion of such inventions should be identical for both groups and not affect the result. However, this is not guaranteed. Additionally, patent counts only comprise granted patents. Hence, the analysis can provide a wrong picture of the changes in innovative efforts if the relationship between the number of granted patents and patent applications in the aftermath of the hurricanes diverges for the treatment and control groups.

Contradicting to my analysis Su and Moaniba (2017) and Miao and Popp (2014), finds evidence for a relationship between climate change and patent numbers. However, the research design of the studies differs considerably from this study. Both papers used data on the country level and investigated other factors related to climate change. Su and Moaniba (2017) studied the effect of greenhouse gas emissions and performed a three-stage econometric approach using fixed effects binary logistic regressions, standard linear regressions, and standard linear autoregressive distributed lag models. Miao and Popp (2014) studied the impact of floods, droughts, and earthquakes using meteorological and geophysical data to create hazard intensity measures as instrumental variables and applied a Poisson fixed-effects model.

Given that the model used in this study is well specified and that there do not exist any factors pushing the effects towards zero, the results of this study indicate a non-existing or weak relationship between patent activities and the three hurricanes, Katrina, Rita, and Wilma. The result is not evidence for a zero effect of natural disasters on patenting or innovation in general, nor is it evidence that the hurricanes of 2005 did not have any effect on patenting. However, if the impact was large and the model is sufficient, the results should have shown a significant relationship between patent numbers and the hurricanes.

7 Conclusion

The main objective of this study was to investigate the impact of Hurricane Katrina and the subsequent hurricanes, Rita and Wilma, on patent activity in impacted counties. Consequently, I sought to answer the following research question:

To what extent did the hurricanes Katrina, Wilma and Rita affect the number of patents in the impacted areas?

The study used patent data and measures of federal support given to counties to perform the analysis. Three types of patent groups were assessed: (i) all patents, (ii) climate-change related patents, and (iii) construction related patents. In addition, I explored five different samples whereby two of them were constructed using propensity score matching.

A difference-in-difference model with time- and county-fixed effects were applied to investigate the research question. The econometric models used in this paper found no evidence for a relationship between the three hurricanes and patent numbers. The results are consistent for all patent groups and samples.

Non-significant results are ambiguous and do not provide evidence for zero effects. Hence, it is not possible to conclude that there exists no relationship between the hurricanes and patent activities based on the findings from this master thesis. The ability to conclude with zero effects relies on the validity of the research design and the absence of factors biasing the result toward zero.

Further research is needed to understand the effects of natural disasters on innovation. Textual analysis is a statistical tool that can be taken advantage of in future studies to identify emerging technologies in the aftermath of disasters or to investigate patents containing specific technologies that are not captured sufficiently through the patent classification schemes. It could also be interesting to study if the impact of natural disasters differs for inventions by individual inventors versus inventions developed by firms. Furthermore, one could expect that countries respond differently to disasters due to variance in governmental institutions. Comparing the aftermath of disasters for countries can therefore also be an interesting approach. Lastly, it is possible to explore other measures of innovation such as RD expenditures or the number of new establishments. Overall, the impact of climate change and natural disasters on innovation is still a young research field full of unfulfilled potential.

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Appendix

A1 Characteristics of subsample 2

Table A1.1: Comparison of characteristics in 2004 between the treatment and control groups of Alabama and Florida. Column (2) presents the difference in means between the control group and the treatment group. Numbers in parenthesis are the normalized difference. A normalized difference of +/- 0.25 indicates that the characteristics is similar for the groups

	Subsample 3	
	(1)	(2)
	Treatment	Control
	Mean	(1) - (2)
Economic characteristics		
Population	341691.750	218568.856
		(0.052)
GDP per capita	29638.988	5844.688
		(0.284)
Personal income per capita	30730.129	5057.340
		(-0.025)
Unemployment Rate (%)	6.375	0.923
		(0.561)
Large firms per 100k	3.404	-0.856
		(-0.107)
All patents		
Inventors	82.000	56.424
		(0.087)
Patent share per 100k	1050.083	385.342
		(-0.027)
Counties with zero patents (%)	20.833	0.833
		(0.203)
Construction-related patents		
Inventors	4.167	2.743
		(0.130)
Patent share per 100k	70.958	13.358
		(0.114)
Counties with zero patents (%)	41.677	-23.039
		(0.018)
Climate-change-related patents		
Inventors	5.750	4.35
		(0.119)
Patent share per 100k	63.792	-30.957
		(-0.032)
Counties with zero patents (%)	45.833	-30.638
		(-0.073)

A2 Trends in average patent shares of subsample 1

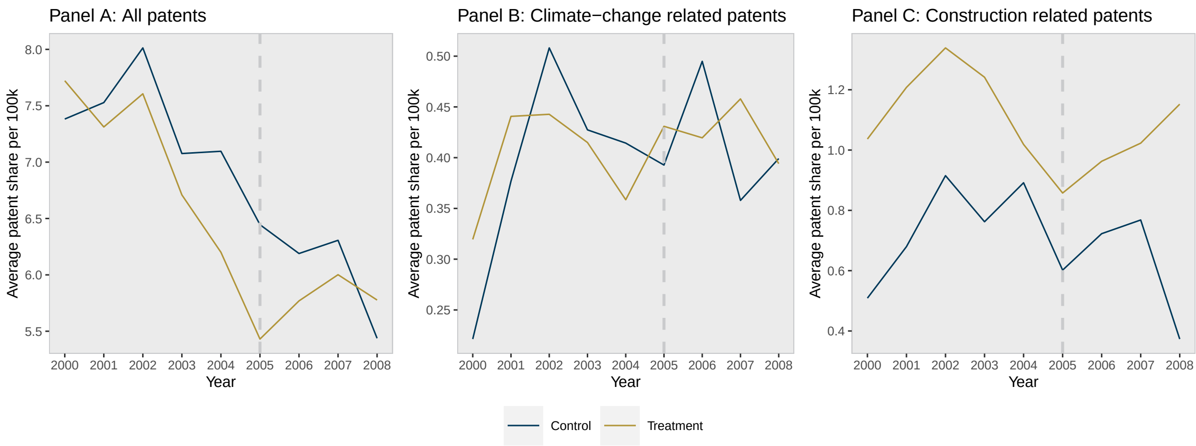

Figure A2.1: Trends in average patent share per 100.000 inhabitant of subsample 1 for all patents (panel A), climate-change related patents (panel B), and construction related patents (panel C) *Data source:* FEMA.

A3 Trends in average patent shares of subsample 2

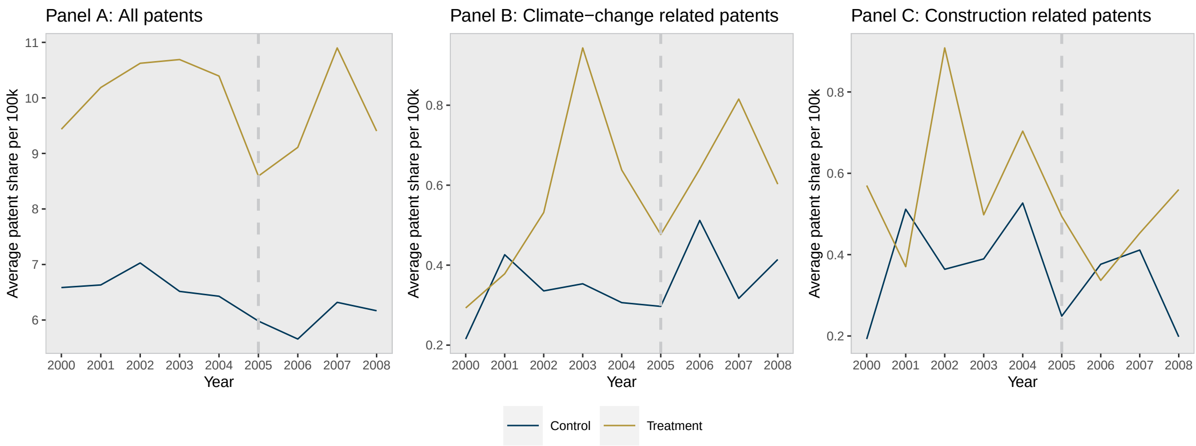

Figure A3.1: Trends in average patent share per 100.000 inhabitant of subsample 2 for all patents (panel A), climate-change related patents (panel B), and construction related patents (panel C) *Data source:* FEMA.

A4 Trends in average patent shares of subsample 3

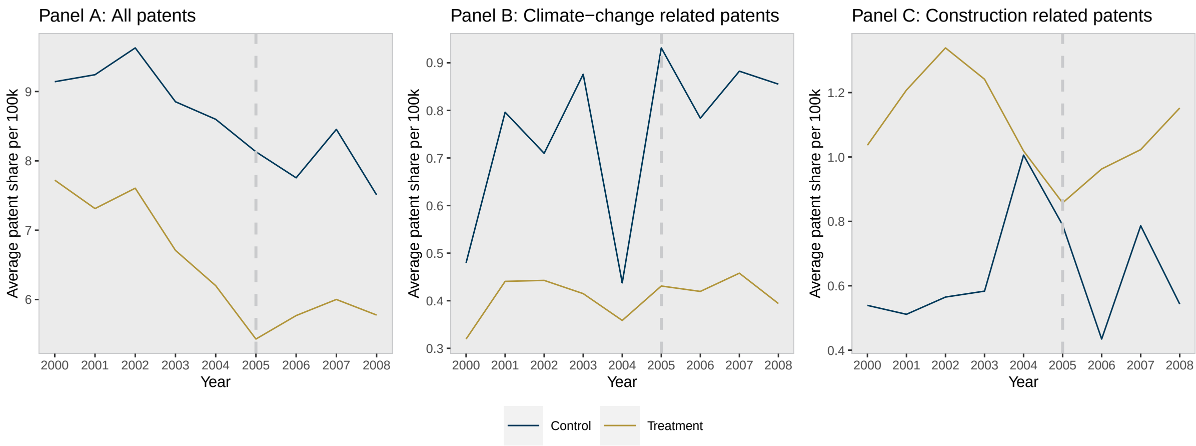

Figure A4.1: Trends in average patent share per 100.000 inhabitant of subsample 3 for all patents (panel A), climate-change related patents (panel B), and construction related patents (panel C) *Data source:* FEMA.

A5 Trends in average patent shares of subsample 4

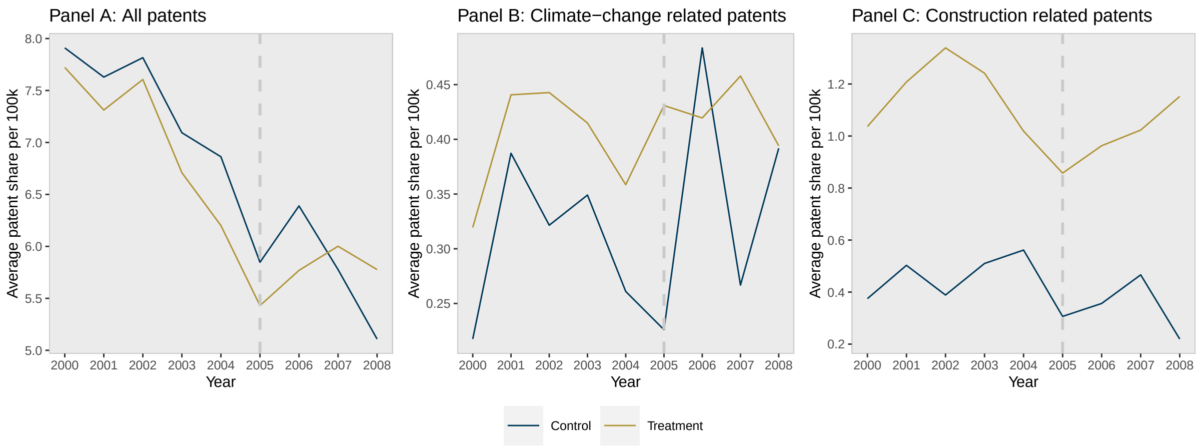

Figure A5.1: Trends in average patent share per 100.000 inhabitant of subsample 4 for all patents (panel A), climate-change related patents (panel B), and construction related patents (panel C) *Data source:* FEMA.

A6 Regression results for climate-change related patents

Table A6.1: Estimates from differences-in-differences regressions for climate-change related patents.

	Climate-related patents				
	Full sample	Subsample 1	Subsample 2	Subsample 3	Subsample 4
	(1)	(2)	(3)	(4)	(5)
Treatment	0.077	0.031	−0.079	0.464	0.079
	(0.809)	(0.614)	(0.427)	(0.703)	(0.435)
	p = 0.925	p = 0.961	p = 0.853	p = 0.510	p = 0.856
Post	0.087	−0.021	0.090	0.109	0.092
	(0.024)	(0.040)	(0.066)	(0.087)	(0.054)
	p = 0.0003***	p = 0.606	p = 0.172	p = 0.211	p = 0.090*
TreatmentPost	−0.076	0.032	−0.041	−0.099	−0.081
	(0.103)	(0.086)	(0.140)	(0.123)	(0.076)
	p = 0.462	p = 0.715	p = 0.767	p = 0.425	p = 0.289
Constant	0.246	0.292	0.244	0.119	0.243
	(0.571)	(0.434)	(0.300)	(0.497)	(0.308)
	p = 0.668	p = 0.502	p = 0.417	p = 0.812	p = 0.430
Time-FE	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
Observations	17,612	4,249	763	1,848	1,848
Adjusted R^2	0.587	0.580	0.473	0.679	0.502
Note:					*p<0.1; **p<0.05; ***p<0.01

A7 Regression results for construction related patents

Table A7.1: Estimates from differences-in-differences regressions for construction related patents.

	Construction-related patents				
	Full sample	Subsample 1	Subsample 2	Subsample 3	Subsample 4
	(1)	(2)	(3)	(4)	(5)
Treatment	4.437	4.436	0.423	−1.198	4.469
	(1.054)	(1.074)	(0.498)	(0.746)	(0.620)
	p = 0.00003***	p = 0.00004***	p = 0.397	p = 0.109	p = 0.000***
Post	−0.173	−0.175	−0.044	−0.171	−0.098
	(0.031)	(0.070)	(0.076)	(0.092)	(0.077)
	p = 0.00000***	p = 0.014**	p = 0.562	p = 0.065*	p = 0.202
Treatment×*Post*	0.101	0.103	−0.157	0.099	0.026
	(0.134)	(0.151)	(0.163)	(0.131)	(0.109)
	p = 0.452	p = 0.497	p = 0.338	p = 0.448	p = 0.809
Constant	0.074	0.075	0.019	1.761	0.042
	(0.744)	(0.759)	(0.350)	(0.527)	(0.438)
	p = 0.921	p = 0.922	p = 0.957	p = 0.001***	p = 0.924
Time-FE	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
Observations	17,612	4,249	763	1,848	1,848
Adjusted R^2	0.602	0.803	0.155	0.707	0.769

Note: *p<0.1; **p<0.05; ***p<0.01

A8 Regression results for climate-change related patents with yearly interactions terms

Table A8.1: Estimates from differences-in-differences regressions for climate-change related patents exhibiting the interaction term of all years

	Climate-change related patents				
	Full sample	Subsample 1	Subsample 2	Subsample 3	Subsample 4
	(1)	(2)	(3)	(4)	(5)
Treatment	0.136	0.093	−0.228	0.299	0.148
	(0.817)	(0.622)	(0.456)	(0.716)	(0.444)
	p = 0.868	p = 0.882	p = 0.617	p = 0.677	p = 0.740
Treatment×2002	−0.142	−0.104	0.016	0.232	−0.060
	(0.191)	(0.160)	(0.259)	(0.228)	(0.141)
	p = 0.459	p = 0.515	p = 0.952	p = 0.310	p = 0.674
Treatment×2003	−0.060	−0.054	0.428	0.009	−0.121
	(0.191)	(0.160)	(0.259)	(0.228)	(0.141)
	p = 0.755	p = 0.737	p = 0.099*	p = 0.968	p = 0.391
Treatment×2004	−0.037	−0.090	0.151	0.417	−0.094
	(0.191)	(0.160)	(0.259)	(0.228)	(0.141)
	p = 0.847	p = 0.572	p = 0.560	p = 0.068*	p = 0.507
Treatment×2006	−0.050	−0.115	−0.067	0.123	−0.274
	(0.191)	(0.160)	(0.259)	(0.228)	(0.141)
	p = 0.795	p = 0.470	p = 0.795	p = 0.591	p = 0.053*
Treatment×2007	−0.117	0.067	0.344	0.049	0.009
	(0.191)	(0.160)	(0.259)	(0.228)	(0.141)
	p = 0.540	p = 0.673	p = 0.184	p = 0.830	p = 0.948
Treatment×2008	−0.240	−0.044	0.045	0.026	−0.185
	(0.191)	(0.160)	(0.259)	(0.228)	(0.141)
	p = 0.210	p = 0.785	p = 0.862	p = 0.910	p = 0.192
Constant	0.204	0.247	0.234	0.301	0.192
	(0.571)	(0.436)	(0.309)	(0.507)	(0.314)
	p = 0.722	p = 0.571	p = 0.450	p = 0.553	p = 0.541
Time-FE	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
Observations	17,612	4,249	763	1,848	1,848
Adjusted R^2	0.588	0.579	0.473	0.680	0.501
Note:					*p<0.1; **p<0.05; ***p<0.01

A9 Regression results for construction related patents with yearly interactions terms

Table A9.1: Estimates from differences-in-differences regressions for construction related patents exhibiting the interaction term of all years

	Construction related patents				
	Full sample	Subsample 1	Subsample 2	Subsample 3	Subsample 4
	(1)	(2)	(3)	(4)	(5)
Treatment	4.431	4.431	0.424	−1.485	4.400
	(1.063)	(1.086)	(0.530)	(0.757)	(0.629)
	p = 0.00004***	p = 0.00005***	p = 0.424	p = 0.050**	p = 0.000***
Treatment×2002	0.041	0.086	0.284	0.684	0.343
	(0.249)	(0.279)	(0.301)	(0.241)	(0.200)
	p = 0.868	p = 0.759	p = 0.347	p = 0.005***	p = 0.087*
Treatment×2003	0.132	0.158	−0.159	0.573	0.125
	(0.249)	(0.279)	(0.301)	(0.241)	(0.200)
	p = 0.596	p = 0.571	p = 0.598	p = 0.018**	p = 0.532
Treatment×2004	−0.149	−0.222	−0.131	−0.110	−0.195
	(0.249)	(0.279)	(0.301)	(0.241)	(0.200)
	p = 0.549	p = 0.426	p = 0.665	p = 0.648	p = 0.331
Treatment×2006	−0.015	−0.091	−0.293	0.444	−0.020
	(0.249)	(0.279)	(0.301)	(0.241)	(0.200)
	p = 0.951	p = 0.745	p = 0.331	p = 0.066*	p = 0.920
Treatment×2007	0.034	−0.081	−0.275	0.145	−0.057
	(0.249)	(0.279)	(0.301)	(0.241)	(0.200)
	p = 0.892	p = 0.771	p = 0.362	p = 0.547	p = 0.778
Treatment×2008	0.303	0.496	0.093	0.569	0.361
	(0.249)	(0.279)	(0.301)	(0.241)	(0.200)
	p = 0.223	p = 0.076*	p = 0.757	p = 0.019**	p = 0.073*
Constant	−0.125	−0.125	−0.126	1.841	−0.095
	(0.744)	(0.761)	(0.360)	(0.535)	(0.445)
	p = 0.867	p = 0.870	p = 0.727	p = 0.001***	p = 0.831
Time-FE	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
Observations	17,612	4,249	763	1,848	1,848
Adjusted R^2	0.603	0.804	0.160	0.709	0.770
Note:				*p<0.1; **p<0.05; ***p<0.01	