ESSAYS ON THE NEGATIVE EXTERNALITIES OF ENERGY DEVELOPMENT:

PERCEPTION AND REALIZATION

by

HAIYAN LIU

(Under the Direction of SUSANA FERREIRA)

ABSTRACT

Nonrenewable energy development is known to have various negative externalities, with air and water pollution, and ecosystems deterioration being the major ones. While water pollution is mainly local and ecosystems deterioration is global, the effects of air pollution could be both local (particulate matter, sulfur dioxide) directly affecting human health and global (greenhouse gas emissions) causing climate change in the long run. To help inform energy and climate policies for a cleaner and sustainable future, this dissertation considers three separate markets to inspect public perception of climate change and other negative externalities of nonrenewable energy development.

Chapter 2 investigates the reaction of energy capital markets to hurricanes. Climate change is expected to increase the intensity and frequency of extreme weather events. Provided that capital markets are rational and relatively efficient, the impact of any information that a hurricane conveys about the immediacy and severity of climate change should be reflected in short-run stock price changes. Because carbon dioxide emissions from the combustion of fossil fuels are a sizeable contributor to greenhouse gas concentrations, and their reduction is a key ingredient in any climate change mitigation strategy, I focus on energy companies. Four hurricanes are examined with an event-study approach: Hugo (1989), Andrew (1992), Katrina (2005), and Sandy (2012).

Chapter 3 and Chapter 4 inspect two important external costs associated with unconventional oil and gas development. In Chapter 3, I use a difference-in-difference hedonic model to evaluate the seismic risk induced by wastewater disposal. Using data from Oklahoma County, I recover hedonic estimates of property value impacts from nearby shale gas development that vary with earthquake exposure. Chapter 4 estimates the costs of shale oil and gas development in Texas' health care market, focusing on four short-term health conditions: circulatory, digestive, respiratory, and skin and sense organs. Using a rich individual hospital visit data from January to June 2010 and a genetic matching method, I estimate the average impact of fracking on hospitalization rate and per capita total (non-covered) costs on the four categories for the entire population and by age group.

INDEX WORDS: CLIMATE CHANGE; HURRICANES; EARTHQUAKES; ENERGY; HYDRAULIC FRACTURING; SEISMICITY RISK; HEALTH CARE

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DOCTOR OF PHILOSOPHY

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DEDICATION

To my loving family

ACKNOWLEDGEMENTS

Eight years ago, I set off on an intellectual journey. The need to start this journey was fostered by the extensive poverty in rural China, the controversy on agricultural development, and the inspiring writings of many great economists.

Now I appear to have come to some milestone. The latest leg has been long and, often, hard going. I have benefited to no end from the advice, encouragement, and inspiration of my advisors, Dr. Susana Ferreira, Dr. Berna Karali, Dr. Brady Brewer, and Dr. John Bergstrom. I am deeply grateful and indebted to all of them. Their guidance has pushed my thinking beyond what I could have imagined when I started my Ph.D., and my work would be radically different without their support. I owe a particular debt to Dr. Ferreira who took me under her wings at the very beginning of my doctoral journey and has shared seemingly endless amounts of her time and attention with me. I am forever thankful for her incredible patience, technical direction and life advice as I completed the entire dissertation research.

Many colleagues and friends also generously took the time to help me during this dissertation process. The comments from Nicholas Magnan and Greg Colson have substantially improved and strengthened this work. I am grateful to Thomas Werth who has been tremendously helpful in producing my job market paper. Without his help on georeferencing the property data, it would have taken me a much longer period to complete the research. Oleksiy Tokovenko deserves a special mention. He has been a friend, a mentor, and an informal advisor when I walked this long and difficult path. Thank you so much for your friendship and advice,

for being so supportive, for always listening, and for helping me reach further and to strive to be more innovative and independent.

I am especially thankful for all the faculty and staff of the Department of Agricultural and Applied Economics and the University of Georgia. I would like to thank the department for the financial support throughout the whole program of study and one extended semester.

Finally, I would like to give my most sincere gratitude to my family for their undying love and support and for their willingness to sacrifice everything for my happiness. Thank you for having not a slightest doubt in my ability to excel. None of this would be possible without you being by my side.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Page

CHAPTER 1

INTRODUCTION

All societies require energy services to meet basic human needs (e.g., lighting, cooking, space comfort, mobility and communication) and to serve productive processes. It was wood — a renewable biomass energy source — that was unquestionably the first fuel used for fire. The fossil fuel coal had been used as a fuel since 1,000 B.C., however, it wasn’t until the arrival of the Industrial Revolution in the mid-1700s that coal began to replace biomass as the primary source of energy. Coal mining became prominent as people recognized there was a shortage across Britain in wood and water yet coal and iron was available in abundance. This demand for coal was both domestic for heating supplies as well as industry which required the conversion of coal to coke; a process similar to the traditional conversion of wood to charcoal. This demand for fuel sparked the industrialization of the coal mines across Britain over the space of 200 years. Massive consumption of oil and natural gas did not start until the late 1800s and early 1900s following their discovery in large quantities in shallow oil reservoirs. In 2015, more than 80% of the global total primary energy supply was from fossil fuels with oil being the leading fuel accounting for 32.9%, coal 29.2% and natural gas 23.85% (World Energy Council 2016). In the United States in year 2015, the three major fossil fuels – petroleum, natural gas, and coal accounted for most of the nation’s energy production with proportions of 32%, 28%, and 21% respectively; 11% of the energy produced was from renewable energy and 9% from nuclear (EIA 2016a). For natural gas, the production is mainly from shale oil and gas boom.

The use of fossil fuels, particularly coal, was instrumental for industrial revolution which helped with technological development and economic growth significantly. Over a two-hundred-year period, the rise in mining rose by astronomical rates from approximately 2.54 million tonnes in 1700 up to 224 million tonnes in 1900. Britain was part of a coal mining boom. Industrial revolution dramatically advanced human civilization, however, such consumption has generated multiple negative externalities. Burning fossil fuels not only releases their energy potential, but also the carbon molecules that make these fuels release powerful energy. This creates 1) local air pollution (e.g. particulate matter, sulfur dioxide, and nitrogen dioxide) which affects human health directly by causing and exacerbating conditions such as asthma, acute bronchitis, and irregular heartbeat; 2) global air pollution, particularly CO_2 emissions, which do not have a direct impact on human health but contribute to climate change in the long run and is much more difficult to internalize. Climate change further has been found to be related with climate variability and weather extremes such as the 2003 summer European Heatwaves which caused economic losses of over $13 billion and dozens of thousands of fatalities (IFRC 2004), the large-scale riverine flood events of the Oder (1997) , Elbe (2002) and Rhone (2002) in Europe, and the 2005 hurricane season in the U.S. where 27 named storms formed, 14 were hurricanes three of which were category 5 – the most Category 5 hurricanes recorded in a single season, and Hurricane Katrina alone induced over $100 billion total losses (NOAA National Centers for Environmental Information 2006). Hill et al. (2009) found that for each billion ethanol-equivalent gallons of fuel produced and combusted in the US, the combined climate-change and health costs are $469 million for gasoline and $472–952 million for corn ethanol depending on biorefinery heat source (natural gas, corn stover, or coal) and technology.

While there has been growing consensus among climate scientists worldwide about anthropogenic climate change and the seriousness of the potential risks (IPCC 2014), the concern reported by citizens and government officials in the United States has lagged behind. According to Gallup, only 34% of Americans expressed "A Great Deal of Concern" about global warming and 35% about climate change in the March 6 – 9 survey (Newport 2014). The survey also showed that Americans don't attribute colder weather to climate change; 70% of those who felt winter temperature in local area was colder than usual perceive the cause to be due to normal variation in temperatures (Jones 2014). Further, there are stark partisan differences on climate change in the U.S. 68% of the democrats consider global climate change to be a very serious problem while only 20% republicans do so, which leads to 82% of democrats supporting limiting greenhouse gas emissions while only 50% republicans approving (Stokes et al. 2015).

There are two reasons that render public policies necessary to support and guide the direction of energy development, and arrange the paths to achieve carbon neutrality. First, mitigating climate change is a global public good, where each country (and individual) faces private costs to reduce greenhouse gas emissions, while the benefits of such efforts are shared by all regardless of their own contributions. Second, greenhouse gas emissions from the burning of fossil fuels is the primary human activity affecting the amount and rate of climate change (Stocker 2014).

Currently in the U.S., two main energy policies towards achieving this goal of transition into clean energy are the Clean Power Plan (announced on August 3, 2015) which was projected to reduce the power sector's carbon emissions to 32 percent below 2005 levels by 2030, and the Renewable Portfolio Standards (it was first established in Iowa in 1983 as Alternative Energy Law and has been established in 29 states plus the District of Columbia by June 2013 (Durkay

2017)) which aims to promote the development and adoption of renewable energy technologies. The final Clean Power Plan also take steps to limit a rush to natural gas which brings considerable consumer (risks of electricity price spikes related to natural gas price volatility), health and climate risks. The final CPP takes measures to limit this rush to gas in four ways: 1) Increasing the role of renewable energy; 2) Allowing renewable energy to displace coal and natural gas generation; 3) Phasing in the coal to gas switch; 4) Ensuring that there aren't perverse incentives to build new natural gas plants.

The U.S Environmental Protection Agency (EPA) proposed the Clean Power Plan in June 2014 and finalized it in August 2015. State implementation proposals were originally set to be due September 2016, but, on February 9, 2016, five justices of the Supreme Court voted to stay the plan — that is, suspend its implementation — pending the resolution of the lawsuit against it. The suit, involves a huge number of parties, including twenty-seven mostly Republican-controlled states, led by West Virginia, along with a number of coal companies and coal-dependent utilities. Eighteen other states — plus seven municipalities, more than a dozen environmental organizations, and a different set of utilities and industry groups — have intervened to support it. After the Supreme Court Stay vote, 19 states – AZ, CA, CO, CT, DE, ID, IL, LA, MA, MD, ME, MN, NH, NY, OR, PA, RI, VA, WA – and the District of Columbia continued their planning and 9 states – FL, IA, MO, NM, NV, OH, SC, TN, WY – went on assessing the planning of implementing the Clean Power Plan according to E&E News. In March 2017, President Donald Trump signed the Executive Order on Energy Independence mandating the EPA to review the Clean Power Plan, and EPA administrator sent letters to state governors advising them that they are under no obligation to adhere to the Clean Power Plan rule. On April 28, 2017, the U.S. Court of Appeals for the District of Columbia granted the Trump administration's request to suspend lawsuits against the Clean Power Plan rule for 60 days, signaling the likely end of President Barack Obama's signature climate policy. Further, on June 1, 2017, Trump announced the withdrawal of the U.S. from the Paris Agreement.

Meanwhile, hydraulic fracturing (fracking) and horizontal drilling techniques which have generated a shale oil and gas boom in the US since the mid 2000s, have been widely accepted as an intermediate energy source between coal and renewables in terms of carbon emissions, and a pathway to make America energy independent by replacing oil imports from the Middle East. According to U.S. Energy Information Administration (EIA), in 2015, U.S. dry natural gas production was equal to about 99% of U.S. natural gas consumption mainly due to increased shale gas production (EIA 2017). The total annual shale gas produced from 18 states across the country in 2015 was 15,213 billion cubic feet, almost three times the amount in 2010 with the increase mostly from Pennsylvania and Texas (EIA 2016b). United States is now the largest producer of petroleum and natural gas in the world and recently surpassed Saudi Arabia in oil production and Russia in natural gas (Hammond 2015).

Local areas facing shale development may see increases in population, employment (Hardy and Kelsey 2015; Paredes et al. 2015), business activity, and government revenues (Kargbo et al. 2010; Newell and Raimi 2015). However, these "boomtowns" may also suffer from negative social, economic, and environmental consequences such as increased crime rates (James and Smith 2017), housing rental costs (Bartik et al. 2016), air pollution (Kemball-Cook et al. 2010; Annevelink et al. 2016), water contamination (Muehlenbachs et al. 2015), earthquakes (Weingarten et al. 2015), and related health problems (Bunch et al. 2014; Rasmussen et al. 2016). Such negative impacts have urged hundreds of towns, tribal territories, cities, and counties across the country to enact bans or moratoria on fracking in recent years. As of March

2017, there are three states that have banned fracking – MD, NY and VT, and 34 states with frackable reserves already fracking – AK, AL, AR, AZ, CA, CO, FL, ID, IL, IN, KS, KY, LA, MI, MO, MS, MT, ND, NE, NM, NV, OH, OK, OR, PA, SD, TN, TX, UT, VA, WI, WV, and WY according to FRACTRACKER. There has been no frackable reserve discovered in other states. Outside the U.S., only Canada, China and Argentina have commercial production from shale (EIA 2015). In Europe, companies didn't find enough gas or oil to keep drilling in Sweden, Poland and Romania, and France, Germany and Scotland have all banned fracking by October 2016 (Neslen 2016). The British government is in favor of developing the resource and has opened up significant acreage in the 14th Onshore Round. Nonetheless, some resistance remains. In Spain, five companies gave up shale gas extraction plans in face of opposition and low prices as of March 2017.

Assuming that voters elect politicians who closely matched their preferences (Stadelmann et al. 2013), it ultimately depends on the public to decide policies to comply to and directions to go in towards achieving the goals of sustainable development. This dissertation examines public perceptions of different energy development options and technologies through investigating the realized impacts of the negative externalities resulting from energy development in three instances. First, I examine the reactions of energy stock returns (which can signal investors' beliefs about the company's potential profitability and value) to hurricanes, one of the most salient impacts of climate change. Specifically, I examine whether the reaction of stock prices is consistent with the anticipation of a regulation on energy companies to reduce carbon emissions, particularly companies that are publicly traded on the stock market. And if so, how has the effect been changing over time.

Then, I study the external costs of hydraulic fracturing in the U.S. Housing prices which are "use" values and in principle (with perfect information, zero transaction cost, free mobility, homogeneous preferences, complete adjustment of the market to changing supply and demand) capture all the positive and negative amenities in the local market are examined to see people's response to the negative externalities caused by fracking. Different from existing literature, I focus on the impacts of wastewater-injection induced seismicity risk. In Oklahoma, since 2009, there has been a swarm of earthquakes associated with wastewater injection activities which are the primary ways to process wastewater from unconventional oil and gas production (Weingarten et al. 2015). In order to identify the effect of induced seismicity risk on property prices, I exploit the occurrence of earthquakes that act as a shock reminding people the risk of wastewater injection and hypothesize that the effects are the strongest for properties that are closest to injection wells.

Finally, at a larger scale (county level instead of property level), I estimate the overall human health care costs due to water and air pollution, earthquake shocks, and other negative externalities in the process of fracking. Given that there are both short-term and long-term health impacts while the benefits generally only last while extraction is economically feasible, the lifetime costs might offset the economic benefits. Therefore, quantifying the public health costs is an important step in conducting the economic impact assessment of fracking. While existing literature has demonstrated that fracking is related to many health issues, particularly respiratory diseases (McKenzie et al. 2012; Peng et al. 2016), the magnitude of these impacts remains unclear. To the best of my knowledge, this paper provides the first monetary estimates of the health care impacts of fracking in Texas which has been the State with the largest number of fracking wells and highest production volumes until 2014 after which Pennsylvania took over the lead.

This dissertation explores the importance of estimating the external costs of energy development which the markets ignore. Particularly, I focus on the costs on climate, housing value, and public health, with the latter two in the context of fracking boom. Expanding the analysis to the entire country with important heterogeneity in the distribution of the net benefits across space in mind, and combining the estimates of costs and benefits, we can assess the overall short-term and long-term *net* benefits of energy policies and energy development techniques. Speaking of net benefits, one must note that net benefits mask potentially large negative external costs in local communities, and that these need to be estimated to fully understand the distributional implications of fracking and the local opposition to these activities - having this information should help design instruments (e.g. taxes on fracking redistributed to local communities) to improve welfare.

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CHAPTER 2

HURRICANES AS INFORMATION SHOCKS? A COMPARISON OF THE IMPACT OF HURRICANES ON STOCK RETURNS OF ENERGY COMPANIES[1]

[1] Liu, H., S. Ferreira, B. Karali. "Hurricanes as Information Shocks? A Comparison of The Impact of Hurricanes on Stock Returns of Energy Companies", submitted to *Climate Change Economics*, 5/3/2017.

2.1. Abstract

Recent hydro-meteorological disasters have sparked popular interest in climate change and on its role in driving these events. We focus on the information provided by one such type of disaster, hurricanes, to capital markets. Because carbon dioxide emissions from the combustion of fossil fuels are a sizeable contributor to greenhouse gas concentrations, and their reduction is a key ingredient in any climate change mitigation strategy, we focus on energy companies. We estimate the reaction of the stock market returns of the largest energy companies in the United States to the most notorious, damaging hurricanes in each of the last four decades in the United States: Hugo (1989), Andrew (1992), Katrina (2005), and Sandy (2012). The event study analysis shows that the impacts are not large. After more recent hurricanes, however, especially after Sandy the impacts differ across energy companies based on their carbon intensity, with negative cumulative average abnormal returns for coal firms relative to the oil, natural gas, and mostly the renewable industry. The stock price reactions to extreme weather events provide a signal for energy companies to plan for climate change now.

Key words: Climate Change; Energy Industry; Environmental Information; Event Study; Hurricane

JEL Codes: G11, G14, Q4, Q54

2.2. Introduction

On August 3, 2015, President Obama and the Environmental Protection Agency (EPA) announced the Clean Power Plan, a federal plan to implement greenhouse gas emission guidelines for existing fossil fuel-fired power plants under the Clean Air Act (EPA 2015). This plan, the centerpiece of the administration's efforts to mitigate climate change, highlights the tremendous challenges and opportunities facing the energy industry due to climate change. As outlined in President Obama's Climate Action Plan (Executive Office of the President 2013), two key pillars in any strategy to combat climate change are (i) to reduce carbon pollution from power plants, and (ii) to expand the clean energy economy. The first pillar will impose costs on carbon intensive industries, and could potentially cripple the coal industry from which much backlash has resulted, while the second will benefit the renewable energy sector.

Amidst the political and judicial turmoil facing climate change regulations,[2] this paper contributes to the discussion by measuring the effect of hurricanes on energy corporations' stock market performance. Although no one particular hurricane can be directly linked to climate change, hurricanes are salient incidents that increasingly trigger public concern about the impacts of climate change. Provided that capital markets are rational and relatively efficient, the impact of any information that a hurricane conveys about climate change should be reflected in short-run stock price changes. These price changes would signal investors' beliefs regarding expected changes in firms' profitability and, in turn, on their value, arising from the costs of climate change to firms (e.g. through mitigation of greenhouse gases).

In our study, the climate change information is not related to the environmental performance of firms. Previous work finds that stock prices significantly react to environmental

[2] On February 9 2016 the Supreme Court issued a "stay" of the Clean Power Plan. This decision bars the EPA from enforcing any of the rule's plans to regulate emissions from coal-fired power plants until the lawsuits against it are fully resolved.

"news" such as those coming from the Toxics Release Inventory, with stock prices declining in response to negative environmental news and increasing in response to positive environmental news (Hamilton 1995; Konar and Cohen 1997; Khanna et al. 1998). Endrikat (2015) provides meta-analytic evidence for positive (negative) market reactions to positive (negative) corporate environmental performance-related events, with stronger reactions to negative events. A pervasive concern in this literature, however, is that environmental data are self-reported and, as such, prone to strategic misreporting.[3]

The information shock in our paper is not the announcement of climate change legislation, either. Environmental legislation in general and climate legislation in particular is itself endogenous to the environmental performance of firms and the ensuing environmental conditions. Moreover, affected firms typically play an important role in the legislative drafting process through consultation and lobbying efforts (Newell and Paterson 1998; Lavelle and Lewis 2009; LeBlanc 2015). Another issue is the difficulty of assigning an event date to legislation that may be months or years in the making.[4] In contrast to much of the related literature, our study examines plausibly exogenous events (at least in the medium run) to the involved firms: the occurrence of rapid-onset and highly destructive hurricanes. We hypothesize that because people are connecting tropical cyclones to the broader narrative of climate change in the aftermath of an event (Lang and Ryder 2015), the occurrence of hurricanes should convey information on the immediacy and severity of climate change.

[3] A notable exception is Beatty and Shimshack (2010). They examined the reaction of stock prices to the exogenous ratings of companies' management of greenhouse gas emissions by a non-profit organization. They find that the release of firm-level ratings of companies scoring their climate-related environmental behavior had statistically significant and large impacts on stock market returns.

[4] For example, although announced on August 3, 2015, the Clean Power Plan had been in gestation for several years. In 2007, the Supreme Court ruled that the EPA has the authority and responsibility to regulate carbon emissions under the Clean Air Act. Six years later, in 2013, President Obama announced his Climate Action Plan, and one year later, on June 2, 2014, the EPA proposed the draft Clean Power Plan.

The last twenty five years have seen an increase in the frequency and intensity of hydro-meteorological disasters globally and in the US, with storms and floods being the most prevalent and costly (CRED 2015; Insurance Information Institute 2016). While one reason behind this trend is an increase in exposure of people and property in floodplains making it more likely that a given hazard becomes a natural disaster (Raschky 2008; IPCC 2012), climate change is expected to increase the frequency and physical intensity of extreme weather events. Emanuel (2005), Mann and Emanuel (2006), and Kunkel et al. (2013) argue that in the North Atlantic region, the decadal variations of the sea surface temperature itself, as well as the upward trend in the destructiveness of large storm systems, are driven mostly by anthropogenic changes in greenhouse gases and aerosols.[5]

Despite its potentially large impacts, the degree to which climate change is perceived as a risk by the wider public varies substantially and has been traditionally low in the US (Leiserowitz et al. 2014). Recent extreme weather events, however, have featured prominently in the political discourse, and have sparked popular interest in climate change, on its role in driving extreme weather, and on climate change mitigation. Personal experience of local weather, in particular abnormal weather, has been shown to be strongly related to attitudes towards climate change (Egan and Mullin 2012; Akerlof et al. 2013; Hamilton and Stampone 2013; Zaval et al. 2014). For example, Spence et al. (2011) show that those who report experience of flooding express more concern over climate change, see it as less uncertain, and feel more confident that their actions will have an effect on climate change. Importantly, these perceptual differences also translate into a greater willingness to save energy to mitigate climate change. If the behavioral

[5] Further, based on a meta-analysis of projected future economic losses under a variety of climate change scenarios, Ranson et al. (2014) find strong support that climate change will cause damages from tropical cyclones and wind storms to increase. Potential changes in damages are greatest in the North Atlantic basin, where the multi-model average predicts that a 2.5°C increase in global surface air temperature would cause hurricane damages to increase by 63%.

implications scale up, one would expect that the stock prices of energy companies react to extreme weather events that alter the climate change perceptions of investors and potentially increase the acceptability of policies that raise the cost of carbon.

Our paper focuses on the information provided by hurricanes in the North Atlantic to the US energy sector. Specifically, we conduct a series of event studies to measure the impact of hurricanes on the stock market returns of the largest, publicly traded energy companies in the US. Recent research shows that public responds to hurricanes by seeking more information on climate change in the aftermath of an event (Lang and Ryder 2015). It remains to be seen if hurricanes are also affecting investors' perceptions of profitability in the energy sector. We categorize energy companies into five groups according to CO_2 emissions intensity: coal, oil, natural gas, nuclear, and renewables.[6] We consider the most notorious, damaging hurricanes affecting the US in each of the last four decades: Hugo (1989) in the 1980s, Andrew (1992) in the 1990s, Katrina (2005) in the 2000s, and Sandy (2012) in the 2010s. We select these specific hurricanes as each of them was, at the time of its occurrence, the costliest Atlantic hurricane on record, and each has remained the costliest in its decade (see Table 1 for damage estimates). We hypothesize that the impact of hurricanes on energy companies depends on their carbon intensity with a negative effect for coal and positive for nuclear and renewables, and that the impact has increased over time.

A related literature has estimated significant negative abnormal returns for nuclear utilities while positive excess returns for renewable energy companies in Japan and Europe following the 2011 Fukushima disaster (Ferstl et al. 2012). These findings have been interpreted in the context of changes in perceptions regarding nuclear safety. An exception is the recent

[6] According to the International Energy Agency (IEA 2005), the fossil CO_2 emission factor (Tonne CO_2/TJ_{ncv}) is 94.6 for hard coal, 74.1 for oil, 56.1 for natural gas, and zero for nuclear and renewable energies (biomass, wind, solar, etc.).

work by Lei and Shcherbakova (2015) who use the Fukushima accident as a natural experiment to reveal attitudes towards climate change. They argue that while the European stock markets realized positive abnormal returns on renewable energy stocks, indicating a preference for that source of energy to replace nuclear generation, the US markets exhibited a significantly more favorable perception of coal energy.

Hurricanes may directly affect energy production, capacity, and infrastructure both offshore and onshore, mostly impairing the oil sector. Assuming that refineries are restored to full capacity within two weeks following Hurricane Katrina, Kirgiz et al. (2009) find that refineries in the Gulf of Mexico lost $23 million. Lewis (2009) finds that wholesale gasoline prices spiked significantly following Hurricane Rita and the effect lasted for 2 weeks to 2 months. Fink et al. (2010) and, Fink and Fink (2013, 2014) further show that tropical storm forecasts had large significant impact on refined petroleum prices and market returns of refineries in the Gulf of Mexico. In contrast to this literature, the focus of our paper is much broader. We estimate the impact of hurricanes on entire energy industry, including but not limited to the petroleum refining sector.

Given the importance of the energy sector in mitigating climate change, extreme events such as hurricanes, by shaping climate change perceptions, can have much broader, long lasting effects on the energy sector that go beyond those to the oil refining industry, affecting the oil sector overall and sectors that rely on other fuel sources according to their carbon intensity. Those are the effects that we estimate in this study. As long as investors believe that the climate information conveyed by hurricane events is novel and consequential to some stakeholders, hurricanes would cause those investors to revise their expectations about future profitability of energy companies (downwards for carbon intensive sectors and upwards for clean energy). This would be in contrast to the conventional rhetoric that carbon emissions are costly for businesses to mitigate and that near-term damages from climate change will be concentrated in already hot/vulnerable locations anyways, so businesses have little incentive to care about climate change today. In this context, stock price reactions to hurricane events would provide an incentive for energy companies to care about climate change now.

2.3. Method

2.3.1 Event Study Method

We are interested in assessing the reaction of stock prices of energy companies following substantially damaging hurricanes. Our research design follows the financial event study methodology developed by Fama et al. (1969) and summarized in Peterson (1989) and MacKinlay (1997). We use a market model to compute abnormal returns which reflect the difference between observed returns and predicted returns for a given security on a given day. Specifically, for each security and event (hurricane) we estimate the following equation:

$$R_{\mathrm{it}} = \alpha_{\mathrm{i}} + \beta_{\mathrm{i}} R_{\mathrm{mt}} + \sum_{\mathrm{k}=t_0-\mathrm{a}}^{\mathrm{k}=t_0+\mathrm{b}} \delta_{\mathrm{ik}} D_{\mathrm{k}} + \varepsilon_{\mathrm{it}} \tag{1}$$

where the estimation period $t \in [-250, 30]$ (discussed in section 3.1), R_{it} is the rate of return on the stock of firm *i* on day *t* and is calculated as the percentage change in a security's closing price, $R_{it} = (P_{it}/P_{i,t-1}) - 1$; R_{mt} is the rate of return on the price index of the market portfolio on day *t*, $R_{mt} = (P_{m,t}/P_{m,t-1}) - 1$;[7] and ε_{it} is the error term with $E(\varepsilon_{it}) = 0$, and $Var(\varepsilon_{it}) = \sigma^2_{\varepsilon_i}$. D_k are event-window dummies which equal 1 if day *k* is in the event window and 0

[7] One concern with event studies is that the market return is influenced by the event. This is unlikely in our case. While one would expect the impact of a natural disaster to be negative for some firms, for other firms it might be positive, averaging a zero net impact on *aggregate market* returns. Previous research has shown that another type of natural disaster, earthquakes, has a negligible impact on aggregate market returns. This is the case even for those earthquakes domestic to the stock market (Ferreira and Karali 2015). Nevertheless, if some endogeneity is present, our results would be understated.

otherwise. δ_{ik} is the abnormal return for firm i on day k, which is the prediction error in the traditional market model, and measures the impact of new information on stock returns.

Our core analysis then examines the relationship between abnormal returns and hurricane events. For each equation, there are a+b+1 dummy variables identifying the days in the event window. Day t_0 ($t_0 = 0$) is the event day which is defined as the date of the first emergency declaration in the US. Day $t_0 - a$ is the day the hurricane formed. Day $t_0 + b$ is the last day in our event window. As described below, we analyze the robustness of the results to differing window lengths up to 30 trading days after the event day, therefore, $b = 30$ in all events. Both a and t_0 are hurricane specific. The sample companies are also hurricane specific, thus we have different numbers of companies for the different events, although, as described below, we also analyze the robustness of the results to limiting the sample to companies for which we have data for the four events. Section 3 discusses the choice of companies and the estimation and event windows in detail.

The validity of the significance tests of the estimated parameters in the market model relies on the assumption of identically and independently distributed (*iid*) residuals. In our case, since the hurricanes occurred in the same time period for all firms and these firms were in the same industry – the energy industry, the *iid* assumption on market model residuals is most likely violated. Therefore, as in Betzer et al. (2013), Ferstl et al. (2012), and Lopatta and Kaspereit (2014), we adopt the model first proposed by Izan (1978) and applied by Binder (1985) to address the contemporaneous correlation in market model residuals, and apply the seemingly unrelated regression (SUR) method by Zellner (1962) to conduct the estimation. Equation (1) is thus estimated for each hurricane separately, in a SUR framework that pools the returns data for all firms in the five energy sectors. We obtain estimates of the daily abnormal returns (AR) for company *i* for each day *k* in the event window, $\widehat{AR}_{ik} = \hat{\delta}_{ik}$, for each of the four hurricane events.

The standard approach to assess statistical magnitudes in event studies aggregates abnormal returns over both securities and days to obtain cumulative abnormal returns. Based on $\widehat{AR}_{ik}$, we calculate the daily average abnormal returns (AAR) for each of the five energy categories for each event. Thus, we have:

$$\widehat{AAR}_{\mathrm{jk}} = \frac{1}{N_j} \sum_{\mathrm{i}=1}^{N_j} \widehat{AR}_{\mathrm{ik}} \tag{2}$$

where *j* = coal, oil, gas, nuclear, and renewables, and N_j is the number of companies in energy category j. The cumulative abnormal returns (CAR) for a certain stock and the cumulative average abnormal returns (CAAR) for a certain industry over a certain period in the event window can be written, respectively, as:

$$\widehat{CAR}_{i,t_1,t_2} = \sum_{\mathrm{k}=t_1}^{\mathrm{k}=t_2} \widehat{AR}_{\mathrm{ik}} \tag{3}$$

$$\widehat{CAAR}_{\mathrm{j},t_1,t_2} = \sum_{\mathrm{k}=t_1}^{\mathrm{k}=t_2} \widehat{AAR}_{\mathrm{jk}} \tag{4}$$

where $[t_1, t_2]$ is a subset of the complete event window with $t_1 \leq t_2$.

The null hypothesis that hurricanes did not have a significant impact on the average daily stock returns of energy firms in category *j* is H_0: $AAR_{\mathrm{jk}} = 0$. The significance of AAR_{jk} is assessed with a standard Wald statistic, where $Var\left(AAR_{\mathrm{jk}}\right) = \frac{1}{{N_j}^2}[\sum_{i=1}^{N_j} Var(AR_{ik}) + \sum_{i \neq l} Cov(AR_{ik}, AR_{lk})]$. To test the hypothesis of zero cumulative average abnormal returns, we calculate the *z*-score, where $Var\left(CAAR_{\mathrm{j},t_1,t_2}\right) = \sum_{k=t_1}^{k=t_2} Var\left(AAR_{jk}\right) + \sum_{t \neq s} Cov(AAR_{jt}, AAR_{js})$, whose square root in a large sample approximates the standard deviation of $CAAR$ — $\sigma(t_1, t_2) \approx \sqrt{(t_2 - t_1 + 1)\sigma_{AAR}^2}$ (MacKinlay 1997; Kawashima and Takeda 2012).

2.3.2 Regression Approach Comparison across Industries

We use regression analysis to test the hypothesis that the impact of hurricanes on abnormal returns of energy companies depends on the carbon intensity of their energy source. For a given hurricane, we regress the estimated, firm-level cumulative abnormal returns $\widehat{CAR}_{i,t_1,t_2}$ on dummy variables denoting energy type.

In addition to energy type, the abnormal returns may be correlated with firm-level characteristics. Renewable energy companies in our sample are substantially smaller than other energy firms, with the average market capitalization of the renewables being only 3.48% of that of oil firms on event days. Thus, if firm size is correlated with abnormal returns, omitting this variable could bias our results. We follow Beatty and Shimshack (2010) and extend our specification to include firm size as measured by market capitalization, and profitability as measured by earnings per share. Specifically, our model can be written as

$$\widehat{CAR}_{i,t_1,t_2} = \beta_0 + \sum_j \beta_j D_j + \theta_1 MC_i + \theta_2 EPS_i + \varepsilon_i \tag{5}$$

where *i* indicates firm, t_1 and t_2 are respectively the first and last day used to calculate CARs with $t_1 \leq t_2$. D_j=1 if firm *i* is in energy sector *j*, where *j* = oil, gas, nuclear, renewables, and zero otherwise. Coal is the reference energy group. *MC* is market capitalization, calculated as *MC* = Stock price × Number of shares outstanding, and *EPS* is earnings per share, calculated as *EPS* = (Net income - Preferred stock dividends) / Number of shares outstanding.[8] Since market capitalization and daily returns are both directly related to stock price, endogeneity might be a concern. Earnings per share is not directly related with price, but the number of shares outstanding can change over time. To minimize endogeneity concerns, we use the *MC* and *EPS* calculated 30 days before the event day. We estimate equation (5) four different ways, depending

[8] Both are adjusted using an energy-specific price index, the Consumer Price Index for All Urban Consumers: Energy from the US Bureau of Labor Statistics.

on the length of the time interval considered to compute the dependent variable: $CAR_{0,0}$, $CAR_{0,10}$, $CAR_{0,20}$, and $CAR_{0,30}$. That is, t_1=0 and t_2 = {0, 10, 20, 30}.[9]

One potential concern is that energy firms of different types differ in terms of the stage in the energy production process at which they operate. For example, coal companies in our sample mostly focus on the exploration and production of coal, with some refining and marketing coal and some generating electricity from coal. Renewable companies, on the other hand, typically are energy conversion or power delivery & conservation companies, with a few producing cleaner fuels, or harvesting and storing green energy. Therefore, besides energy type and firm level characteristics, we also control for the production stage, and categorize firms into four types: exploration & production, downstream and services, utilities, and vertically integrated. Firms that have businesses in more than one category are classified into the category that accounts for a majority of their production capacity. The number of companies by production stage and energy sector is shown in the right side of Table 2.

The larger model can be written as

$$\widehat{CAR}_{i,t_1,t_2} = \beta_0 + \sum_j \beta_j D_j + \sum_m \beta_m D_m + \theta_1 MC_i + \theta_2 EPS_i + \varepsilon_i \tag{6}$$

where D_m=1 if firm *i* is in production stage *m* (*m* = exploration & production, downstream and services, utilities), and zero otherwise. Vertically integrated is the reference stage.

2.4. Data

2.4.1 Hurricanes and Window Selection

The hurricane occurrence dates and damage information are retrieved from the National Oceanic and Atmospheric Administration's (NOAA) National Hurricane Center (NHC). In event studies with daily data, typical lengths for the estimation period range from 100 to 300 days prior the

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[9] $CAR_{0,0}$ is the cumulative abnormal return for a certain stock on the event day (that is, AR_0), $CAR_{0,10}$ aggregates the abnormal returns from the event day to the 10th day after the event, and so on.

event, while typical lengths for the event period range from 21 to 121 days (Peterson 1989). For our analysis, we define the day of the first emergency declaration associated with the hurricane as the event day. The Federal Emergency Management Agency (FEMA) records the dates of major disaster and emergency declarations by disaster and state, with emergency declarations generally preceding major disaster declarations. To avoid the problem of anticipation which is prevalent in event studies, we use the first emergency declaration date as the event day ($t_0=0$), but use the date in which the hurricane *formed* to create a pre-event window.[10] For cases in which the event happened after trading hours, the event day is assigned as the next trading day (in the case of hurricanes Sandy and Katrina). For hurricane Katrina, the emergency declaration was on a Saturday (8/27/2005), thus the event day is taken as the next Monday (8/29/2005). For hurricane Sandy, the emergency declaration was on a Sunday (10/28/2012) and the stock markets were closed on the following Monday and Tuesday; therefore, the event day is determined as the following Wednesday (10/31/2012).

The four hurricanes examined in this study all started as tropical storms in the Central or North Atlantic Ocean, and moved towards mainland US several days later. Emergency declarations were issued on the first day the hurricane landed on the US or one or two days later, so by using a pre-event window that begins from the day the hurricane formed, we avoid the anticipation problem. In summary, for each of our four events, the estimation window consists of the 250 trading days prior to the day the hurricane formed, corresponding to approximately one year. Abnormal returns are then calculated from the day the hurricane formed till 30 trading days

[10] Researchers have used pre-event windows of different lengths. Lei and Shcherbakova (2015), for instance, used a pre-event window of five trading days, Lopatta and Kaspereit (2014) used ten days, and Betzer et al. (2013) used a longer pre-event window of 20 trading days. The length of the pre-event window in our study is hurricane-specific, ranging from 4 trading days for Katrina to 9 trading days for Hugo.

after the first emergency declaration (day zero). Table 1 shows the hurricane names, important dates, and associated monetary damages.

2.4.2 Stock Price Data

Closing prices of publicly traded US energy companies' stocks are collected from Thomson Reuters DataStream. We use Standard & Poor's (S&P) 500 Index to represent the broad market index R_{mt} in equation (1). This index includes 500 large companies and captures approximately 80% of the market capitalization listed on the NYSE or NASDAQ.

In order to select the companies for each of the five energy types, we rely on widely used energy indices. For the coal industry, we use the Stowe Global Coal Index. To be included in this index, a company must generate at least 50% of its revenues from coal mining or coal related activities. We include all the ten US companies listed in this index. In addition, we add 13 other companies listed as the major US coal producers in 2012 by Ventyx Velocity Suite and U.S. Department of Labor (2013). Each produced more than 5 million short tons of coal in 2012, though their capacities are smaller than those of the companies in the Stowe Global Coal Index. Because this is not a random sample, but rather a sample of the largest and most prominent firms in the coal sector, one should not extrapolate our results to smaller firms or other sectors (the same applies to the other energy sectors).

For the oil and natural gas companies, we rely on NYSE Arca Indices. The NYSE Arca Oil Index is a price-weighted index of the leading companies involved in the exploration, production, and development of petroleum. Of its 20 constituents, we include the 12 companies domiciled in the US. The NYSE Arca Natural Gas Index is designed to measure the performance of highly capitalized companies in the natural gas industry involved primarily in natural gas exploration and production, and natural gas pipeline transportation and transmission. The index has 20 constituents, and, similarly, we include the 18 companies domiciled in the US and exclude the two domiciled in Canada.

To identify nuclear companies, we start with all the holding companies of the 100 nuclear power plants in the US from the Nuclear Energy Institute, which can also be retrieved from the Power Reactor Information System (PRIS) by the International Atomic Energy Agency (IAEA). From those 100 companies, only 22 are publicly traded; and from those 22 companies, only Exelon Corporation and Public Service Enterprise Group, Inc. have more than 50% of their electricity generated from nuclear. The other 20 companies own nuclear power stations but have a lower percentage of nuclear shares in their electricity generation portfolio. For robustness checks, we compared the results with only Exelon and Public Service Enterprise Group included in the nuclear group to those with all the 22 nuclear firms included and reached similar conclusions. In addition, we checked the components of the S&P Global Nuclear Energy Index to ensure that we include all the most important companies. The S&P Global Nuclear Energy Index is comprised of the 24 largest publicly-traded companies in nuclear energy that meet investability requirements from both developed and emerging markets. Seven of the constituents in this index are from the US and are included in the 22 companies selected above, so we believe that all the major US nuclear companies are included in our analysis.

We use the constituents of the WilderHill Clean Energy Index (ECO) to identify "green" energy companies. ECO has been widely used to measure the stock market performance of renewable energy companies (Henriques and Sadorsky 2008; Kumar et al. 2012; Sadorsky 2012; Managi and Okimoto 2013). The index is comprised of publicly traded companies "whose businesses stand to substantially benefit from a societal transition toward the use of cleaner forms of energy" such as hydrogen fuel cells, wind, solar, wave, tidal, geothermal energy and biofuels (www.wilderhill.com). The index (as of the start of the 4th quarter of 2012) consisted of 51 stocks. We exclude 15 companies that are not domiciled in the US and three companies for which DataStream does not have data (Kaydon, Power-one, and Zoltek). We include one additional company — Covanta Holding Corp, which is the largest biomass company in the US with more than 50% of its revenue from clean energy. Thus, we have 34 companies in the renewable category, including all the major firms in each renewable energy type.

Table 2 shows the number of companies by energy type and hurricane. There were fewer companies that were publicly traded in earlier time periods. This is especially obvious in the case of coal and renewables. Regarding missing values, Brown and Warner (1985) dropped stocks that have less than 30 daily returns in their entire 250 day estimation period or have missing return data in the last 20 days of the estimation period. Ferstl et al. (2012) excluded companies with data missing for more than 90 trading days in the estimation period or 5 trading days in the event period. We follow this second, more conservative approach.[11] In total, we have 107 companies in the five energy groups for hurricane Sandy, 81 for Katrina, 54 for Andrew, and 48 for Hugo. Appendix Table A.1 lists all the companies included in each category for each hurricane.

Table 3 shows the descriptive statistics of the daily returns of the energy companies over the estimation windows. Except for renewables before Sandy, all the energy sectors displayed small positive average daily returns over the estimation windows in all four events, with the largest estimated average returns before hurricane Katrina. They are not statistically different from zero, however, as expected with return series measured at daily frequency. Looking at the

[11] All of the companies in our analysis have more than 30 days of stock return data during the estimation period, and we do not have missing values in the last 20 days of our estimation period, but some companies have data missing for more than 90 days during the estimation period.

standard deviations, the returns to coal and renewables companies exhibited the largest variations out of the five energy sectors, while the nuclear industry experienced the least variation.

2.5. Results

2.5.1 Event Study

Figure 2.1 shows the patterns of daily average abnormal returns (AAR) for each hurricane estimated in equation (1) for each enery group. (The complete set of AAR and CAAR estimates are available upon request). For coal (the first column) there is very weak evidence that hurricanes influenced market returns. The abnormal returns in the aftermaths of Hugo, Katrina, and Sandy exhibit a flat pattern; they are statistically indistinguishable from zero 95% of the time. AARs following Andrew fluctuated more, especially towards the end of the event window. However, the 95% confidence intervals still contain zero most of the time.

Similarly, the AARs in the oil sector (column 2) are also not statistically different from zero in most cases; however, abnormal returns were especially volatile following hurricane Katrina. AARs of natural gas firms experienced similar patterns as those of oil firms (column 3), except for hurricane Andrew after which statisticaly significant abnormal returns (both positive and negative) were observed.

Column 4 shows the AARs for the nuclear industry. After hurricanes Katrina and Sandy, there were more days when the abnormal returns were significantly different from zero compared to hurricanes Hugo and Andrew. Despite of this, zero was contained in most of the confidence intervals during the event period. In contrast, the AARs in the renewable industry fluctuated less after hurricanes Katrina and Sandy compared to Hugo and Andrew, though the four confidence intervals also include zero throughout most of the event window (column 5).

Looking at the magnitude and variability of the AARs across fuel types, we observe that the stock prices of oil, natural gas and especially nuclear companies react less to hurricane shocks than that of coal and renewables firms – the 95% confidence intervals of the daily average abnormal returns in these sectors are narrower in general. The daily average excess returns of coal and renewable equities are comparable; however, coal firms display larger variability. The AARs of renewable firms appear much less volatile in the aftermath of Katrina and Sandy, compared to past events and to coal.

The boxplot in Figure 2.2 offers a glimpse at the distribution of daily abnormal returns by energy industry for the four events. A boxplot splits the data set into quartiles. The body of the boxplot consists of a "box", which goes from the first quartile (Q1) to the third quartile (Q3). Within the box, a horizontal line is drawn at the Q2, the median of the sample. Two lines, called whiskers, extend away from the box. The bottom whisker goes from Q1 to the smallest non-outlier in the sample, and the top whisker goes from Q3 to the largest non-outlier. If the sample includes one or more outliers, they are plotted separately as points on the chart. From Figure 2.2 we can see that the median ARs are very close to zero, regardless of the energy sectors the firms were in. Coal securities had the most outliers, especially in the aftermath of hurricane Andrew, with daily AR ranging from -8% to 12%, although if the outliers are excluded, the daily AR ranged from -1% to 1%. There are multiple outliers in the boxplots for oil firms following hurricanes Hugo and Andrew; however, the data still fall within a narrow interquartile range. Excluding the outliers, we can clearly see that the ARs all fall within the -5% to 5% range, and that the nuclear sector exhibited the smallest variance.

Overall, the daily excess returns are close to zero across all firms and sectors and this holds for all the storms. Histograms of the daily abnormal returns of individual companies within a given sector (not reported here but available upon request) further show that they are tightly concentrated around zero. This suggests that there is no significant intra-industry competition effect, where an adverse event harms some firms within a sector while benefiting competitors in the same sector that are better positioned to handle such event, resulting in a zero aggregate effect (see e.g. Pattern and Nance 1999) .

Table 2.4 reports the CAARs by energy group for varying event-window lengths: the date in which the hurricane formed, the first emergency declaration date (t_0=0), and days 1, 10, 20, and 30 after the event. The complete list of average and cumulative abnormal returns is available upon request. On the first day in the pre-event windows (i.e. the day when the hurricane formed), the CAARs were not statistically significant with two exceptions: the natural gas industry saw a significant (at the 5% level) decrease of -1.5% in its returns the day hurricane Andrew formed, and coal firms experienced a significant (at the 10% level) 2.52% increase in returns when hurricane Sandy formed. Consistent with the findings from the graphical analysis, we do not observe significant CAARs on the event days, except for the natural gas industry in the case of hurricane Andrew (-4.38% CAAR on day 0 and -4.17% on day 1, both statistically significant at the 5% level).

Moving further away from the event day, natural gas exhibited large significant and positive CAAR following Katrina (10.62% on day 20 at the 10% level). The nuclear industry, on the other hand, experienced highly significant negative CAARs following Sandy (about -7% on days 10, 20, and 30), which did not happen in any of the other three hurricanes. Renewable energy stocks displayed a positive and significant CAAR on day 10 after hurricane Katrina, but this gain was offset by subsequent negative ARs which resulted in a negative and insignificant

CAAR at the end of the event window. Finally, we do not observe any significant CAARs in the oil sector throughout the entire event window for all the four events.

In sum, the small and largely insignificant abnormal returns in Figure 2.1 and Table 2.4 suggest that investors in the stocks of energy companies did not strongly react to hurricane shocks, and that different energy sectors experienced different abnormal return patterns following different hurricanes.[12] However, the question remains as to whether the differences are statisticaly significant *across energy types*, and, in particular, whether more recent hurricanes, happening at a time of scientific consensus on the importance of limiting carbon emissions to reduce potentially larger costs of climate change, have had a larger effect on the CARs of the renewables and coal sectors. To answer these questions, we regress the estimated firm-specific CARs on energy industry dummy variables, while controlling for market capitalization, earnings per share, and production stage as presented in equations (5) and (6).

2.5.2 Regression Analysis

Tables 2.5 – 2.8 present the regression results for each hurricane. Each column in the tables refers to a regression, with headings indicating that the dependent variables are the CARs for individual firms with event windows of varying lengths (the event day, 10, 20, and 30 days after the event day, respectively). Before turning to the main results, we note that the *R*-squared and *F*-statistics suggest that the energy sector dummies and firm characteristics explain an unignorable portion of the variability in CARs during the event window.

Compared to the coal industry (the reference group), the CARs for oil companies after hurricane Hugo were significantly lower during the event windows [0, 20] and [0, 30], but the

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[12] The average abnormal returns in this study are all equally-weighted abnormal returns; they are computed, according to equation (2), as a simple average of abnormal returns. We also conducted the analysis with value-weighted returns, with weights equal to the relative market capitalization of a given company within its sector. The results also failed to reveal a clear pattern across energy types.

CARs for gas, nuclear, and renewable companies were overall not significantly different from those for coal companies even at the 10% significance level (Table 2.5). This is not what one would expect if hurricane Hugo conveyed information about climate change and firms' future profitability conditional on their carbon intensity. Negative CARs for nuclear and renewable companies 20 and 30 days after hurricane Andrew are also inconsistent with this hypothesis (Table 2.6). A look at more recent hurricanes, however, reveals that the CARs for firms in the renewable energy sector were significant and positive after hurricanes Katrina (10 days after the event) and Sandy (10, 20, and 30 days after the event), compared to the coal industry. For example the CAR[0, 30] was more than 15% higher for renewables than that for coal firms after Sandy (-10% for coal and 5% for renewables) at the 5% significance level. The CARs for the oil and gas sectors after Katrina and Sandy, also tended to be higher than for firms in the coal industry. Investors do not seem to have shied away from oil and gas (relative to coal), despite the disruption brought by Katrina to the oil and gas production and distribution in the Gulf of Mexico.

In summary, Tables 2.5 - 2.8 suggest that although the stocks of oil, natural gas, and renewable energy companies did not perform better than those of the coal industry following hurricane Hugo or Andrew, they did better when hurricanes Katrina and Sandy landed in the US. In Table 2.4 the CAARs for renewables 10, 20, and 30 days after Sandy are positive, but not statistically different from zero. On the other hand, coal firms exhibit large negative (and also statistically insignificant) CAARs 10, 20, and 30 days after Sandy. When directly compared to coal, in Table 2.8, the CARs for renewable companies are positive and statistically significant after Sandy (CAR[0, 10], CAR[0, 20] and CAR[0, 30]) and after Katrina (CAR[0, 10] in Table 2.7). Similarly, although in Table 2.4, nuclear firms exhibited a negative and statistically significant CAAR following Sandy – perhaps due to a post-Fukushima enhanced fear of nuclear accidents following natural disasters – Table 2.8 suggests that nuclear firms did in fact not fare worse than coal companies after Sandy.

Regarding the variables representing firms' characteristics, earnings per share is statistically insignificant in all the specifications except on the event day of hurricane Hugo and when production stage is taken into consideration (Table 2.5 column (2)). Market capitalization, on the other hand, is statistically significant in several specifications, although its sign changes. While it was positively associated with CARs after hurricane Hugo in 1989; the relationship is negative for more recent events. This might be because in early days economies of scale dominated, but investors nowadays pay more attention to the growing potential of energy companies that is not necessarily related to firm size. Additionally, in the face of a shock, smaller companies may offer more flexibility. In any case, after hurricane Sandy, larger energy companies in terms of market capitalization fared worse than smaller ones.

As previously discussed, firms differ in terms of the stage in the energy production process at which they operate, according to fuel type. In our sample, the correlation coefficient between a production stage variable (where larger values indicate downstream operations) and an energy sector variable (where larger values indicate lower carbon emission intensity) ranges from 0.31 to 0.35. The energy production stage mostly has an insignificant effect on abnormal returns, especially in recent events.

2.5.3 Robustness Checks

Given the increase in the number of companies in both the coal and renewable sectors over time (Table 2.2 Panel *Event*), one might be concerned that late entrants are fundamentally different from earlier entrants, and that it is these differences rather than an increased awareness about climate change driving the results. Therefore, in this section we re-estimate the abnormal returns in model (1) using only the 48 firms we observe for all hurricanes: 7 coal firms, 8 oil firms, 8 natural gas firms, 20 nuclear firms, and 5 renewable firms.

Another potential concern comes from horizontal integration, whereby a firm relies on multiple energy sources. This is a challenge only for the nuclear companies in the sample; firms in the other four sector either only do business in their own energy sector or a majority of the capacity is in that energy sector. The 20 nuclear firms that we observe across hurricanes are all utility companies whose supply of fuel is a mixture of coal, oil, natural gas, nuclear and renewables which stays relatively constant across time (the proportion of renewables has increased slightly). From the results in section 2.4.1, we know that nuclear firms experienced the least amount of variation in their stock returns following hurricanes, which suggests that horizontal integration makes energy firms more resilient to exogenous shocks.

Appendix table A.2 shows the CAARs for all the energy companies included in all the four events. Like in Table 2.4, for simplicity, we only report the results for the first day in the pre-event windows and certain days since the event happened (1, 10, 20, and 30); the complete list of average and cumulative abnormal returns is available upon request. Daily and cumulative average abnormal returns are quite comparable with the previous results overall. However, the positive CAARs for the coal industry in hurricanes Katrina and Sandy in Table A.2, statistically significant around the event day, and larger than the estimated CAARs in Table 2.4, suggest that later entrants in these sectors generated more negative abnormal returns than the early entrants. The number of nuclear companies stayed relatively constant over the sample period, so the CAARs are comparable with our previous findings. The CAARs for renewables firms are also very similar across Tables 2.4 and A.2.

Tables A.3 - A.6 present the regression results for each hurricane similar to those in Tables 2.5 – 2.8, but now using only firms that are observed for all four events. Again, we report both results with and without controls for the firms' production stage. The inclusion of these controls does not qualitatively affect the impact of energy type on the cumulative abnormal returns, although the significance is weakened in some cases. Consistent with the results in Table A.2, it seems that newer entrants into the coal business react more negatively to recent hurricanes, as illustrated by comparison of the constant term (negative and significant in Table 2.8, and negative but smaller in magnitude and insignificant in Table A.6). Results for the other sectors also suggest that later entrants reacted more positively to hurricanes since hurricane Katrina, relative to coal firms; the respective coefficients tend to be larger and stronger statistically in Tables 2.7 and 2.8.

2.6. Conclusion and Discussion

This paper estimates the impact of hurricanes on the stock returns of the largest energy companies in the US. We consider the most notorious, damaging hurricanes in each decade over the last 4 decades: Hugo (1989), Andrew (1992), Katrina (2005), and Sandy (2012). We categorize energy companies into five groups according to CO_2 intensity: coal, oil, natural gas, nuclear, and renewables.

Daily average abnormal returns for the five energy categories are generally not statistically different from zero when a catastrophic hurricane occurs. This is the case even for the oil and gas sectors following hurricane Katrina which is blamed for much disruption to these sectors. During the 30-40 day long event window, the confidence intervals of estimated average abnormal returns contain zero for all energy types, regardless of the hurricane or the damages that the hurricane caused. Cumulative abnormal returns associated with hurricanes experienced very different paths for different types of energy stocks. Hurricane Sandy resulted in negative cumulative average abnormal returns for coal firms relative to other energy companies although this effect was not clearly observed following other, earlier hurricanes. In the aftermath of hurricane Sandy, the returns to the stocks of firms in the oil, natural gas, and especially in the renewables industries performed better than those in the coal industry. When interpreting the results, however, one should keep in mind that nuclear accounted for less than 20% of the total energy produced in the US, and that renewable energy accounted for less than 14% before year 2013, which perhaps might explain investors not paying much attention to these stocks, especially in earlier years.

Overall, the evidence that capital markets react to climate-related events is stronger for more recent events. The significant and large negative cumulative abnormal returns in the coal industry relative to those for oil and renewables after Sandy suggest that investors in the capital markets are paying more attention to environmental information. The stock price reactions to extreme weather events provide a signal for energy companies to plan for climate change now. Lemoine (2013) found that the unexpected collapse of the US Senate's 2010 climate effort (carbon pricing bill) generated positive excess returns in coal futures markets. This showcases the impact of policies aimed to climate change mitigation in the energy industry and their negative effect on carbon intensive sectors.

The stronger impact of hurricane Sandy compared to earlier hurricanes is consistent with the scientific consensus and an increased awareness among the public regarding the causes of climate change. However, we might think of some potential alternative explanations. The American Recovery and Reinvestment Act of 2009 –the “Stimulus”– was designed to spur economic growth while creating new jobs and saving existing ones. Through the Recovery Act, the Energy Department invested more than $31 billion to support a wide range of clean energy projects across the nation – from investing in the smart grid and developing alternative fuel vehicles to helping homeowners and businesses reduce their energy costs with energy efficiency upgrades and deploying carbon capture and storage technologies (energy.gov/recovery-act). Hurricane Sandy is the only storm in our study that happened after the enactment of the stimulus. Also, the Renewable Portfolio Standards (RPS) requires electric utilities and other retail electric providers to supply a specified minimum percentage (or absolute amount) of customer demand with eligible sources of renewable electricity, ranging from 10% to 40% in mandatory states and 10% to 50% in voluntary states. With more states adopting RPS, renewable energy may become more desirable since there is a guaranteed demand, which may help stabilize investors' beliefs in renewable energy. Strong investor confidence would prevent downward risk for renewable energy companies, and therefore avoid the drop in market returns relative to other energy sectors. Our results, however, suggest that energy investors rebalanced their portfolios away from coal, more evidently after Sandy, but also after Katrina. In addition, the positive performance relative to coal was not limited to the stocks of renewables, it also affected oil.

Previous literature has found that changes in the seasonal timing and experience with flooding significantly increase belief in climate change and stated willingness to save energy (Akerlof et al. 2013; Spence et al. 2011). Using Google trends as a "revealed" preference approach, Lang and Ryder (2016) observed that search interest for the term "*hurricane*" spikes in areas that are impacted by tropical storms and hurricanes in the month of the event, and that online engagement with climate change increases with a lag over the following two months. Further, high risk areas show greater online engagement with climate change when hit by tropical cyclones than low-risk areas. Although we cannot attribute any single hurricane to climate change, these findings suggest that a heuristic learning mechanism is at play and that extreme weather events do present a window of opportunity to build political support for greenhouse gas mitigation policy. Our result that stock prices of energy companies react differently to recent hurricanes depending on their carbon intensity is consistent with the same type of availability heuristic.

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Table 2.1: Events, Estimation and Event Windows

Event	Formed	Dissipated	Event Day	Estimation Period	Event Window	Damage in 2012 USD (billions)
Hugo	9/9/1989	9/23/1989	9/22/1989	9/14/1988-9/8/1989	9/11/1989-11/03/1989	12.96
Andrew	8/14/1992	8/28/1992	8/24/1992	8/20/1991-8/13/1992	8/14/1992-10/06/1992	43.37
Katrina	8/23/2005	8/31/2005	8/29/2005	8/26/2004-8/22/2005	8/23/2005-10/11/2005	146.95
Sandy	10/22/2012	10/31/2012	10/31/2012	10/25/2011-10/19/2012	10/22/2012-12/13/2012	50

Data source: National Oceanic and Atmospheric Administration's (NOAA) National Hurricane Center (NHC), Federal Emergency Management Agency (FEMA) and EM-DAT, accessed December 2014.
Note: Hurricane Rita (9/18/2005 – 9/26/2005) started on the 18th day of Katrina's event window. Results for the first 17 days should not be contaminated. Even if there is any contamination, Rita should have intensified Katrina's impacts in the same direction.

Table 2.2: Composition of Companies

	Event					Vertical Production Stage				
Industry	Hugo	Andrew	Katrina	Sandy	Total	E&P	Downstream, Services	Utilities	Integrated	Total
Coal	7	7	16	23	53	36	5	12	0	53
Oil	8	10	10	11	39	22	5	0	12	39
Natural Gas	8	10	15	18	51	31	4	8	8	51
Nuclear	20	20	22	22	84	0	0	84	0	84
Renewables	5	7	18	33	63	4	49	10	0	63
Total	48	54	81	107	290	93	63	114	20	290

Table 2.3: Descriptive Statistics of the Daily Stock Returns over Estimation Windows (%)

Event	Industry	N	Mean	Std. Dev.	Min	Max
Hugo	Coal	1750	0.13	3.93	-33.33	50
	Oil	2000	0.15	1.68	-6.15	11.39
	Gas	2000	0.20	2.64	-11.11	87.2
	Nuclear	5000	0.05	1.08	-15.85	17.98
	Renewables	1250	0.09	2.87	-15.79	16.03
Andrew	Coal	1750	0.11	6.81	-33.33	180
	Oil	2500	0.03	1.93	-8.4	8.17
	Gas	2500	0.08	1.83	-9.09	15.58
	Nuclear	5000	0.08	1.01	-5.77	10.38
	Renewables	1668	0.04	4.34	-27.41	42.11
Katrina	Coal	4000	0.34	7.45	-75.25	304
	Oil	2500	0.23	1.69	-7.69	9.48
	Gas	3750	0.22	1.86	-9.69	14.03
	Nuclear	5500	0.09	1.02	-6.51	6.96
	Renewables	4500	0.15	3.24	-35.9	52
Sandy	Coal	5750	0.06	6.51	-51.64	344.83
	Oil	2750	0.06	1.96	-11.74	15.16
	Gas	4466	0.02	2.21	-14.59	15.84
	Nuclear	5500	0.04	1	-6.45	8.14
	Renewables	8250	-0.08	3.84	-39.24	30.91

Table 2.4: Cumulative Average Abnormal Returns (%)

Event	Day	Coal	Oil	Natural Gas	Nuclear	Renewables
Hugo	-9	0.80	-0.04	-0.20	0.05	-1.20
	0	-0.80	-2.44	-1.83	0.78	-1.58
	1	-0.71	-3.39	-2.05	0.87	-1.63
	10	-2.31	-3.53	-2.33	-0.93	0.26
	20	-0.40	-5.93	-3.98	-0.18	1.88
	30	-1.46	-6.71	-4.55	2.90	2.19
Andrew	-6	-0.30	-0.56	-1.50**	-0.33	-0.78
	0	-0.59	-1.42	-4.38**	0.43	0.77
	1	-1.01	-1.32	-4.17**	0.36	0.54
	10	-1.23	-0.40	2.33	-1.29	2.67
	20	3.34	0.76	2.91	-3.09	-0.16
	30	8.83	-3.75	0.66	-2.09	-6.70
Katrina	-4	1.16	-0.10	0.53	0.75	-0.08
	0	0.96	0.23	1.48	1.32	0.37
	1	4.38	2.43	3.67	1.45	3.15
	10	-3.19	4.60	4.67	1.69	6.74**
	20	-0.75	8.35	10.62*	1.35	3.31
	30	-4.96	2.17	8.52	-0.29	-3.67
Sandy	-5	2.52*	-0.72	-0.99	-0.37	-0.25
	0	2.83	0.95	-0.91	-0.30	2.34
	1	3.75	-0.11	-1.69	-1.60	2.32
	10	-5.72	3.69	-1.51	-7.07***	0.35
	20	-5.32	2.75	-4.50	-7.11***	3.02
	30	-5.25	4.01	-5.49	-6.80**	7.59

The returns are accumulated from the first day in each event window (t<0) till the days reported. For convenience, here we only select 6 days to report for each event. Complete results are in Appendix B. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 2.5: Cumulative Abnormal Returns – Hurricane Hugo, %

VARIABLES	CAR[0, 0]		CAR[0, 10]		CAR[0, 20]		CAR[0, 30]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Industry								
Oil	-0.33	-0.75	-0.05	-0.83	-7.23**	-8.60***	-8.26*	-8.11*
	(0.67)	(0.54)	(2.34)	(2.10)	(2.96)	(2.68)	(4.89)	(4.51)
Gas	-0.51	-0.50	0.35	-0.23	-3.26	-3.42	-1.79	-2.08
	(0.34)	(0.34)	(1.73)	(1.83)	(2.43)	(2.75)	(2.85)	(3.62)
Nuclear	-0.02	-0.20	-0.14	1.72	-2.29	0.44	0.69	2.48
	(0.30)	(0.41)	(1.50)	(2.15)	(1.63)	(2.29)	(2.87)	(3.21)
Renewables	1.07	-1.03	4.44	6.63*	3.99	4.81	5.91	11.03
	(0.86)	(0.63)	(3.79)	(3.77)	(5.91)	(6.09)	(6.81)	(9.40)
Firm Characteristics								
Market Capitalization	0.93	1.07	1.73	-0.07	25.87***	28.05**	40.71***	40.35**
	(1.60)	(1.32)	(5.19)	(4.81)	(9.10)	(10.54)	(14.79)	(16.40)
Earnings per share	18.29	38.64*	-10.16	1.23	0.60	57.00	191.31	171.50
	(21.46)	(20.73)	(69.13)	(74.52)	(119.72)	(100.59)	(180.75)	(194.95)
Production Stage								
E&P		-0.52		-0.28		1.92		1.42
		(0.49)		(2.79)		(4.65)		(6.02)
Downstream, Services		2.24***		-3.89		-0.42		-5.91
		(0.68)		(4.59)		(7.52)		(11.33)
Utilities		-0.32		-3.48		-3.32		-1.59
		(0.51)		(3.01)		(4.81)		(6.31)
Constant	-0.22	0.01	-1.48	0.07	0.23	-0.00	-2.77	-2.71
	(0.30)	(0.55)	(1.46)	(3.04)	(1.71)	(4.76)	(2.78)	(6.80)
Observations	48	48	48	48	48	48	48	48
R-squared	0.181	0.376	0.114	0.171	0.219	0.263	0.276	0.298
Prob>F	0.248	0.0004	0.929	0.704	0.0529	0.0500	0.0026	0.0012

Robust standard errors are given in parentheses; ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 2.6: Cumulative Abnormal Returns – Hurricane Andrew, %

VARIABLES	CAR[0, 0]		CAR[0, 10]		CAR[0, 20]		CAR[0, 30]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Industry								
Oil	1.62*	1.94*	4.00	3.17	-0.03	-1.38	-10.80	-11.11
	(0.93)	(1.03)	(2.44)	(2.82)	(3.38)	(3.61)	(9.46)	(11.02)
Gas	-0.34	-0.28	6.83**	7.13**	2.41	2.83	-5.36	-5.03
	(0.67)	(0.75)	(3.17)	(3.45)	(4.05)	(3.94)	(9.87)	(10.63)
Nuclear	-0.14	-0.33	-0.72	0.31	-6.38***	-3.17	-11.00	-8.16
	(0.61)	(0.46)	(1.44)	(1.93)	(2.26)	(2.08)	(7.15)	(5.12)
Renewables	-1.14	-0.02	1.17	-1.60	-6.59*	-6.97*	-18.66*	-13.93
	(1.07)	(0.73)	(2.50)	(2.88)	(3.70)	(3.89)	(10.27)	(9.64)
Firm Characteristics								
Market Capitalization	1.00	0.75	-6.83**	-1.32	-5.78	5.06	0.44	8.37
	(1.24)	(1.28)	(3.07)	(4.29)	(3.76)	(4.68)	(4.52)	(7.57)
Earnings per share	-20.20	-30.44	-49.15	2.32	-151.93	-30.15	-170.04	-82.33
	(22.60)	(24.16)	(71.78)	(56.54)	(102.04)	(74.54)	(235.82)	(160.98)
Production Stage								
E&P		-0.03		3.86		8.96**		7.67
		(0.66)		(3.05)		(3.34)		(5.06)
Downstream, Services		-1.55*		7.42**		8.50**		0.15
		(0.90)		(3.14)		(4.09)		(9.93)
Utilities		0.44		0.97		0.95		0.96
		(0.71)		(2.95)		(3.04)		(6.57)
Constant	-0.22	-0.31	-0.52	-3.57	4.84*	-1.69	10.42	4.89
	(0.66)	(0.96)	(1.68)	(3.31)	(2.56)	(3.82)	(9.47)	(11.17)
Observations	54	54	54	54	54	54	54	54
R-squared	0.306	0.362	0.311	0.383	0.356	0.492	0.197	0.233
Prob>F	0	0	0.0100	0.0013	0.0001	0.0001	0.262	0.378

Robust standard errors are given in parentheses; ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 2.7: Cumulative Abnormal Returns – Hurricane Katrina, %

VARIABLES	CAR[0, 0]		CAR[0, 10]		CAR[0, 20]		CAR[0, 30]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Industry								
Oil	0.67	0.63	9.29**	9.57*	10.39*	10.43*	9.34	9.67
	(0.73)	(0.79)	(4.58)	(4.98)	(5.25)	(6.09)	(6.20)	(7.34)
Gas	-0.12	-0.16	7.14	7.66	10.69*	10.80	13.13*	12.95
	(0.68)	(0.64)	(5.02)	(5.34)	(6.13)	(6.71)	(7.18)	(7.87)
Nuclear	-0.08	0.24	4.37	3.57	1.63	1.82	4.70	3.16
	(0.64)	(0.79)	(4.81)	(3.22)	(5.79)	(4.17)	(6.82)	(4.71)
Renewables	0.29	1.33	10.88*	6.47	4.87	5.10	1.58	4.61
	(0.73)	(1.31)	(6.06)	(5.03)	(7.49)	(5.90)	(8.64)	(6.59)
Firm Characteristics								
Market Capitalization	-0.79***	-0.51*	-2.06	-1.38	-0.63	0.04	1.03	0.70
	(0.25)	(0.30)	(1.58)	(1.25)	(1.63)	(1.75)	(2.07)	(2.35)
Earnings per share	1.73	0.03	33.36	47.57	0.36	2.26	-140.14	-152.59
	(16.11)	(15.86)	(153.93)	(157.54)	(186.86)	(193.47)	(214.74)	(222.53)
Production Stage								
E&P		0.70*		0.55		1.33		-0.20
		(0.41)		(1.47)		(2.22)		(2.97)
Downstream, Services		-0.93		7.44		0.97		-4.87
		(1.20)		(4.51)		(5.64)		(6.64)
Utilities		0.05		2.47		0.98		1.07
		(0.69)		(4.26)		(5.93)		(6.89)
Constant	0.15	-0.21	-4.21	-6.09	-1.53	-2.77	-4.67	-4.03
	(0.64)	(0.73)	(6.24)	(7.32)	(7.60)	(9.27)	(8.82)	(10.89)
Observations	81	81	81	81	81	81	81	81
R-squared	0.033	0.119	0.123	0.151	0.097	0.097	0.086	0.096
Prob>F	0.0342	0.0729	0.0040	0.0039	0	0	0.0006	0.0014

Robust standard errors are given in parentheses; ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 2.8: Cumulative Abnormal Returns – Hurricane Sandy, %

VARIABLES	CAR[0, 0]		CAR[0, 10]		CAR[0, 20]		CAR[0, 30]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Industry								
Oil	1.37	1.67	13.06***	13.52***	13.12***	13.58***	13.34**	13.93**
	(1.21)	(1.27)	(4.32)	(4.43)	(3.18)	(3.37)	(5.14)	(5.47)
Gas	0.78	0.91	8.91**	9.46**	5.56*	5.65*	4.43	4.56
	(1.30)	(1.32)	(4.38)	(4.50)	(3.10)	(3.21)	(5.48)	(5.60)
Nuclear	1.94*	0.67	3.67	2.58	3.57	0.29	3.54	0.75
	(1.15)	(1.00)	(4.06)	(3.59)	(2.90)	(3.65)	(5.22)	(5.04)
Renewables	1.56	2.21	9.25*	10.62**	10.83***	10.61**	15.75**	16.97**
	(1.54)	(1.62)	(5.24)	(4.92)	(4.12)	(4.68)	(6.70)	(6.93)
Firm Characteristics								
Market Capitalization	-0.16	0.15	-8.59**	-5.67	-5.23*	-4.84*	-8.96**	-9.27**
	(0.96)	(0.83)	(4.31)	(3.86)	(2.75)	(2.62)	(4.46)	(4.40)
Earnings per share	17.71	19.22	190.74	208.29	10.94	11.42	166.27	163.55
	(41.72)	(43.91)	(153.78)	(158.04)	(113.50)	(118.20)	(187.52)	(196.60)
Production Stage								
E&P		0.76		5.47*		0.43		-0.09
		(0.64)		(2.80)		(2.24)		(3.45)
Downstream, Services		-0.20		3.53		0.82		-1.92
		(1.29)		(4.04)		(3.68)		(5.73)
Utilities		2.05*		6.19		4.24		2.87
		(1.18)		(4.39)		(4.10)		(6.24)
Constant	-1.43	-2.25	-11.11**	-16.57**	-9.49***	-10.48**	-10.43*	-10.47
	(1.43)	(1.82)	(4.84)	(6.40)	(3.38)	(4.51)	(6.28)	(8.21)
Observations	107	107	107	107	107	107	107	107
R-squared	0.040	0.065	0.109	0.116	0.154	0.161	0.142	0.147
Prob>F	0.160	0.0324	0.0001	0.0004	0	0.0001	0	0.0005

Robust standard errors are given in parentheses; ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

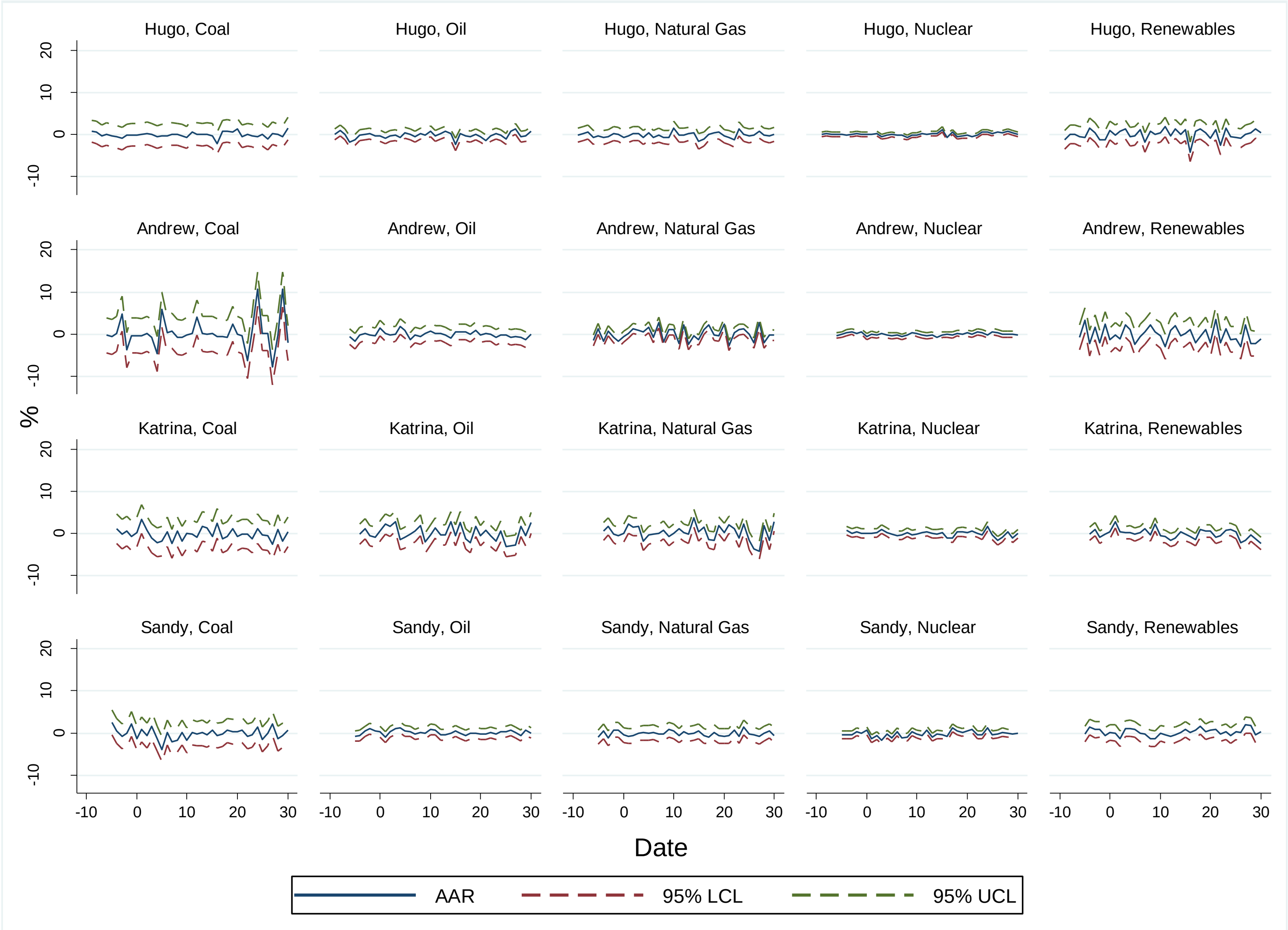

Figure 2.1: Daily Average Abnormal Returns with 95% Confidence Bands, by Event and Industry

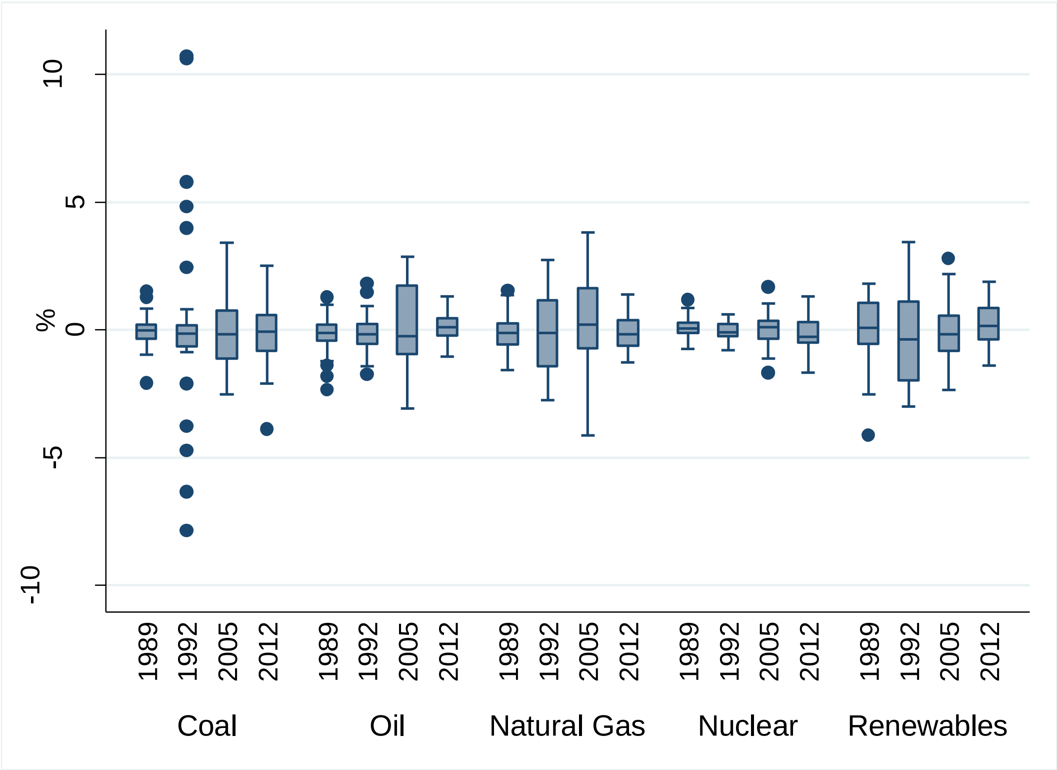

Figure 2.2: Daily Abnormal Returns by Hurricane and Industry (1989=Hugo, 1992=Andrew, 2005= Katrina, 2012=Sandy)

Appendix A. APPENDIICES FROM CHAPTER 2

Table A.1: Companies Included in Each Industry in Each Event

Name	Ticker	Industry	Type	Hugo	Andrew	Katrina	Sandy
Arch Coal	ACI	Coal	E&P	Yes	Yes	Yes	Yes
Alliance Holdings Gp Lp	AHGP	Coal	E&P				Yes
Allete Inc.	ALE	Coal	Utilities	Yes	Yes	Yes	Yes
Alpha Natural Resources	ANR	Coal	E&P				Yes
Alliance Resource Partners Lp	ARLP	Coal	E&P			Yes	Yes
America West Resources Inc	AWSR	Coal	E&P			Yes	Yes
Black Hills Corporation	BKH	Coal	Utilities	Yes	Yes	Yes	Yes
Peabody Energy Corp	BTU	Coal	E&P			Yes	Yes
Cloud Peak Energy Inc	CLD	Coal	E&P				Yes
CONSOL Energy Inc	CNX	Coal	E&P			Yes	Yes
Hallador Energy Co	HNRG	Coal	E&P	Yes	Yes	Yes	Yes
Headwaters Inc	HW	Coal	Downstream, Services			Yes	Yes
Joy Global Inc	JOY	Coal	Downstream, Services			Yes	Yes
James River Coal Co	JRCCQ	Coal	E&P			Yes	Yes
Nacco Industries Inc	NC	Coal	E&P	Yes	Yes	Yes	Yes
Natural Resource Partners Lp	NRP	Coal	E&P			Yes	Yes
Oxford Resource Partners LP	OXF	Coal	E&P				Yes
Freightcar America	RAIL	Coal	Downstream, Services				Yes
Rhino Resource Partners LP	RNO	Coal	E&P				Yes
Suncoke Energy Inc	SXC	Coal	E&P				Yes
TECO Energy Inc	TE	Coal	Utilities	Yes	Yes	Yes	Yes
Westmoreland Coal Co	WLB	Coal	E&P	Yes	Yes	Yes	Yes
Walter Energy Inc	WLT	Coal	E&P			Yes	Yes
Anadarko Petroleum Corporation	APC	Oil	E&P	Yes	Yes	Yes	Yes
ConocoPhillips	COP	Oil	Integrated	Yes	Yes	Yes	Yes

Chevron Corporation	CVX	Oil	Integrated	Yes	Yes	Yes	Yes
EOG Resources, Inc.	EOG	Oil	E&P		Yes	Yes	Yes
Hess Corporation	HES	Oil	E&P	Yes	Yes	Yes	Yes
Marathon Petroleum Corporation	MPC	Oil	Downstream, Services				Yes
Marathon Oil Corporation	MRO	Oil	E&P		Yes	Yes	Yes
Noble Energy, Inc	NBL	Oil	E&P	Yes	Yes	Yes	Yes
Occidental Petroleum Corporation	OXY	Oil	E&P	Yes	Yes	Yes	Yes
Valero Energy Corporation	VLO	Oil	Downstream, Services	Yes	Yes	Yes	Yes
Exxon Mobil Corporation	XOM	Oil	Integrated	Yes	Yes	Yes	Yes
Apache Corporation	APA	Natural Gas	E&P	Yes	Yes	Yes	Yes
Chesapeake Energy	CHK	Natural Gas	E&P			Yes	Yes
Cabot Oil & Gas Corporation	COG	Natural Gas	E&P		Yes	Yes	Yes
Devon Energy Corporation	DVN	Natural Gas	E&P	Yes	Yes	Yes	Yes
EQT Corporation	EQT	Natural Gas	E&P	Yes	Yes	Yes	Yes
AGL Resources Inc.	GAS	Natural Gas	Utilities	Yes	Yes	Yes	Yes
Kinder Morgan, Inc.	KMI	Natural Gas	Downstream, Services				Yes
National Fuel Gas Company	NFG	Natural Gas	Integrated	Yes	Yes	Yes	Yes
Newfield Exploration Co.	NFX	Natural Gas	E&P			Yes	Yes
NiSource Inc.	NI	Natural Gas	Utilities	Yes	Yes	Yes	Yes
Pioneer Natural Resources Co.	PXD	Natural Gas	E&P			Yes	Yes
QEP Resources, Inc.	QEP	Natural Gas	Downstream, Services				Yes
Range Resources Corporation	RRC	Natural Gas	E&P		Yes	Yes	Yes
Questar Corporation	STR	Natural Gas	Integrated	Yes	Yes	Yes	Yes
Southwestern Energy Co.	SWN	Natural Gas	E&P	Yes	Yes	Yes	Yes
Ultra Petroleum Corp.	UPL	Natural Gas	E&P			Yes	Yes
Williams Companies	WMB	Natural Gas	Downstream, Services			Yes	Yes
WPX Energy, Inc.	WPX	Natural Gas	E&P				Yes
Ameren Corp	AEE	Nuclear	Utilities	Yes	Yes	Yes	Yes
American Electric Power Co. Inc	AEP	Nuclear	Utilities	Yes	Yes	Yes	Yes

Dominion Resources, Inc.	D	Nuclear	Utilities	Yes	Yes	Yes	Yes
DTE Energy Co.	DTE	Nuclear	Utilities	Yes	Yes	Yes	Yes
Duke Energy Corp	DUK	Nuclear	Utilities	Yes	Yes	Yes	Yes
El Paso Electric Co.	EE	Nuclear	Utilities			Yes	Yes
Edison International	EIX	Nuclear	Utilities	Yes	Yes	Yes	Yes
Entergy Corp.	ETR	Nuclear	Utilities	Yes	Yes	Yes	Yes
Exelon Corp.	EXC	Nuclear	Utilities	Yes	Yes	Yes	Yes
FirstEnergy Corp.	FE	Nuclear	Utilities	Yes	Yes	Yes	Yes
Great Plains Energy, Inc.	GXP	Nuclear	Utilities	Yes	Yes	Yes	Yes
NextEra Energy, Inc.	NEE	Nuclear	Utilities	Yes	Yes	Yes	Yes
NRG Energy, Inc.	NRG	Nuclear	Utilities			Yes	Yes
PG&E Corp.	PCG	Nuclear	Utilities	Yes	Yes	Yes	Yes
Public Service Enterprise Group, Inc	PEG	Nuclear	Utilities	Yes	Yes	Yes	Yes
PNM Resources, Inc.	PNM	Nuclear	Utilities	Yes	Yes	Yes	Yes
Pinnacle West Capital Corp.	PNW	Nuclear	Utilities	Yes	Yes	Yes	Yes
PPL Corp.	PPL	Nuclear	Utilities	Yes	Yes	Yes	Yes
SCANA Corp.	SCG	Nuclear	Utilities	Yes	Yes	Yes	Yes
Southern Co.	SO	Nuclear	Utilities	Yes	Yes	Yes	Yes
Westar Energy, Inc.	WR	Nuclear	Utilities	Yes	Yes	Yes	Yes
Xcel Energy, Inc.	XEL	Nuclear	Utilities	Yes	Yes	Yes	Yes
Ameresco	AMRC	Renewables	Downstream, Services				Yes
Amyris	AMRS	Renewables	Downstream, Services				Yes
American Superconductor	AMSC	Renewables	Downstream, Services		Yes	Yes	Yes
Air Products & Chemicals	APD	Renewables	Downstream, Services	Yes	Yes	Yes	Yes
Calpine	CPN	Renewables	Utilities				Yes
Cree	CREE	Renewables	Downstream, Services			Yes	Yes
Covanta Holding Corp	CVA	Renewables	Utilities		Yes	Yes	Yes
Echelon Corporation	ELON	Renewables	Downstream, Services			Yes	Yes
EnerNoc	ENOC	Renewables	Downstream, Services				Yes

FuelCell Energy	FCEL	Renewables	Downstream, Services			Yes	Yes
First Solar	FSLR	Renewables	E&P				Yes
Fuel Systems Solutions	FSYS	Renewables	Downstream, Services	Yes	Yes	Yes	Yes
Gevo	GEVO	Renewables	Downstream, Services				Yes
GT Advanced	GTATQ	Renewables	Downstream, Services				Yes
Idacorp	IDA	Renewables	Utilities	Yes	Yes	Yes	Yes
International Rectifier	IRF	Renewables	Downstream, Services	Yes	Yes	Yes	Yes
ITC Holdings	ITC	Renewables	Downstream, Services				Yes
Itron	ITRI	Renewables	Downstream, Services			Yes	Yes
Kior	KIOR	Renewables	Downstream, Services				Yes
Molycorp	MCP	Renewables	Downstream, Services				Yes
Maxwell Technologies, Inc.	MXWL	Renewables	Downstream, Services	Yes	Yes	Yes	Yes
Universal Display	OLED	Renewables	Downstream, Services			Yes	Yes
OM Group	OMG	Renewables	Downstream, Services			Yes	Yes
PowerSecure	POWR	Renewables	Downstream, Services			Yes	Yes
Polypore Intl.	PPO	Renewables	Downstream, Services				Yes
Quanta Services	PWR	Renewables	E&P			Yes	Yes
Rare Element Resources	REE	Renewables	Downstream, Services			Yes	Yes
SunPower	SPWR	Renewables	E&P				Yes
STR Holdings	STRI	Renewables	Downstream, Services				Yes
SUNEDISON	SUNE	Renewables	Utilities			Yes	Yes
Solazyme	SZYM	Renewables	Downstream, Services				Yes
Gentherm	THRM	Renewables	Downstream, Services			Yes	Yes
Tesla Motors	TSLA	Renewables	Downstream, Services				Yes

Table A.2: Cumulative Average Abnormal Returns for Energy Companies Included in all Events (%)

Event	Day	Coal	Oil	Natural Gas	Nuclear	Renewables
Hugo	-9	0.79	-0.04	-0.20	0.05	-1.21
	0	-0.93	-2.47	-1.90	0.80	-1.70
	1	-0.84	-3.42	-2.13	0.89	-1.78
	10	-2.61	-3.54	-2.43	-0.89	0.07
	20	-0.79	-5.99	-4.16	-0.12	1.52
	30	-1.95	-6.82	-4.80	2.99	1.67
Andrew	-6	-0.23	-0.62	0.37	-0.35	-2.77
	0	-0.82	-0.26	-1.95	0.14	0.24
	1	-1.22	-0.53	-1.62	0.03	-0.08
	10	-1.37	0.82	1.95	-1.92	3.79
	20	3.26	2.13	1.48	-4.07**	2.14
	30	8.42	-0.97	-1.62	-3.49	-4.07
Katrina	-4	3.27***	0.07	0.69	0.80	1.04
	0	4.38	0.40	0.66	1.42	0.17
	1	9.16***	2.46	2.55	1.45	5.66**
	10	1.13	4.34	3.35	1.91	4.56
	20	8.98	7.63	7.10	1.48	-0.96
	30	7.41	1.80	5.47	-1.15	-6.70
Sandy	-5	2.23**	-0.55	-0.81	-0.31	0.18
	0	6.39***	0.26	0.42	0.21	-0.21
	1	6.70***	-0.50	-0.12	-1.18	-1.23
	10	4.93	2.31	-0.24	-6.05***	3.15
	20	0.84	1.49	-2.38	-6.53**	6.44
	30	4.31	3.00	-2.76	-6.47**	6.55

Robust standard errors are given in parentheses; ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table A.3: Cumulative Abnormal Returns with Firms Included in All Events – Hurricane Hugo, %

VARIABLES	CAR[0, 0]		CAR[0, 10]		CAR[0, 20]		CAR[0, 30]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Industry								
Oil	-0.30	-0.73	0.10	-0.65	-7.04**	-8.28***	-8.07	-7.69*
	(0.66)	(0.52)	(2.34)	(2.10)	(2.98)	(2.73)	(4.93)	(4.48)
Gas	-0.49	-0.47	0.57	0.01	-2.94	-3.04	-1.45	-1.64
	(0.33)	(0.33)	(1.71)	(1.82)	(2.47)	(2.79)	(2.81)	(3.56)
Nuclear	0.00	-0.19	0.04	1.90	-2.02	0.64	1.02	2.67
	(0.29)	(0.41)	(1.46)	(2.11)	(1.59)	(2.29)	(2.83)	(3.24)
Renewables	1.11	-1.01	4.52	6.80*	4.06	5.06	5.92	11.35
	(0.85)	(0.62)	(3.78)	(3.97)	(6.00)	(6.46)	(6.98)	(9.97)
Firm Characteristics								
Market Capitalization	0.87	1.06	1.83	0.16	26.08***	28.53**	41.15***	41.27**
	(1.60)	(1.32)	(5.28)	(4.79)	(9.34)	(10.66)	(15.22)	(16.43)
Earnings per share	18.52	39.02*	-4.52	6.27	9.81	63.14	206.56	181.37
	(21.31)	(20.37)	(68.57)	(72.58)	(121.00)	(99.70)	(182.55)	(194.47)
Production Stage								
E&P		-0.49		-0.18		2.13		1.79
		(0.48)		(2.78)		(4.68)		(5.91)
Downstream, Services		2.28***		-3.90		-0.40		-5.87
		(0.66)		(4.75)		(7.80)		(11.71)
Utilities		-0.29		-3.39		-2.98		-0.97
		(0.50)		(3.00)		(4.83)		(6.24)
Constant	-0.24	-0.03	-1.71	-0.25	-0.15	-0.62	-3.25	-3.62
	(0.29)	(0.54)	(1.42)	(3.01)	(1.69)	(4.79)	(2.73)	(6.70)
Observations	48	48	48	48	48	48	48	48
R-squared	0.187	0.386	0.111	0.169	0.211	0.253	0.277	0.300
Prob>F	0.246	0.0001	0.934	0.765	0.0694	0.0651	0.0027	0.0011

Robust standard errors are given in parentheses; ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table A.4: Cumulative Abnormal Returns with Firms Included in All Events – Hurricane Andrew, %

VARIABLES	CAR[0, 0]		CAR[0, 10]		CAR[0, 20]		CAR[0, 30]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Industry								
Oil	1.93*	2.23*	4.39*	3.89	0.44	-0.35	-8.46	-9.11
	(1.02)	(1.14)	(2.26)	(2.58)	(3.64)	(3.82)	(9.92)	(11.43)
Gas	-0.23	-0.19	4.07*	4.32*	-1.36	-0.73	-9.67	-9.47
	(0.72)	(0.79)	(2.09)	(2.30)	(3.18)	(3.09)	(9.25)	(9.84)
Nuclear	-0.11	-0.26	-1.13	-0.82	-7.11***	-4.41**	-11.89	-8.98*
	(0.63)	(0.47)	(1.23)	(1.31)	(2.41)	(1.73)	(7.39)	(4.95)
Renewables	-0.78	0.24	3.23	0.62	-3.34	-3.58	-14.71	-12.42
	(1.28)	(1.12)	(2.49)	(2.02)	(3.94)	(3.09)	(11.10)	(10.12)
Firm Characteristics								
Market Capitalization	0.86	0.61	-6.26**	-3.78	-5.22	1.29	-0.97	2.64
	(1.40)	(1.46)	(2.94)	(3.92)	(3.60)	(4.04)	(4.24)	(5.63)
Earnings per share	-17.26	-27.71	-48.79	-23.13	-164.53*	-71.76	-171.80	-87.66
	(24.10)	(25.88)	(58.11)	(51.08)	(94.99)	(65.08)	(240.31)	(164.53)
Production Stage								
E&P		-0.03		1.48		6.08**		4.47
		(0.77)		(2.73)		(2.67)		(3.79)
Downstream, Services		-1.21		4.50*		4.76		-0.03
		(1.12)		(2.57)		(2.98)		(7.68)
Utilities		0.38		0.42		-0.34		-1.97
		(0.79)		(2.69)		(2.70)		(6.40)
Constant	-0.36	-0.42	-0.57	-1.81	4.97	0.88	10.15	7.77
	(0.69)	(1.03)	(1.46)	(3.05)	(2.95)	(3.80)	(10.05)	(11.21)
Observations	48	48	48	48	48	48	48	48
R-squared	0.305	0.333	0.424	0.458	0.481	0.589	0.199	0.226
Prob>F	0	0	0.0003	0	0	0	0.0201	0.111

Robust standard errors are given in parentheses; ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table A.5: Cumulative Abnormal Returns with Firms Included in All Events – Hurricane Katrina, %

VARIABLES	CAR[0, 0]		CAR[0, 10]		CAR[0, 20]		CAR[0, 30]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Industry								
Oil	0.53	0.64	10.22**	8.99*	5.00	2.31	1.45	-1.04
	(0.79)	(0.75)	(4.88)	(5.17)	(3.20)	(3.00)	(5.05)	(5.80)
Gas	-0.37	-0.25	6.86*	6.79	2.72	1.45	3.28	1.87
	(0.56)	(0.56)	(3.99)	(4.52)	(3.12)	(2.56)	(5.31)	(5.30)
Nuclear	-0.13	-0.49	4.73	3.90	-3.62	-0.40	-4.23	-0.85
	(0.45)	(0.62)	(3.85)	(3.18)	(2.40)	(2.96)	(4.11)	(3.66)
Renewables	0.43	-0.14	8.45	1.82	-4.98	-6.71	-9.03	-9.30
	(0.96)	(0.75)	(5.97)	(5.39)	(4.50)	(6.50)	(6.49)	(9.13)
Firm Characteristics								
Market Capitalization	-0.78***	-0.63**	-0.69	-0.25	1.06	0.52	2.02	1.01
	(0.28)	(0.30)	(1.57)	(1.16)	(1.25)	(1.43)	(2.05)	(2.49)
Earnings per share	-0.16	0.79	-153.06	-138.94	-163.09	-156.87	-230.68	-227.14
	(25.90)	(25.85)	(140.24)	(143.53)	(111.75)	(108.79)	(170.93)	(178.37)
Production Stage								
E&P		0.12		-0.61		-0.91		-1.53
		(0.49)		(1.60)		(2.19)		(3.82)
Downstream, Services		1.01		7.96*		-0.38		-2.85
		(0.63)		(4.23)		(6.34)		(9.04)
Utilities		0.74		0.60		-6.56**		-7.35
		(0.50)		(3.48)		(3.12)		(4.68)
Constant	0.26	-0.13	-2.16	-2.15	5.75**	9.05***	4.48	8.49
	(0.40)	(0.54)	(4.18)	(5.09)	(2.41)	(2.96)	(4.38)	(5.81)
Observations	48	48	48	48	48	48	48	48
R-squared	0.115	0.163	0.201	0.263	0.349	0.437	0.235	0.282
Prob>F	0.0180	0.0014	0.0157	0.0250	0	0	0.0814	0.121

Robust standard errors are given in parentheses; ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table A.6: Cumulative Abnormal Returns with Firms Included in All Events – Hurricane Sandy, %

VARIABLES	CAR[0, 0]		CAR[0, 10]		CAR[0, 20]		CAR[0, 30]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Industry								
Oil	-0.18	-0.04	5.54*	3.23	10.13***	7.30*	8.32**	5.56
	(0.95)	(1.12)	(3.15)	(3.53)	(3.66)	(4.28)	(3.73)	(4.49)
Gas	-0.72	-0.60	0.40	0.29	2.93	2.41	-0.85	-1.72
	(0.76)	(0.85)	(2.93)	(2.63)	(3.12)	(3.42)	(3.20)	(3.49)
Nuclear	0.22	0.13	-4.19*	-1.15	-0.15	0.75	-3.57	-2.25
	(0.55)	(0.55)	(2.32)	(1.71)	(2.84)	(2.26)	(3.02)	(2.15)
Renewables	-0.15	0.10	4.74	2.16	12.25*	4.11	8.95	2.21
	(0.88)	(0.81)	(4.29)	(3.35)	(6.10)	(4.46)	(6.54)	(4.57)
Firm Characteristics								
Market Capitalization	1.05*	1.27	-2.83	-0.22	-1.11	-0.29	-2.11	-2.23
	(0.59)	(0.83)	(2.28)	(2.08)	(2.50)	(2.27)	(2.39)	(2.15)
Earnings per share	-47.46*	-46.56*	-80.25	-69.23	-203.19**	-173.11*	-184.87*	-167.81
	(24.04)	(25.41)	(100.70)	(88.58)	(98.34)	(97.76)	(100.34)	(101.47)
Production Stage								
E&P		0.43		4.37**		0.15		-1.35
		(0.89)		(2.13)		(2.05)		(2.54)
Downstream, Services		0.16		5.89*		9.69***		6.33
		(0.92)		(3.00)		(3.48)		(3.79)
Utilities		0.56		-1.33		-1.76		-3.79
		(0.89)		(2.42)		(2.94)		(3.47)
Constant	1.03*	0.54	-0.19	-2.19	-3.54	-3.05	-0.19	2.11
	(0.60)	(1.08)	(1.88)	(3.07)	(2.64)	(3.87)	(2.88)	(4.44)
Observations	48	48	48	48	48	48	48	48
R-squared	0.198	0.208	0.411	0.522	0.433	0.511	0.414	0.469
Prob>F	0.0626	0.0254	0.0003	0.0003	0.0028	0.0004	0.0011	0

Robust standard errors are given in parentheses; ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

CHAPTER 3

THE HOUSING MARKET IMPACTS OF WASTEWATER INJECTION INDUCED SEISMICITY RISK[13]

[13] Liu, H., S. Ferreira, B. Brewer. "The Housing Market Impacts of Wastewater Injection Induced Seismicity Risk", submitted to *Journal of Environmental Economics and Management*, 2/23/2017.

3.1. Abstract

Using data from Oklahoma County, an area severely affected by the increased seismicity associated with injection wells, we recover hedonic estimates of property value impacts from nearby shale oil and gas development that vary with earthquake risk exposure. Results suggest that the 2011 Oklahoma earthquake in Prague, OK, and generally, earthquakes happening in the county and the state have enhanced the perception of risks associated with wastewater injection but not shale gas production. This risk perception is driven by injection wells within 2 km of the properties.

Keywords: Earthquake; Wastewater Injection; Oil and Gas Production; Housing Market; Oklahoma

JEL classification: L71, Q35, Q54, R31

3.2. Introduction

The injection of fluids underground has been known to induce earthquakes since the mid-1960s (Healy et al. 1968; Raleigh et al. 1976). However, few cases were documented in the United States until 2009. Since 2009, the central and eastern United States (CEUS) has seen an unprecedented increase in seismicity, and many earthquakes are believed to be induced by injection wells (Ellsworth 2013). Weingarten et al. (2015) examined the location and timing of earthquakes and their relationship to the location and operation of injection wells across the CEUS. They found that the number of earthquakes associated with injection wells has tripled since the year 2000 and that the entire increase in seismicity since 2009 is associated with fluid injection wells.

Unconventional oil and gas production, also referred to as shale gas development, has experienced a boom since the mid-2000s that has revolutionized the energy sector (Bartik et al. 2016). It arose from new techniques to extract oil and gas from shale resources previously believed to be commercially inaccessible. These techniques (commonly known as hydraulic fracturing, “fracking”, or “fracing”) involve the injection of a mixture of water, sand, and chemicals at high pressure into deep rock formations to enhance oil and gas recovery. The injection wells associated with oil and natural gas production (Class II injection wells) include wells used for enhanced oil recovery and those for used for wastewater disposal.

Existing studies estimating the external costs of unconventional oil and gas production (Muehlenbachs et al. 2013; Gopalakrishnan and Klaiber 2014; Muehlenbachs et al. 2015; Boslett et al. 2016b) have mainly analyzed activity on the Marcellus shale play where an increase in seismicity has not been observed and, thus, have ignored the seismicity risk induced by injection wells. These studies have estimated the net benefits of shale gas development or focused on one important external cost of unconventional oil and gas production: groundwater contamination. Indeed, many of the substances involved in the unconventional oil and gas production process have been linked to reproductive and developmental health problems and pose a serious threat if drinking water is contaminated (Elliott et al. 2016). Muehlenbachs et al. (2013) estimate that adjacency to shale gas wells (1.5 km or closer) reduces the value of groundwater-dependent homes from 9.9 to 16.5 percent.

Our study is the first to estimate the effects of unconventional oil and gas production on housing markets in Oklahoma, an area severely affected by the unprecedented increase in seismicity since 2009, and the first paper to monetize the earthquake risk induced by injection wells. While earthquake risk has been found to negatively affect housing values (Beron et al. 1997; Naoi et al. 2009; Hidano et al. 2015), existing studies have focused on single, massive earthquakes in San Francisco Bay and Tokyo, with causes independent of wastewater injection activity.

We use a difference-in-differences hedonic model framework exploiting the timing of earthquakes, earthquake characteristics, and the distance of properties to injection wells to estimate the impacts of injection-induced earthquake risk on property values in Oklahoma County. Estimates of risk perceptions from hedonic pricing models show that providing information that identifies areas of varying risk creates price differentials between houses located in different risk zones (Brookshire et al. 1985; Bernknopf et al. 1990; McCluskey and Rausser 2001; Troy and Romm 2004). The occurrence of a hazardous event (e.g. a flood or an earthquake) heightens risk perceptions as reflected by increasing price differentials across risk zones (Bin and Polasky 2004; Carbone et al. 2006; Naoi et al. 2009; Skantz and Strickland 2009; Kousky 2010; Atreya et al. 2013; Bin and Landry 2013).

This finding is consistent with the "availability heuristic" (Tversky and Kahneman 1973), a cognitive heuristic whereby decision makers rely upon knowledge that is readily available (e.g. what is recent or dramatic) rather than searching alternative information sources. Under this explanation, the occurrence of a hazardous event acts as a source of new information, increasing salience and heightening risk perceptions. In a hedonic framework, this translates into a reduction in the value of properties with higher exposure to the risk; e.g. properties in the floodplain after a flood event or properties in earthquake prone areas after an earthquake. Accordingly, in our paper we use the occurrence of earthquakes, and the distance of properties to injection wells (whose activity is the proximate cause of seismic activity in the region) to identify and monetize earthquake risks associated with unconventional oil and gas production.

We find, across multiple indicators of seismic activity in the region, that earthquakes have depressed the value of those residential properties in Oklahoma County with injection activity in close proximity (2 km). On average, the price of properties with one injection well within 2 km dropped by 2.2 percent after the 5.6-magnitude 2011 Oklahoma earthquake with epicenter in Prague, Lincoln County, OK. Our estimates are not confounded by damages to structures which have been very small to date and, in the case of the Prague earthquake, nonexistent for properties in Oklahoma County. Results are also robust to controlling for oil and gas production activity, and drinking water sources. However, we present some evidence that potential groundwater contamination risk is related to injection wells while public water is perceived to be at risk from production wells. In addition, large earthquakes (of magnitude larger than 4) exacerbate the perception of both types of water contamination risk, estimated at 12.5 and 3.9 percent of the price of the average home on private groundwater and in public water serviced areas, respectively.

The rest of the paper proceeds as follows. Section 2 provides background on injection wells and their connection to earthquakes in Oklahoma. Section 3 discusses the methodology used to identify the different types of impacts of injection wells on housing prices and isolate the induced-seismicity risk. Data sources are introduced in section 4 along with a brief descriptive analysis. We report the empirical results and robustness checks in section 5. Finally, we conclude with our major findings.

3.3. Background: Injection Wells and Earthquakes in Oklahoma

The oil and gas industry in Oklahoma dates back more than a century, and it accounts for 10% of its GDP (Oklahoma Chamber of Commerce 2014). In 2014 there were 15,560 oil and gas production wells and 14,705 Class II injection wells, most of which were concentrated in the east central region of the state.

Class II injection wells are used to inject fluids associated with oil and gas production. It is estimated that over two billion gallons of Class II fluids (primarily brines - salt water- brought to the surface while producing oil and gas) are injected in the US every day (EPA 2016) for recovery of residual oil and sometimes gas, or for disposal.[14] Most of the injection wells in Oklahoma are injecting water coming not from hydraulic fracturing *per se* but from the "dewatering" of production wells. The water exists in the producing formation and comes up with the oil and natural gas in a recovery process developed in the last decade, known as dewatering (Chesapeake Energy Corporation 2009; Oklahoma Corporation Commitession 2016).

[14] There are two main types of class II injection wells: saltwater disposal wells and enhanced recovery wells. Saltwater disposal wells are used to dispose of the brines brought to the surface during oil and gas extraction. Disposal wells make up about 20 percent of the total number of Class II wells in the United States (EPA 2016), but in our sample they are about 35 percent. Enhanced recovery wells are used to inject fluids to displace extractable oil and gas that are then available for recovery.

While Oklahoma has only 8% of all injection wells in the CEUS region,[15] it is home to 40% of all earthquake-associated injection wells. Wells injecting wastewater into the Arbuckle formation, a 7,000-foot-deep sedimentary formation under Oklahoma are the main contributors to the dramatic increase in associated seismicity in that region (Weingarten et al. 2015).

With the increase in seismic activity, much public and media attention has been paid to the connection between earthquakes and the unconventional oil and gas production in Oklahoma. A simple keyword search of “Oklahoma earthquakes and fracking” results in over 8,000 news articles since 2010. However, the response from state government’s officials has lagged. In 2011, two days after the 5.6-magnitude Oklahoma earthquake with epicenter near Prague, OK, which was at the time the largest in the swarm of earthquakes that affected the state since 2009, the governor of Oklahoma declined to address the cause of the earthquake since injection wells had not been scientifically linked to the earthquakes at that time. The governor would not publicly link the activity of injection wells and earthquakes until early 2015 (Soraghan 2015).

Compared to other states, the response of Oklahoma’s Corporation Commission (OCC) to address wastewater injection induced earthquakes has been less aggressive. Rules targeting operators in “areas of interest”[16] in the Arbuckle formation went into effect only in September 2014, merely requiring the provision of more detailed and frequent data on injection volume and pressure. Subsequent regulations in March 2015 expand the definition of “areas of interest”, and require operators to prove that their wells are not in contact with granite basement rock (a major risk factor for triggering earthquakes) (Wertz 2016). We note that the period covered by our

[15] Injection wells are geographically clustered in basins and regions of major oil and gas operations; Texas, Oklahoma, Kansas and Wyoming contain approximately 85 percent of all Class II injection wells in the US (Weingarten et al. 2015).
[16] These include wells within 10 km of the epicenter of a 4.0-magnitude or larger earthquake.

analysis: 2010-2014 precedes the tightening of OCC regulations and that, during that period, none of the wells in our sample falls within an “area of interest”.[17]

The increase in seismic activity has not resulted in casualties, but has been blamed for structural damage to buildings (Reith and Stewart 2016). In one instance, earthquakes were given partial blame for the collapse of a building (Hermes 2015). In general, the material damages to date have been relatively small. The 5.6-magnitude earthquake in Prague in 2011 buckled road pavement and damaged dozens of homes. According to State Farm spokesman Jim Camoriano, 50 claims were filed throughout the state following the 5.8-magnitude Pawnee earthquake (the largest ever in the state) and its aftershocks in 2016 (Summars 2016). Because physical damage to structures has been small to date, it should not contaminate our interpretation of hedonic pricing estimates as reflecting changes in subjective risk perception of injection activity.

Despite small claims, insurers are hiking premiums and deductibles, and some have stopped writing new earthquake insurance altogether.[18] This reflects an increasing concern that insurers would be too exposed in the event of a "big one" even as demand for earthquake insurance is soaring(Cohen 2016).

3.4. Methodology

3.4.1. Impact Categories

We follow Muehlenbachs et al.’s (2015) categorization of impacts of nearby shale gas activity on housing values. There are *adjacency effects* - costs and benefits associated with close proximity

[17] There were only three earthquakes with a magnitude larger than 4.0 in Oklahoma County, and they occurred before July 2014.

[18] Earthquake damage is not covered under a regular homeowner's policy. According to the Oklahoma Insurance Department (OID), many Oklahomans have earthquake insurance policies but the coverage protects a home "from catastrophic damage." The typical earthquake insurance policy covers home repairs, replacement of personal property directly damaged by the earthquake, debris removal and living expenses while the home is being repaired or rebuilt. However, most policies do not cover replacement of brick, rock or stone covering the outside of the edifice, damage to the lot, vehicle damage or external water damage (Summars 2016).

to injection wells (or generally oil and gas wells). Costs might include noise and light pollution, local air pollution, drinking water contamination, and visual disamenities associated with drilling equipment and cleared land. The benefits are mainly royalty or lease payments from the oil and gas company for the use of the property for wastewater injection or oil and gas extraction or for the mineral rights owner's share of proceeds. In Oklahoma, it is possible to sever the mineral property rights from the surface property rights. Without access to detailed data on leases and deeds, we do not know whether that is the case for the properties in our sample. Thus, like in Muehlenbachs et al. (2015), our estimates are of the overall net effect: the benefits of lease payments for those households who may be receiving them[19] (tempered by those who do not receive them) and the negative externalities of being located near an injection well. We acknowledge, however, that accounting for mineral rights ownership can make a big difference. Boslett et al. (2016a) estimate that houses in Colorado within one mile of an unconventional drill site and in areas of federal mineral ownership (i.e. without mineral rights) sell for 34.8% less than comparable properties without proximate drilling.

There are also *vicinity effects* from the drilling of injection wells. Muehlenbachs et al. (2015) define them as the impact of shale gas development on houses within a broadly defined area (e.g. 20 km) surrounding wells and possibly including increased traffic congestion and road damage from trucks, increased local employment and demand for local goods and services and impacts on local public finance. Oklahoma City is very spread out; it is the largest city (whose government is not consolidated with that of a county or borough) by land area in the U.S. Together with the consideration that workers in the shale gas industry generally do not drive

[19] For hydraulic fracturing (oil and gas production) wells, the horizontal portion is approximately 1 mile (1.6 km) (US Energy Information Administration 2013). Lease payments would only be made to those households whose property is located above the well. Therefore, the overall effect of proximity is the combined impact on houses receiving payments and houses not receiving them.

more than 20 miles (30 km) in one direction to work in a day, and that they operate in port-to-port contracts (Langston 2003), we define the vicinity effect to be in the neighborhood of 30 km of a well. Furthermore, there are *macro effects* (e.g. recovery of the national economy, interest rates, mortgage availability) which are not specifically related to shale gas activity and are assumed to be common to all the properties in the sample.

As mentioned in the introduction, an important externality of living in proximity to injection wells, and the focus of our study, is an increase in s*eismicity risk.* Hydrogeologists and geophysicists consider any earthquake within up to 15 km of an active injection well to be associated with that well (Weingarten et al. 2015). The OCC uses a related but less conservative criterion. In its March 2015 regulations to deal with induced seismicity, the OCC has targeted wells within "areas of interest" covering a 10 km-radius area around the central mass of "seismic swarms."[20]

Anecdotal evidence suggests that the perception of seismicity risk has been dramatically enhanced by the swarm of earthquakes since 2009, especially after the 5.6- magnitude "Prague" earthquake in November 5, 2011, that until September 2016 was the largest in Oklahoma history. Because earthquakes have provided information about the seismicity risk associated with active injection wells, we exploit the occurrence of earthquakes and the presence of active injection wells at differing distances of properties in Oklahoma County to identify perceived seismicity risk.

[20] Swarm is defined as an area consisting of at least two events with epicenters within 0.25 miles of one another, with at least one event of magnitude 3 or higher. Previous rules targeted wells within 10 km of the epicenter of a 4.0-magnitude or larger earthquake.

3.4.2. Identification Strategy

Figure 3.1 is useful in describing our strategy to identify seismicity risk. Area A represents a 2 km buffer drawn around a well that defines *adjacency* – being in close proximity to injection wells. In Oklahoma, royalty and lease payments from hydraulic fracturing and wastewater disposal are typically distributed by squared mile lines, which means that properties within 2.3 km of a well may be eligible for the benefits. This choice is also consistent with the finding by Muehlenbachs et al. (2015) that properties located less than 2 km from an active shale gas well are most affected by proximity.

We follow Weingarten et al. (2015) in considering any earthquake within 15 km of an active injection well to be associated with that well. Accordingly, a buffer of 15 km around an active injection well defines the "catchment area" for the epicenters of *potentially* induced earthquakes. Area B in Figure 3.1, located outside the adjacency buffer but within 15 km from the well, helps to isolate the seismicity risk from injection activities from an adjacency effect. Finally, Area C is located outside of both the adjacency buffer and the 15 km spatially-associated earthquake buffer, but is within the vicinity (30 km) of an injection well.

Based on this intuition, in deriving our empirical specification, the price of house i at time t is a function of the number of injection wells surrounding the property at differing distances. Because we are interested in isolating the seismicity risk, and this is associated to active injection wells, we consider the wells that were operational in the last 3 months preceding the sale of the property. We chose this time window as the average homebuyer searches for approximately 3 months before purchasing a home.[21]

[21] According to Zillow, the real estate website, the average buyer searches for 12 weeks before purchasing a home. According to the National Association of Realtors, in 2015 people under 50 spent an average 11 weeks, and those over 50 about 8 weeks searching for a home. (http://www.realtor.org/sites/default/files/reports/2015/2015-home-buyer-and-seller-generational-trends-2015-03-11.pdf)

(1) $$lnP_{it} = \alpha_0 + \alpha_1(wells\ in\ 2\ km)_{it} + \alpha_2(wells\ in\ 2 - 15\ km)_{it} + \alpha_3(wells\ in\ 15 - 30\ km)_{it} + \mu_i + v_t + q_t + \epsilon_{it}$$

Equation (1) includes a house fixed effect μ_i to control for any time-invariant unobservable characteristics at the individual property level, temporal fixed effects v_t and q_t indicating the year and quarter of the transaction to control for time-varying unobservables at the macro level. ϵ_{it} is the error term. Referring back to Figure 3.1, properties that fall within area A, i.e. properties with active injection wells within a 2-km buffer, experience adjacency, seismicity and vicinity effects captured by coefficient α_1; properties in the non-overlapping ring B (further than 2 km but closer than 15 km from an active injection well) experience seismicity and vicinity effects (α_2); and properties falling in ring C, beyond 15 km of an active injection well, experience only vicinity effects (α_3). Thus, $\alpha_2 - \alpha_3$ captures the seismicity risk from injection activities.

We note that the risk of *inducing* an earthquake, which is associated with nearby (within 15 km) injection activity is different from *experiencing* an earthquake. For example, the 5.8-magnitude Pawnee earthquake in September 2016 was felt across the state and in neighboring states. We allow the occurrence of earthquakes to alter the perception of induced seismicity risk in the following specification:

(2) $$lnP_{it} = \alpha_0 + \alpha_1(wells\ in\ 2\ km)_{it} + \alpha_2(wells\ in\ 2 - 15\ km)_{it} + \alpha_3(wells\ in\ 15 - 30\ km)_{it} + \alpha_4 Earthquake_{it} + \alpha_5(wells\ in\ 2\ km)_{it} * Earthquake_{it} + \alpha_6(wells\ in\ 2 - 15\ km)_{it} * Earthquake_{it} + \mu_i + v_t + q_t + \epsilon_{it}$$

where *Earthquake* is an indicator of the seismicity experienced in the area surrounding the property. *Earthquake* is interacted with the variables reflecting injection activity at distances up to 15 km from the home, which is the distance that defines the "catchment area" for the epicenters of potential earthquakes induced by injection activity.

Anecdotal evidence suggests that the 2011 Oklahoma ("Prague") earthquake marked a before and after in the perception of seismicity risk (and possibly other adjacency effects) associated with oil and gas operations in the state of Oklahoma. We formally test this hypothesis, and estimate the model with a dummy variable: afterprague = 1 as our first *Earthquake* indicator. It takes the value of one if the sale happened after Saturday, November 5th, 2011, the date of the earthquake shock, and zero otherwise.

We employ two alternative sets of seismicity indicators. The first one is the number of earthquakes with a magnitude equal to or greater than 3 (or 4) in the 3 months prior to the sale of the property.[22] Earthquakes with magnitude less than 3 are generally not felt, so we only consider those that can be felt by people to reveal their risk perception. The second set uses the Modified Mercalli Intensity (MMI), an intensity scale developed by seismologists as a more meaningful measure of severity to the nonscientist than the magnitude as it refers to the effects actually experienced at a specific place. It is a function of both the distance of the property to the epicenter and the earthquake's magnitude. We use an intensity prediction equation with attenuation coefficients specific to the CEUS region by Atkinson and Wald (2007),[23] which has been shown to provide a good fit for moderate events such as those experienced in Oklahoma (Hough 2014).

Assuming that the perception of seismicity risk increases with the frequency and intensity of earthquakes, we sum the MMI of the earthquakes that happened in the 3 months prior to the sale date of the property. It is also possible that people barely note and ignore smaller

[22] As noted above, the average homebuyer searches for approximately 3 months before purchasing a home (see footnote 10). The results were robust to using longer time search windows, of 6 and 12 months.

[23] $MMI = 12.08 + 2.36(M\text{-}6) + 0.1155(M\text{-}6)^2 - 0.44\log_{10}R - 0.002044R + 2.31B - 0.479M\log_{10}R$, where $R = \sqrt{D^2 + 17^2}$, $B = \begin{cases} 0, & R \le 80 \\ log10(R/80), & R > 80 \end{cases}$. M is the magnitude of an earthquake, D is the distance between the epicenter of the earthquake and the location where the quake was felt, and R is the transition distance in the attenuation shape.

earthquakes, thus, we use an alternative indicator constructed as the maximum of the MMIs over the same time period. Furthermore, the perception of seismicity risk is likely to be shaped by the diffusion of news about earthquakes in local news outlets and informal interactions with friends and colleagues. We therefore, calculate the intensity measures in relation to the earthquakes in both Oklahoma County and Oklahoma State.

Between January 2010 and December 2014, all earthquakes with $M \geq 3$ in Oklahoma County were associated with at least one active injection well according to the 15-km buffer criterion by Weingarten et al. (2015). However, they do not fall in an “area of interest” as defined by OCC rules enacted in September 2014. Subsequent regulations in March 2015 expanding the definition of “areas of interest”, and closures of injection wells in the aftermath of the Pawnee M 5.8 earthquake on September 3rd, 2016 are outside of our study period. Moreover, the Prague earthquake’s epicenter in Lincoln County is about 60 km from Oklahoma County (as the crow flies), and 34 km from the closest active well in our sample. Thus, we do not believe that the threat of closure of injection wells associated to earthquakes affects the interpretation of *our* estimates as reflecting the loss of potential rents (for those properties with mineral rights over injection wells). We further note that the legislature and the executive branch in the state government have remained friendly to shale gas development activity. In May 2015, Oklahoma’s governor signed Senate Bill 809 which prohibits cities from enacting oil and gas drilling bans, and allows “reasonable” restrictions for setbacks, noise, traffic issues and fencing.

3.5. Data

With the increase in the number of earthquakes as well as injection wells concentrated in central and north-central Oklahoma, we focus on Oklahoma County which has experienced the largest number of earthquakes of magnitude 3 or larger since 2010 in this region. As of the 2010 census, its population was 718,633, making it the most populous county in Oklahoma, accounting for 19% of the total population. Oklahoma County is also the most urbanized county in the state. These guarantees that the property market is sufficiently thick, with enough transactions of relatively uniform properties to recover estimates of seismicity risk.

We obtained transaction records of all properties sold in Oklahoma County between January 2010 and December 2014 from PVPlus, a local real estate data provider. The records contain information on the transaction date and price, exact address, and property characteristics (square footage, year built, lot size, number of rooms, etc.) of single family residences. We start with 70,438 unique observations of sale transactions that have information on the location of the property. After excluding properties without a listed price, a price in the top or bottom 1% of all prices, and properties sold more than once in a single year, we are left with 55,362 observations. We consider only homes that were sold from one person to another (i.e., excluding made-to-order homes), thus we drop approximately 6,834 properties that were sold in the year built. Of these, there are 48,249 sales of properties designated as a residential use, and 48,015 sales were single family residences. We only include these 48,015 properties in our main specifications in order to estimate the impact on (likely) owner-occupied residential homes, rather than properties that are more likely transient or rented. Of this remaining 48,015 sales, 8,662 are repeated sales – a necessary condition for including property fixed effects to control for unobserved heterogeneity at the property level.

Data on production and injection activity (location, year and month reported, well type, well status) come from OCC[24] and Weingarten et al. (2015). During the period of analysis (January 2010 to December 2014), there were a total of 189 active Class II injection wells and 459 shale gas production wells in Oklahoma County. About 65% of the active injection wells

[24] http://www.occeweb.com/og/ogdatafiles2.htm

operated for the purposes of enhanced oil recovery (EOR), whereas the remaining 35% wells were designated as salt water disposal (SWD) wells. Active SWD wells are more than 1.5 times as likely as active EOR wells to be associated with an earthquake. However, most earthquakes in the CEUS region (66%) are associated with EOR wells (Weingarten et al. 2015). Moreover, it is difficult for a layman to distinguish the two types of wells and we are interested in people's risk perception towards injection activity in general. Thus, the count of injection wells within each buffer includes both types of wells. We count wells that were active in the 3 months prior to the sale of the property.

Earthquake data (origin time, location of epicenter, depth, and magnitude) come from the Oklahoma Geological Survey. During our sample period there were 864 earthquakes with magnitude (M) ≥ 3 in the state of Oklahoma. Among these quakes, 121 (14%) originated in Oklahoma County, 24 were of M ≥ 4.0, and one, in Prague, Lincoln County on November 5th 2011 was of M = 5.6. There was a sharp jump in the number of earthquakes in Oklahoma in year 2013 with 109 earthquakes of M ≥ 3.0, and in year 2014 with 578 earthquakes of M ≥ 3.0, accounting for 70% of all the earthquakes of M ≥ 3.0 since the year 2010. Of the 121 quakes with M ≥ 3.0 in Oklahoma County, 3 were of M ≥ 4.0 and they all took place after year 2013. Locations of properties with repeated sales, oil and gas production wells, injection wells, and epicenters of earthquakes with M ≥ 3 are shown in Figure 3.2, overlaying with public water serviced areas.

Table 3.1 displays the summary statistics of the properties in our sample. The average selling price was $159,781. There were 0.84 active injection wells within 2 km of a property in the past 3 months before the house was sold, with a maximum of 15 wells. Between 2 and 15 km of a property, there were 40 injection wells on average, with a maximum of 93. For the outer buffer between 15 and 30 km, 64 injection wells were operating in the past 3 months on average, and the maximum exceeded 100. Home owners in Oklahoma County experienced an average of 6.65 earthquakes with $M \geq 3$ in the 3 months before they sold the house, while earthquakes with $M \geq 4$ were much less frequent. 75 percent of the properties with repeated sales between 2010 and 2014 were sold after the Prague earthquake.

3.6. Results

3.6.1 Main Results

We estimate models (1) and (2) with repeated sales of owner-occupied residential properties in Oklahoma County, controlling for property, year, and quarter fixed effects. Results are presented in Table 3.2. In the baseline model (equation 1), we estimate the net impacts of having injection wells nearby without accounting for earthquake activity. In the results, reported in column (1), we do not observe any statistically significant impacts of injection wells on housing prices regardless of their proximity, suggesting that the positive effects are offsetting the negative external costs at all distances. However, when we add in earthquake activity in the specification to explicitly estimate how earthquakes enhance the perceived seismicity risk from wastewater injection (equation 2), we find a highly statistically significant and negative impact brought by the occurrence of earthquakes, that manifests for properties with injection wells in close proximity (in the 2 km buffer). This impact is robust across alternative seismicity indicators.

In column (2), one additional injection well within 2 km of a property induces a 2.15% lower value for the property after the Prague earthquake, suggesting that Prague altered home owners' perception of wastewater injection in close proximity to the property dramatically. As we would expect, an additional earthquake of magnitude 3 or larger (column 3) has a much smaller impact on housing prices than one more earthquakes of magnitude 4 or larger (column 4), The former reduces the price of properties with one injection well within 2 km by 0.22% while the later reduces them by 1.55%.[25] However, there are many more earthquakes with $3 \leq M < 4$ than with $M \geq 4$ in a year, so cumulatively $M \geq 3$ earthquakes have a much larger impact over the course of a year. Using the average price of houses with one injection well within 2 km that sold in year 2014, we estimate the loss from induced earthquakes with $M \geq 3$ in Oklahoma County to be $6,282 over that year, and the loss from earthquakes with $M \geq 4$ to be $2,229. The two MMI measures in columns (5) and (6), which account for both earthquake magnitude and proximity to the epicenter, are also highly statistically significant when interacted with the number of wells within 2 km. Not surprisingly, the impact for Max(MMI) is larger than for Sum(MMI) suggesting, again, that property prices react more strongly to stronger earthquakes.

3.6.2 Robustness

In this section, we present several robustness checks of our results. We first re-estimate equations (1) and (2) using all the earthquakes in the state of Oklahoma (not just in the county). Second, we test the impacts on the results of using only injection wells that have been associated with earthquakes.

3.6.2.1 All Earthquakes in Oklahoma

We hypothesize that residents pay more attention to the local earthquakes than to the ones that do not directly affect their lives, but it could be that local earthquakes are smaller and larger earthquakes happen in other counties. Given that information nowadays spreads fairly rapidly and broadly through television, newspapers and social media, we surmise that earthquakes in a broader area are also important in shaping risk perceptions. Thus, we re-examine the estimates

[25] The two estimates are statistically different from each other at 10% significance level (p-value = .0771). Recall that the average property has 0.84 injection wells within 2 km (Table 1).

using all the earthquakes that occurred in Oklahoma during the sample period. Results are reported in Table 3.3.

Estimates are qualitatively similar to those in Table 3.2. We do not observe any statistically significant effects from proximity to injection wells in the baseline specification. A significant impact associated with seismic activity is observed in the estimates of equation (2), reported in columns (2) - (6), for those properties with injection wells within 2 km. Because the epicenter of Prague is in Lincoln County, the estimates in column (2) are identical to the corresponding ones in Table 3.2. The impact of max(MMI) is also almost unchanged. The occurrence of earthquakes with $M \geq 3$, $M \geq 4$, and the sum(MMI), however, all have much smaller impacts on housing prices than before. An additional earthquake of magnitude $M \geq 4$ in the state depresses the value of properties with one injection well within 2 km by 0.52 percent, which is one third of the effect of a local earthquake of the same magnitude. Although there were more earthquakes with larger magnitude throughout the state, they were much farther from the properties in Oklahoma County, thereby, the marginal effects are smaller overall.

3.6.2.2 Associated Injection Wells

Tables 3.2 and 3.3 report results for all injection wells, both earthquake-associated and non-associated. 92 percent of our sample injection wells are earthquake associated. It is possible that non-associated injection wells could induce an earthquake in the future even if they have not so far, so they are associated with potential seismicity risk as well. Nonetheless, we speculate that currently associated injection wells are perceived to be riskier. We thus re-estimate models (1) and (2) with only associated injection wells. Considering that there were only 3 earthquakes with

M ≥ 4 in Oklahoma County during 2010 – 2014, potentially lacking variation, we re-estimate the models with all earthquakes in Oklahoma State. Results are presented in Table 3.4.[26]

As in previous results, seismic activity depresses housing prices for those properties with injection activity within 2 km. The effects are similar in magnitude to those in the specification with all injection wells in Table 3.3, although their statistical significance is slightly lower. One explanation might be that people perceive injection wells that have already induced earthquakes to be less likely to cause more earthquakes and therefore less dangerous (gambler's fallacy). However, the effects continue to be statistically significant at a 5% level (except for the less frequent M ≥ 4 earthquakes for which the effect is significant at a 10% level). Moreover, we see a statistically significant impact of associated injection wells within 2 to 15 km of the property (in levels).

Together, these findings suggest that people perceive associated injection wells to be related with seismicity risk. In the baseline specification in column (1), the negative coefficient on wells between 2 and 15 km suggests that there is a seismicity effect (given the insignificance of vicinity effects for wells 15-30 km from the property). A negative seismicity effect is not apparent for wells within 2 km of the property in the baseline model, as this effect is possibly counterbalanced by positive adjacency effects (e.g. royalty receipts). It does become apparent, however, in model (2) that explicitly includes earthquake activity (columns 2-6). For example, after Prague, one additional earthquake-associated injection well within 2 km of a property reduces the value of the property by 2.14%.

[26] We did estimate the models with only earthquakes in Oklahoma County; the results are comparable, except that the coefficients on seismicity risk for wells within 2 km brought by earthquakes are larger, and earthquakes with M ≥ 4 are not statistically significant at conventional levels.

3.6.3 Common trends and "Prague" Falsification Tests

Our difference-in-differences identification strategy relies on the assumption that there are not distinct preexisting trends in the prices of houses located at different distances of injection wells. If, for example, houses within 2 km of an injection well were experiencing slower growth in prices relative to homes located further from injection activity, this could lead to estimating a spurious negative effect of earthquakes in our difference-in-differences analysis.

Figure 3.3 illustrates the evolution of housing prices for those properties with and without injection activity within 2 km. Both lines follow the same trends. As an additional analysis, we run two separate regressions – for properties with and without active injection wells within 2km – of the log price on property characteristics controlling for year and quarter. We then estimate two price functions with local polynomial regressions using as dependent variables the residuals from the previous regressions. Figure 3.4 depicts the results from the local polynomial regressions. The two lines show that the residuals are generally close to zero, and that, consistent with the evolution of prices in Figure 3.3, they follow similar trends. Both figures suggest that prices of houses in closer proximity to injection wells are slightly more volatile before the Prague earthquake; then the residuals compress until they are nearly identical in recent times. Thus, this graphical analysis bolsters the argument that our difference-in-differences estimates are causal.

Another check for whether the decrease in housing price for properties with active injection wells within 2km after Prague is due to differential trends in housing prices in these areas is to conduct a falsification test. We do this by estimating equation (2) using three randomly selected false earthquake dates during our study period, one before Prague and two after Prague: February 1st, 2011, July 15th, 2012, and October 31st, 2013. The results presented in

Table 3.5 show that there was not a statistically significant price differential between houses with and without injection wells in 2km after the first fake earthquake in 2011. This insignificance provides no evidence of a spurious effect driven by different housing price trends *before* the earthquake and thus supports the causal interpretation of our DD model estimates of the impact of Prague on housing prices.

In contrast, we estimate statistically significant price differentials for houses with injection activity within 2 km for the two false earthquakes dates after Prague and the impacts are slightly larger than that of Prague. This suggests that the impact of Prague is persistent and possibly enhanced by the increasing incidence of earthquakes, locally and across the state.

3.6.4 Further Exploration: Mechanisms

The literature posits several links between shale gas development and real estate markets, notably royalties from oil and gas production and water contamination. In this section, we explore the impacts of production wells, water contamination risk, and the interaction between them and seismicity risk on housing prices.

3.6.4.1 Impacts of Production Wells

Although only injection (not production) wells are associated with seismicity risk, the public might not know this difference and might therefore have an incorrect perception that production wells also induce earthquakes, or incorrectly assume that production wells are always in close proximity to injection wells. Production wells are much larger and more conspicuous than injection wells, adding a potentially strong visual disamenity effect to the suite of external effects of injection wells discussed in Section 3.4.1. Thus, we expand model (2) with a set of variables indicating the proximity of production wells to isolate the effects of injection-induced seismicity from these potentially confounding effects.[27]

(3) $$lnP_{it} = \alpha_0 + \alpha_1(injection\ wells\ in\ 2\ km)_{it} + \alpha_2(injection\ wells\ in\ 2 - 15\ km)_{it} + \alpha_3(injection\ wells\ in\ 15 - 30\ km)_{it} + \alpha_4(production\ wells\ in\ 2\ km)_{it} + \alpha_5(production\ wells\ in\ 2 - 15\ km)_{it} + \alpha_6(production\ wells\ in\ 15 - 30\ km)_{it} + \alpha_7 Earthquake_{it} + \alpha_8(injection\ wells\ in\ 2\ km)_{it} * Earthquake_{it} + \alpha_9(injection\ wells\ in\ 2 - 15\ km)_{it} * Earthquake_{it} + \alpha_{10}(production\ wells\ in\ 2\ km)_{it} * Earthquake_{it} + \alpha_{11}(production\ wells\ in\ 2 - 15\ km)_{it} * Earthquake_{it} + \mu_i + v_t + q_t + \epsilon_{it}$$

Results with only earthquakes in Oklahoma county are presented in Table 3.6. Like for injection wells, we do not detect statistically significant impacts of production wells on housing prices regardless of their proximity, suggesting that the positive and negative effects associated with shale gas production offset each other all distances. This is also the case in the specifications that include earthquake activity.

The coefficients for injection wells are strikingly similar to those in Table 3.2 in both significance and magnitude. Seismic activity decreases property prices of houses with injection wells within 2 km. The statistically indistinguishable estimates of seismicity risk in Tables 3.2 and 3.6, and the lack of significance of effects associated with production wells suggest that people correctly perceive production wells as independent from injection wells in triggering earthquakes.

3.6.4.2 Water Contamination Risk

Earthquakes might disrupt infrastructures, change the pressure beneath the surface and cause underground injection wells to leak, threatening aquifer and then drinking water quality. In

[27] See Table 1 for their descriptive statistics. Production wells are more common than injection wells at any distance.

March 2016, an underground pipe broke and released over 700,000 gallons of wastewater from drilling activities in Oklahoma (Rangel 2016). This pipe belonged to a wastewater injection well and contaminated a nearby public water supply. With many residents on private groundwater especially in rural areas, the contamination risk posed by dewatering techniques and fluid injection may factor into the perceived risk of buying a property. Such risk perception on water contamination may also be exacerbated by the occurrence of earthquakes. Muehlenbachs et al. (2015) find an economically and statistically significant groundwater contamination risk from shale gas development in Pennsylvania, where induced earthquakes have not been observed. In this section, we investigate whether earthquakes have intensified water contamination risk or not for residents in Oklahoma County. We estimate this effect separately by water source: private groundwater dependent area and public water serviced area (PWSA), and denote the risk as *groundwater Water* (*GW*) *Contamination Risk* and *Public Water* (*PW*) *Contamination Risk*, respectively.[28]

There is a slight difference in the way we measure water contamination risk for the two types of areas. The distance between injection wells and water supply wells is what is relevant in engendering this risk. For private groundwater areas, we do not have exact locations of the private wells, so we simply use a groundwater dummy and the well intensity around the property to reflect groundwater contamination risk. This is a reasonable approximation given that people normally drill groundwater wells on/near their property. For PWSAs, we measure this risk more accurately by using the intensity of injection wells around the closest public water supply (PWS)

[28] Private water wells access groundwater, while public water wells access either groundwater or surface water. We use the term groundwater to denote only private groundwater and GWCR for private groundwater contamination risk henceforth in this paper. We acknowledge that this is a slightly abuse of the terms.

well for a property.[29] According to relevant official documents and communication with experts, we choose 1.5 km as the buffer size.[30] We then calculate the number of injection wells within 1.5 km of the closest PWS well to a property to determine the potential PW contamination risk.

Risk perception of water contamination may be exacerbated by the occurrence of earthquakes; thus, we include interaction terms of water source dummies, number of injection wells in close distance to the water supply well/house, and earthquake indicators. Although we find no evidence that oil and gas production wells are related to seismicity risk in the last section, they might be related to water contamination risk since the extraction process uses substantial amounts of water and produces even larger amounts of wastewater to recycle or dispose, during which pollutants might flow to drinking water sources and cause contamination. Therefore, we include the set of variables related to production wells in model (4) as well. The extended model can then be written as:

(4) $lnP_{it} = \alpha_0 + \alpha_1(wells\ in\ 2\ km)_{it} + \alpha_2(wells\ in\ 2 - 15\ km)_{it} + \alpha_3(wells\ in\ 15 - 30\ km)_{it} + \alpha_4(wells\ in\ 2\ km)_{it} * GW_i + \alpha_5(wells\ in\ 1.5\ km\ of\ PWS\ well)_{it} * PWSA_i +$

[29] We understand that some homes may get water from a public water well that is not the closest due to geography or zoning. However, considering that people want to minimize the cost of laying down pipeline, they would prefer the closest public water well. We acknowledge that there may be some measurement error, yet we believe that this assumption is plausible.

[30] The hydrogeological literature does not provide a distance for reference, so we resort to official regulations for wellhead protection. The Oklahoma Water Resource Board (OWRB) suggests to keep potential sources of contamination (e.g. septic system and composting areas) at least 50 feet down-gradient from the water supply well location, but does not give a reference distance for injection or shale gas production wells. University of Hawaii at Manoa suggests ¼ mile (0.4 km) as the minimum distance from potable water wells to treated effluent injection wells (Cooperative Extension Service 2000) in December 2000. Michigan's Department of Environmental Quality recommends a 2,000 feet (0.61km) minimum isolation distance between brine wells/injection wells and private and public water wells. We also consulted a groundwater pollution expert at Princeton Groundwater Inc. - Robert W. Cleary - and were told that the State of Florida requires a minimum of 1,500 feet radius from wells in an unconfined aquifer with no known contamination. When there is contamination from a known contamination threat, wells must be located using a 5-year travel time or 2,500 feet (0.76km), whichever is greater from the source of contamination (depends on hydrogeology factors). Finally, according to Advanced Purification Engineering Corp (APEC), the leading manufacturer of residential reverse-osmosis drinking water filtration systems in the United States, the water we drink probably entered the ground less than a mile (1.6km) from our water supply wells if they are on ground water. Given that public water supply wells are either on surface water or ground water, we choose the largest distance from these regulations and company suggestions and use 1.5km as the approximate buffer to calculate the injection well intensity around public water supply wells to measure the risk of injection activities on public water sources.

$$\alpha_6 Earthquake_{it} + \alpha_7 (wells\ in\ 2\ km)_{it} * Earthquake_{it} + \alpha_8 (wells\ in\ 2 - 15\ km)_{it} * Earthquake_{it} + \alpha_9 (wells\ in\ 2\ km)_{it} * Earthquake_{it} * GW_i + \alpha_{10} (wells\ in\ 1.5\ km\ of\ PWS\ well)_{it} * Earthquake_{it} * PWSA_i + \mu_i + v_t + q_t + \epsilon_{it}$$

GW and *PWSA* denote whether the property relies on private groundwater or is on a PWSA. The other variables are defined as in model (3), and *wells* refers to both injection wells and production wells. α_4 and α_5 are the measures of GW and PW contamination risk associated with the proximity of wells without earthquakes, and α_9 and α_{10} measure the additional water contamination risk perception brought by earthquakes to GW-dependent and PWSA-dependent homes, respectively.

We obtained the GIS boundaries of the PWSAs in Oklahoma from the Oklahoma Comprehensive Water Plan (OCWP) and assume that any property outside these boundaries is groundwater dependent. Public water service is available in most of the regions in Oklahoma County (Figure 3.2); only 13% of our properties are dependent on groundwater. We further acquired the locations of each PWS well in Oklahoma from the Oklahoma Department of Environmental Quality.

Table 3.7 presents the regression results with earthquakes only in Oklahoma county. For GW contamination risk, estimates from both, wastewater injection and shale gas production activity are statistically insignificant regardless of model specification. There seems to be some significant PW contamination risk associated with production activity, however. One more production well within 1.5 km of a house's PWS well reduces its value by ~5% in the baseline specification. This effect is not observed for injection wells around PWS wells, suggesting that pollution to public water is perceived to be most likely through surface water, such as partially-treated wastewater to rivers or streams or accidental releases of contaminants, while injection wells operate deep underground and are seen as less likely to contaminate surface water and are thus not considered to be a risk to public drinking water.

We find that the additional water contamination risk brought by earthquakes is generally small and not significant except for large ($M \geq 4$) earthquakes. One thing worth noting is that, this additional risk is much larger for homes dependent upon private GW than for those on PW. For GW-dependent homes with one injection well within 2 km, the occurrence of a $M \geq 4$ earthquake reduces their value by 12.53% on average, whereas, for a PW-serviced home, the risk is associated with production wells and is much smaller (a reduction in value of 3.9%). This suggests that injection wells are perceived to be a substantial threat to groundwater but not surface water. Using these estimated impacts from GWCR and PWCR (columns 4 in Table 3.7, triple interaction terms) and the average price of houses sold in year 2014 with one injection well within 2 km (one production well within 1.5 km from the PWS well), we calculate that the loss resulting from the perception of water contamination risk brought by $M \geq 4$ earthquakes is \$24,870 and \$7,748 for homes on groundwater and in public water serviced areas, respectively.

Finally, we note that the estimates of seismicity risk resulting from injection wells in proximity (2 km) of the property are very similar to those in Table 3.6. Production wells are overall not perceived to be associated with seismicity, regardless of the distance between the wells and the properties, and the occurrence or earthquakes does not alter risk perceptions.

3.7. Conclusion

Development of shale deposits has become increasingly widespread due to advances in technology, generating plentiful debate about the benefits of a relatively cleaner domestic fuel and the local negative impacts associated with the extraction technology. Bartik et al. (2016) estimate positive net benefits at the local level; the mean willingness-to-pay for allowing fracking equals about $1,300 to $1,900 per household annually among original residents of counties with high fracking potential. However, there is abundant heterogeneity in the WTP measures among homeowners and across shale plays.

A big concern in the Central and Eastern US since 2009 is the increase in seismicity induced by fluid injection wells (Ellsworth 2013; Weingarten et al. 2015). Our paper is the first to identify the induced seismicity risk and specifically measure the net capitalization of benefits and costs of shale gas development at various levels of proximity and seismicity exposure in housing prices in Oklahoma County.

Our identification strategy exploits the timing of earthquakes, earthquake intensity and location, the distance of properties to injection wells (and production wells), and drinking water sources. We find that seismic activity has lowered housing prices in Oklahoma County, but the impact is limited to houses with injection wells within 2 km distance. The results are robust to using a variety of earthquake indicators – a "Prague" shock, the number of earthquakes with a magnitude equal to or greater than 3 (and 4), and the sum and max of Modified Mercalli Intensity of earthquakes in both Oklahoma County and Oklahoma State. Further, the estimated effects are not confounded by damages caused by earthquakes, and are robust to controlling for oil and gas production activity, and the type of drinking water source. Using data on houses with one injection well within 2 km and sold in the most recent year (2014), we calculate the average loss for properties in Oklahoma County to be $4,112 (2.2%) after the Prague earthquake. Similarly, we calculate the average property value loss due to one additional $M \geq 3$ and $M \geq 4$ earthquake in Oklahoma County to be $411 (0.2%) and $2,990 (1.6%), respectively.

In contrast, our results suggest that shale oil and gas production wells are not perceived to induce earthquakes. Pondering on the science that it is injection wells that are associated with the increase in recent earthquakes, it seems that people are actually able to differentiate injection wells from production wells in triggering earthquakes. We also find that large earthquakes ($M \geq 4$) exacerbate water contamination risk, both for properties dependent upon private and public water services. Interestingly, residents in Oklahoma County seem to be able to distinguish the causes of water contamination associated with shale gas development. They correspond wastewater injection wells with groundwater contamination, and oil and gas production wells with potential public water contamination.

Overall, we believe that our findings can be interpreted as evidence of availability bias in the perception of risks associated with injection activity. A negative impact of injection wells in hedonic prices is observed only when accounting for seismic activity, suggesting that earthquakes provide information that updates the subjective perception of injection risks and only for properties in close proximity of injection wells.

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Table 3.1. Summary Statistics

Description	Obs	Mean	SD	Min	Max
Properties					
Selling price (k $ 2010 Q4)	8662	159.78	128.61	2.92	827.41
Injection wells in 2 km	8662	0.84	1.8	0.00	15.00
Injection wells in 2 -15 km	8662	39.71	24.07	6.00	93.00
Injection wells in 15 - 30 km	8662	64.4	27.79	15.00	127.00
Associated injection wells in 2 km	8662	0.78	1.71	0.00	14.00
Associated injection wells in 2 -15 km	8662	36.66	21.87	4.00	88.00
Associated injection wells in 15 - 30 km	8662	59.53	26.38	14.00	127.00
Production wells in 2 km	8662	1.57	2.06	0.00	27.00
Production wells in 2 -15 km	8662	86.32	30.26	10.00	247.00
Production wells in 15 - 30 km	8662	165.27	66.85	52.00	721.00
1 = Public water serviced area	8662	0.87	0.34	0.00	1.00
Injection wells in 1.5 km of PWS well	8662	0.66	1.57	0.00	13.00
Production wells in 1.5 km of PWS well	8662	0.60	1.06	0.00	10.00
1 = Sale after November 5, 2011	8662	0.75	0.43	0.00	1.00
Earthquakes					
In Oklahoma County					
Earthquakes with $M \geq 3$	8662	6.65	6.85	0.00	26.00
Earthquakes with $M \geq 4$	8662	0.20	0.56	0.00	2.00
Sum(MMI)	8662	23.56	24.91	0.00	100.06
Max(MMI)	8662	3.48	1.31	0.00	5.54
In Oklahoma State					
Earthquakes with $M \geq 3$	8662	43.50	53.17	0.00	195.00
Earthquakes with $M \geq 4$	8662	1.30	1.72	0.00	6.00
Sum(MMI)	8662	124.45	148.55	0.00	538.60
Max(MMI)	8662	3.90	0.94	0.00	6.06

Table 3.2. Log(Price) on Number of Injection Wells, Earthquakes in Oklahoma County

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Prague	M>=3	M>=4	Sum(MMI)	Max(MMI)
Injection wells in 2 km	0.12	1.98	1.51	0.50	1.46	3.80
	(2.93)	(2.92)	(2.89)	(2.92)	(2.89)	(2.90)
Injection wells in 2 -15 km	0.08	0.18	0.19	0.05	0.19	-0.14
	(0.37)	(0.41)	(0.43)	(0.39)	(0.42)	(0.42)
Injection wells in 15 - 30 km	-0.12	-0.15	-0.06	-0.08	-0.06	-0.03
	(0.27)	(0.29)	(0.29)	(0.28)	(0.29)	(0.28)
Earthquake		-4.08	0.19	0.45	0.06	-1.93
		(5.89)	(0.27)	(2.73)	(0.07)	(1.27)
Injection wells in 2 km ×		-2.15**	-0.22***	-1.55**	-0.06***	-1.27***
Earthquake		(0.86)	(0.06)	(0.75)	(0.02)	(0.32)
Injection wells in 2 - 15 km		-0.03	0.00	0.05	0.00	0.04
× *Earthquake*		(0.08)	(0.00)	(0.05)	(0.00)	(0.03)
Constant	1,148.01***	1,144.28***	1,138.63***	1,146.58***	1,138.15***	1,153.49***
	(27.46)	(27.52)	(29.42)	(27.85)	(29.30)	(28.29)
Observations	8,662	8,662	8,662	8,662	8,662	8,662
Adjusted R-squared	0.170	0.172	0.173	0.171	0.173	0.175

Notes: (1) Each column represents a separate regression. The dependent variable in all regressions is the log sale price. The price is adjusted using the housing price index (HPI) from the Federal Housing Finance Agency. We use the HPI for Metropolitan Statistical Areas and Divisions for sales of properties in Oklahoma City, and the HPI for Oklahoma State Nonmetropolitan Areas for all the other sales. We set the price index in quarter 4 year 2010 as 100.

(2) *Earthquake* = Prague, Number of Earthquakes with $M \geq 3$, Number of Earthquakes with $M \geq 4$ Sum(MMI), and Max(MMI), as indicated by the column headings. Only earthquakes that happened in Oklahoma County are included in specifications (3) – (6). In the Prague model, the earthquake dummy is perfectly collinearly related with the two interaction terms, therefore, it drops out.

(3) Coefficients are in percentage terms. Robust standard errors are clustered by property and shown in parentheses. Property, Year and Quarter fixed effects are included in all specifications. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 3.3. Log(Price) on Number of Injection Wells, All Earthquakes in Oklahoma

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Prague	M>=3	M>=4	Sum(MMI)	Max(MMI)
Injection wells in 2 km	0.12	1.98	0.81	0.66	0.78	4.17
	(2.93)	(2.92)	(2.92)	(2.93)	(2.93)	(3.02)
Injection wells in 2 -15 km	0.08	0.18	-0.24	0.03	-0.22	-0.42
	(0.37)	(0.41)	(0.53)	(0.46)	(0.53)	(0.46)
Injection wells in 15 - 30 km	-0.12	-0.15	0.11	-0.05	0.11	-0.09
	(0.27)	(0.29)	(0.29)	(0.29)	(0.30)	(0.28)
Earthquake		-4.08	0.02	0.04	0.01	-3.82**
		(5.89)	(0.05)	(1.15)	(0.02)	(1.75)
Injection wells in 2 km ×		-2.15**	-0.02***	-0.52**	-0.01***	-1.29***
Earthquake		(0.86)	(0.01)	(0.26)	(0.00)	(0.42)
Injection wells in 2 - 15 km ×		-0.03	0.00	0.02	0.00	0.06*
Earthquake		(0.08)	(0.00)	(0.02)	(0.00)	(0.03)
Constant	1,148.01***	1,144.28***	1,146.81***	1,145.27***	1,145.85***	1,173.00***
	(27.46)	(27.52)	(30.12)	(30.22)	(30.36)	(30.14)
Observations	8,662	8,662	8,662	8,662	8,662	8,662
Adjusted R-squared	0.170	0.172	0.173	0.171	0.173	0.174

Notes: Each column represents a separate regression. The dependent variable in all regressions is log sale price. Property, County-year and Quarter fixed effects are included in all specifications. Coefficients are in percentage terms. Robust standard errors are clustered by property and shown in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 3.4. Log(Price) on Number of Associated Injection Wells, All Earthquakes in Oklahoma

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Base	Prague	M>=3	M>=4	Sum(MMI)	Max(MMI)
Injection wells in 2 km	1.12	2.82*	1.57	1.42	1.56	5.42***
	(1.54)	(1.59)	(1.55)	(1.56)	(1.55)	(1.96)
Injection wells in 2 -15 km	-0.38**	-0.37**	-0.35**	-0.41***	-0.36**	-0.47***
	(0.15)	(0.16)	(0.17)	(0.16)	(0.17)	(0.18)
Injection wells in 15 - 30 km	-0.04	-0.02	0.06	-0.02	0.05	-0.02
	(0.11)	(0.11)	(0.13)	(0.12)	(0.13)	(0.11)
Earthquake		-4.60	0.05	0.41	0.02	-2.58*
		(5.62)	(0.05)	(1.06)	(0.02)	(1.56)
Injection wells in 2 km ×		-2.08**	-0.03**	-0.64*	-0.01**	-1.32***
Earthquake		(0.88)	(0.01)	(0.35)	(0.00)	(0.47)
Injection wells in 2 - 15 km ×		-0.01	0.00	-0.00	0.00	0.03
Earthquake		(0.07)	(0.00)	(0.02)	(0.00)	(0.03)
Constant	1,160.01***	1,156.87***	1,153.35***	1,160.28***	1,154.52***	1,169.74***
	(10.78)	(10.88)	(13.26)	(12.41)	(12.96)	(11.99)
Observations	8,662	8,662	8,662	8,662	8,662	8,662
Adjusted R-squared	0.172	0.173	0.173	0.172	0.173	0.175

Notes: Each column represents a separate regression. Dependent variables in all regressions are log sale price. Property, County-year and Quarter fixed effects are included in all specifications. Coefficients are in percentage terms. Robust standard errors are clustered by property and shown in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 3.5. Falsification Tests: Hypothetical Earthquake Dates

VARIABLES	(1) Feb2011	(2) Prague	(3) Jul2012	(4) Oct2013
Injection wells in 2 km	0.18	1.98	2.71	1.08
	(3.35)	(2.92)	(2.82)	(2.87)
Injection wells in 2 -15 km	0.48	0.18	0.07	-0.02
	(0.42)	(0.41)	(0.43)	(0.49)
Injection wells in 15 - 30 km	-0.28	-0.15	0.21	0.00
	(0.28)	(0.29)	(0.31)	(0.29)
Earthquake	19.29***	-4.08	-11.82**	9.10
	(6.36)	(5.89)	(4.95)	(5.74)
Injection wells in 2 km × *Earthquake*	-0.03	-2.15**	-3.43***	-2.82***
	(1.66)	(0.86)	(0.92)	(0.92)
Injection wells in 2 - 15 km × *Earthquake*	-0.36***	-0.03	0.13	0.10
	(0.13)	(0.08)	(0.08)	(0.10)
Constant	1,144.01***	1,144.28***	1,123.52***	1,144.57***
	(28.34)	(27.52)	(28.29)	(28.18)
Observations	8,662	8,662	8,662	8,662
Adjusted R-squared	0.172	0.172	0.175	0.174

Notes: Each column represents a separate regression. Dependent variables in all regressions are log sale price. *Earthquake* = 1 if the transaction happened on or after February1st, 2011 (or November 5th, 2011; July 15th, 2012; October 31st, 2013), and 0 otherwise. Property, Year and Quarter fixed effects are included in all specifications. Coefficients are in percentage terms. Robust standard errors are clustered by property and shown in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 3.6. Impacts of Shale Gas Production Wells

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Prague	M>=3	M>=4	Sum(MMI)	Max(MMI)
Injection wells in 2 km	0.02	1.75	1.44	0.47	1.38	4.09
	(2.93)	(2.93)	(2.91)	(2.94)	(2.91)	(2.91)
Injection wells in 2 -15 km	-0.01	0.05	0.13	0.00	0.13	-0.17
	(0.38)	(0.41)	(0.43)	(0.40)	(0.42)	(0.42)
Injection wells in 15 - 30 km	-0.13	-0.46	-0.08	-0.12	-0.07	-0.07
	(0.27)	(0.31)	(0.29)	(0.28)	(0.29)	(0.29)
Production wells in 2 km	-0.48	-0.92	-0.82	-0.54	-0.84	-1.91*
	(0.94)	(1.09)	(0.94)	(0.95)	(0.94)	(1.09)
Production wells in 2 -15 km	0.02	-0.06	0.01	0.04	0.01	0.01
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)
Production wells in 15 - 30 km	0.05	0.03	0.06	0.05	0.06	0.05
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Earthquake		-18.42**	0.21	-6.75	0.06	-2.21
		(8.03)	(0.56)	(6.58)	(0.15)	(2.48)
Injection wells in 2 km ×		-2.60***	-0.23***	-1.76**	-0.07***	-1.39***
Earthquake		(0.87)	(0.07)	(0.78)	(0.02)	(0.33)
Injection wells in 2 - 15 km ×		-0.04	0.00	0.06	0.00	0.03
Earthquake		(0.09)	(0.01)	(0.06)	(0.00)	(0.03)
Production wells in 2 km×		0.74	0.02	0.68	0.01	0.40
Earthquake		(0.80)	(0.06)	(0.74)	(0.02)	(0.25)
Production wells in 2 - 15 km×		0.17**	0.00	0.08	0.00	0.00
Earthquake		(0.07)	(0.01)	(0.07)	(0.00)	(0.02)
Constant	1,136.56***	1,168.70***	1,127.12***	1,134.67***	1,126.32***	1,144.90***
	(28.00)	(30.21)	(29.86)	(28.37)	(29.80)	(30.16)
Observations	8,662	8,662	8,662	8,662	8,662	8,662
Adjusted R-squared	0.171	0.174	0.174	0.172	0.174	0.175

Notes: Each column represents a separate regression. Dependent variables in all regressions are log sale price. Property, County-year and Quarter fixed effects are included in all specifications. Coefficients are in percentage terms. Robust standard errors are clustered by property and shown in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 3.7. Water Contamination Risk

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Prague	M>=3	M>=4	Sum(MMI)	Max(MMI)
Injection wells in 2 km	1.15	3.50	2.84	1.81	2.84	7.11*
	(3.40)	(3.57)	(3.53)	(3.49)	(3.53)	(3.82)
Injection wells in 2 -15 km	0.06	0.09	0.20	0.04	0.21	-0.09
	(0.38)	(0.41)	(0.43)	(0.40)	(0.43)	(0.43)
Injection wells in 15 - 30 km	-0.21	-0.52*	-0.18	-0.22	-0.18	-0.15
	(0.28)	(0.31)	(0.30)	(0.28)	(0.30)	(0.29)
Production wells in 2 km	0.72	-0.01	-0.08	0.53	-0.10	-0.82
	(1.21)	(1.37)	(1.23)	(1.23)	(1.23)	(1.40)
Production wells in 2 -15 km	0.07	-0.02	0.07	0.09	0.07	0.08
	(0.09)	(0.10)	(0.09)	(0.09)	(0.09)	(0.11)
Production wells in 15 - 30 km	0.03	0.01	0.04	0.02	0.04	0.02
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
GW × Injection wells in 2 km	-9.11	-7.90	-6.09	-8.01	-5.83	-0.74
	(13.55)	(15.14)	(14.42)	(12.95)	(14.31)	(15.39)
GW × Production wells in 2 km	3.98	4.63	3.72	3.28	3.63	2.38
	(5.32)	(5.79)	(5.51)	(5.37)	(5.49)	(6.77)
PWSA × Injection wells in 1.5 km of PWS well	-0.53	-2.32	-0.82	-0.43	-0.97	-4.69
	(4.86)	(5.42)	(5.09)	(5.01)	(5.09)	(5.56)
PWSA × Production wells in 1.5 km of PWS well	-5.17**	-3.71	-3.65	-4.93**	-3.64	-5.24*
	(2.40)	(2.70)	(2.52)	(2.42)	(2.51)	(3.16)
Earthquake		-19.32**	0.26	-5.06	0.07	-2.31
		(8.13)	(0.57)	(6.62)	(0.16)	(2.55)
Injection wells in 2 km × *Earthquake*		-2.76**	-0.25***	-1.33	-0.07***	-1.96***
		(1.26)	(0.09)	(1.00)	(0.03)	(0.53)
Injection wells in 2 - 15 km × *Earthquake*		-0.04	0.00	0.05	0.00	0.03
		(0.09)	(0.01)	(0.06)	(0.00)	(0.03)
Production wells in 2 km× *Earthquake*		0.55	0.08	1.62*	0.02	0.35
		(0.98)	(0.07)	(0.93)	(0.02)	(0.30)
Production wells in 2 - 15 km× *Earthquake*		0.17**	-0.00	0.07	-0.00	0.00
		(0.07)	(0.01)	(0.07)	(0.00)	(0.02)

GW × Injection wells in 2 km × *Earthquake*		3.11	-0.42	-12.53**	-0.13	-2.45
		(9.16)	(0.53)	(5.43)	(0.14)	(2.55)
GW × Production wells in 2 km× *Earthquake*		3.46	0.05	0.93	0.02	0.47
		(2.97)	(0.23)	(2.69)	(0.06)	(1.19)
PWSA × Injection wells in 1.5 km of PWS well × *Earthquake*		0.57	0.07	-0.17	0.02	1.16*
		(1.74)	(0.10)	(1.44)	(0.03)	(0.65)
PWSA × Production wells in 1.5 km of PWS well × *Earthquake*		-0.58	-0.24*	-3.90**	-0.07*	0.26
		(2.03)	(0.14)	(1.87)	(0.04)	(0.63)
Constant	1,139.45***	1,171.40***	1,131.06***	1,139.73***	1,130.27***	1,146.64***
	(27.91)	(30.11)	(29.70)	(28.23)	(29.64)	(30.23)
Observations	8,662	8,662	8,662	8,662	8,662	8,662
Adjusted R-squared	0.172	0.175	0.175	0.174	0.175	0.177

Notes: Each column represents a separate regression. Dependent variables in all regressions are log sale price. Property, County-year and Quarter fixed effects are included in all specifications. Coefficients are in percentage terms. Robust standard errors are clustered by property and shown in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

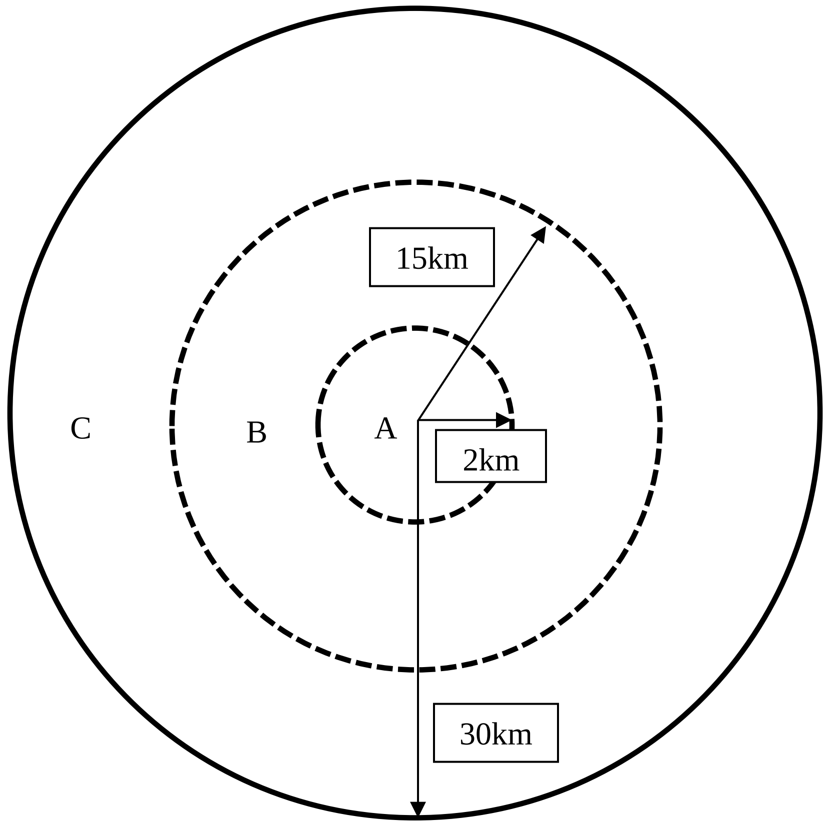

Figure 3.1. Types of Areas Examined

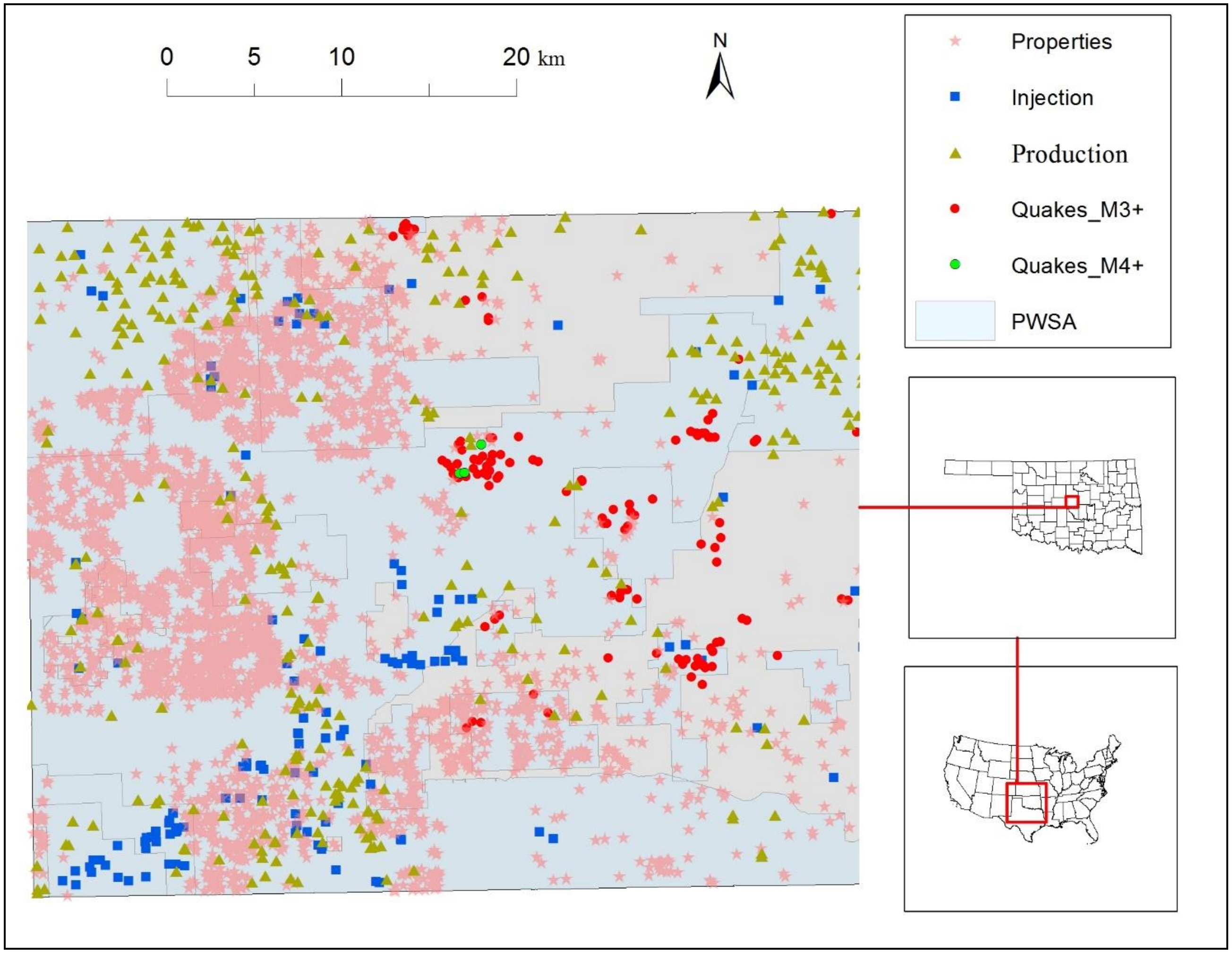

Figure 3.2. Location of Properties, Wells, Earthquakes, and Water Service Areas

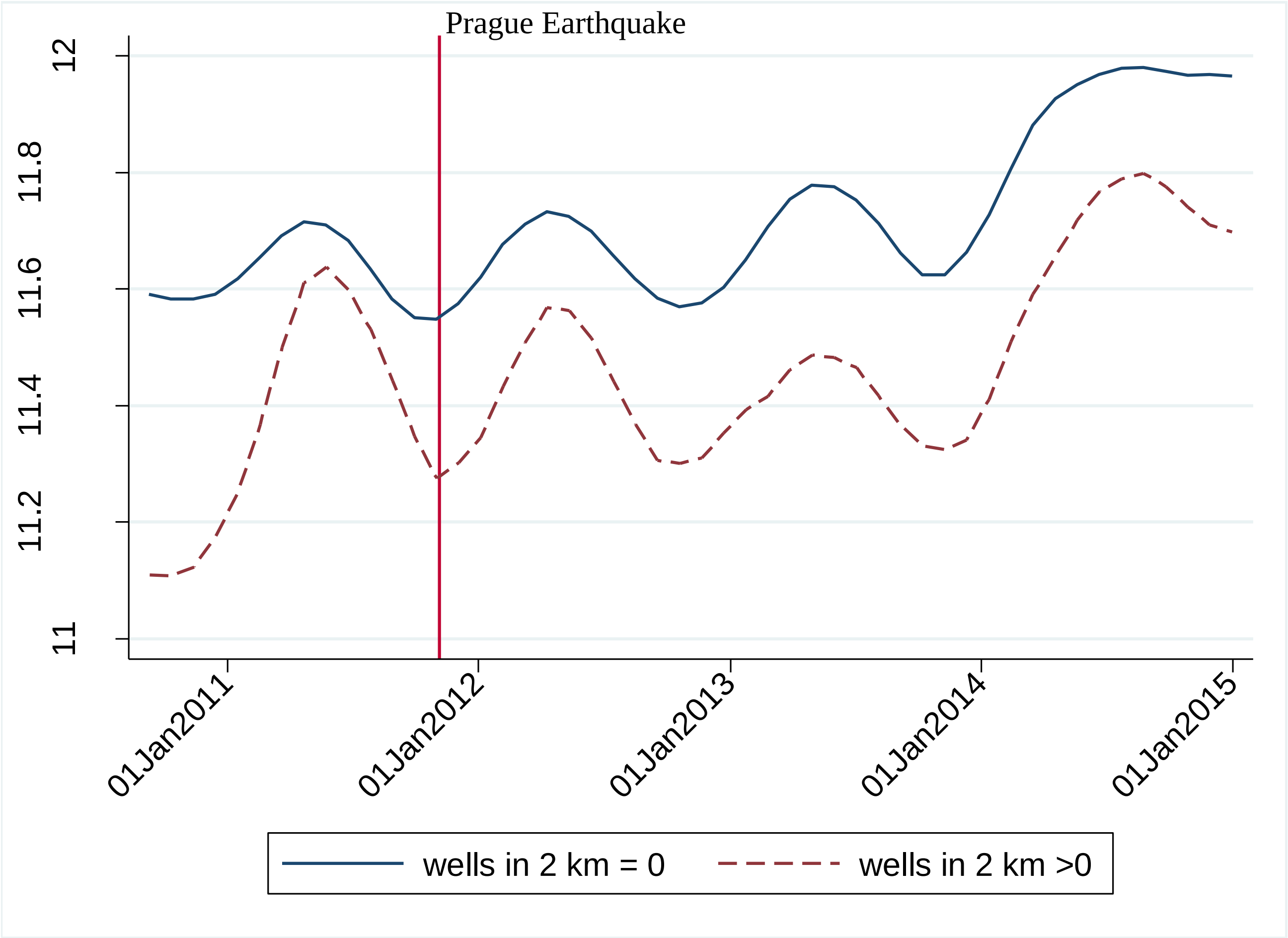

Figure 3.3. Plot of Log Price over time

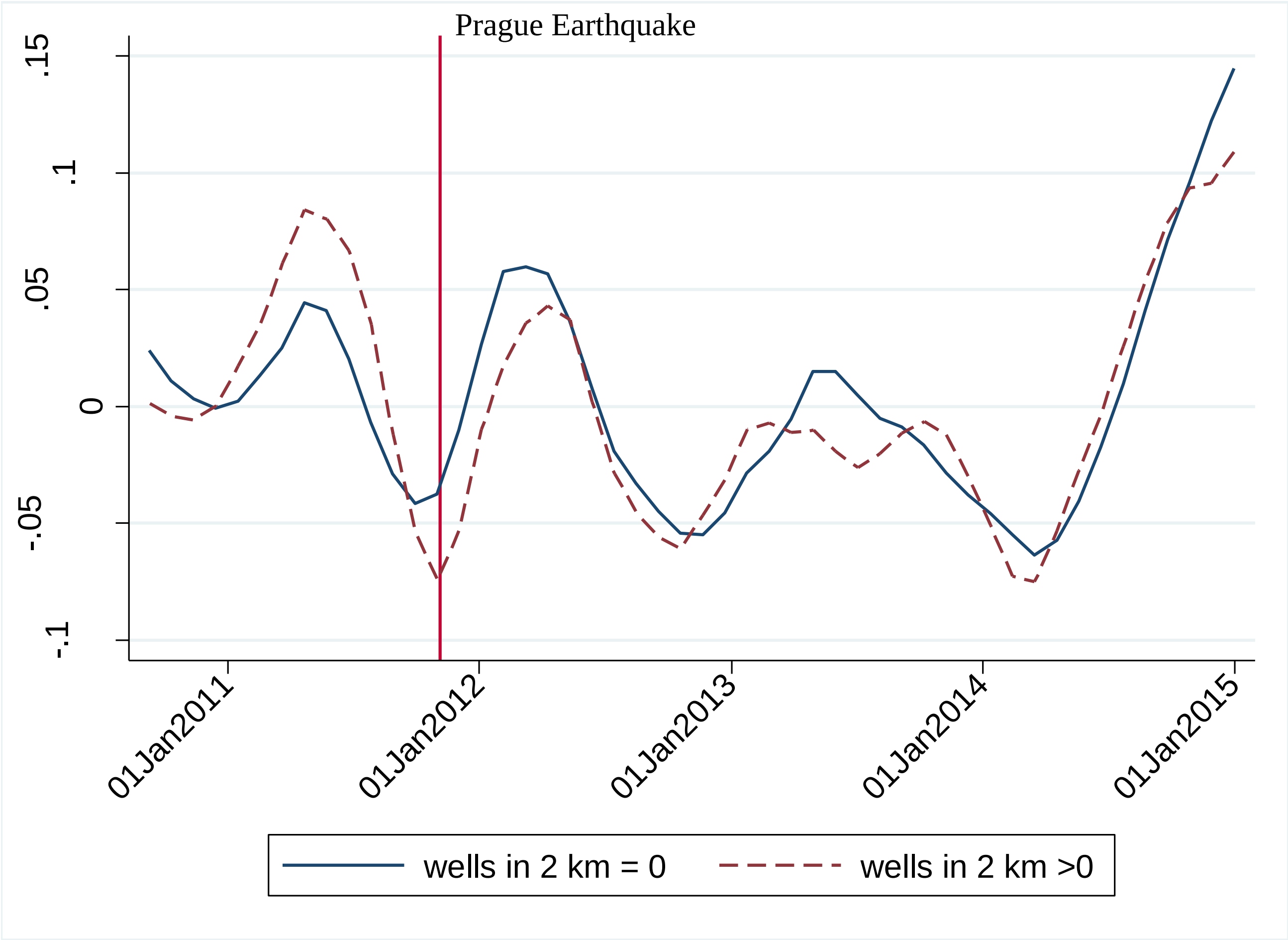

Figure 3.4. Residual Plot of Log Price Regression over time

CHAPTER 4

HUMAN HEALTH CARE COSTS OF SHALE GAS DEVELOPMENT[31]

[31] Liu, H. "Human Health Care Costs of Shale Gas Development", to be submitted to *Public Health*.

4.1. Abstract

Using data from all 254 counties in Texas and a genetic matching technique, we estimate the average impacts of shale oil and gas development on human health care costs. Estimation based on data from January to June 2010 shows that hospitalization rates and per capita costs for circulatory, digestive, respiratory, and skin and sense organ illnesses were not highly different between counties that had active fracking activities and those not. However, infections to circulatory and digestive systems were relatively more likely. There was clear heterogeneity of the impacts between age groups. People in the 0-4, 10-14, and 15-19 age groups were most affected. Sensitivity analysis indicates that our results may suffer from hidden bias due to small sample size. Future research should expand the scope of the study both in time and space, and include health conditions that manifest in the long-run.

Keywords: Health Care Cost; Shale Gas Development; Texas; Matching

JEL Classification: Q32, Q40, Q51, I10

4.2. Introduction

Many regions of the United States hold large reserves of unconventional natural gas resources in coalbeds, shale, and tight sands. Recent technological improvements, such as horizontal drilling and hydraulic fracturing (fracking), have made these resources more accessible and the development more economical. In 2015, U.S. dry natural gas production was equal to about 99% of U.S. natural gas consumption mainly due to increased shale gas production (EIA 2017a). United States is now the largest producer of petroleum and natural gas in the world and recently surpassed Saudi Arabia in oil production and Russia in natural gas (Hammond 2015). Although natural gas has been hailed as a bridge to a clean future between coal and renewables in terms of carbon emission, and a pathway to energy independence by replacing oil imports from the middle east, opposition to the unconventional methods of extraction has emerged, due to the various revealed and potential economic and environmental threats, among which public health concerns have drawn broad attention.

There are potentially three major groups of health effects occurring in the process of unconventional natural gas development ("fracking") (Witter et al. 2013). The first group of health effects is associated with exposure to chemical air emissions, such as volatile organic compounds, oxides of nitrogen, particulate matter. Table 4.1 lists the Automated Gas Chromatography (autoGC) levels in year 2009 and 2010 in Texas, measured by Texas Air Monitoring Information System. There is not much difference in the pollutant levels between the two years in the Dallas/Fort Worth region overall, however, there might be significant difference across counties in a broader area which we do not have information on yet. The second group is related to exposure to industrial operations, including truck traffic, accidents or malfunctions, and noise pollution. The third group of health risk comes from changes to community character and economic impacts, for example perceived decline in community livability, decreased appeal of outdoor amenities and experience, inflow of itinerant workers and property value loss. Experience to such impacts will result in both short-term health effects (such as headache and mucous membrane irritation from air pollution) and long-term health effects (such as cancer, birth defects, and asthma from exposure to chemical substances). In addition to physical deterioration, residents living close to fracking sites may also suffer from stress and decline of social cohesion due to worse community amenities and livability.

The impact of shale gas development on human health has become the focus of a growing body of literature. Colborn et al. (2011) identified 353 of 632 chemicals contained in 944 products used for natural gas operations in Colorado, and found more than 75% of the chemicals are known to negatively impact the skin, eyes and other sensory organs, the respiratory system, the gastrointestinal system, and the liver. McKenzie et al. (2012) found that shale gas development is positively related to cancer risk for residents in Colorado, Finkel (2016) finds that the observed number of urinary bladder cases in Pennsylvania was higher than expected in counties with shale gas activity while the increase was essentially non-existent in counties with the fewest number of producing wells. Conditions in respiratory, digestive, and gastrointestinal systems were also reported by residents living close to shale gas wells in Pennsylvania (Ferrar et al. 2013; Steinzor et al. 2013; Rabinowitz et al. 2015). Besides, Hill (2013) finds that shale gas drilling increased the incidence of low birth weight and decreased term birth weight among mothers living within 2.5 km of a well compared with mothers living with 2.5 km of a future wells. Similarly, Casey et al. (2016) find that shale gas activity is associated with higher chances of preterm birth.

More recently, there have been a few studies that examine the health effects from an economic perspective. Jemielita et al. (2015) use a Poisson model to estimate the association of inpatient prevalence rates for 25 medical categories and the number of shale gas wells per zip code in three counties in Pennsylvania. They find that cardiology inpatient prevalence rates were significantly higher for zip codes with higher number of wells and neurology inpatient prevalence rates were significantly associated with wells per square km. Peng et al. (2016) extend this research to the entire state of Pennsylvania and focus only on five respiratory conditions. They find significant associations between shale gas development and hospitalization rates for acute myocardial infarction, pneumonia, and upper respiratory infections.

In this paper, we combine the two strings of literature and investigates the health care costs of major short-term health conditions that are likely caused or exacerbated by nearby shale oil and gas development in Texas between January 2010 and June 2010. The state of Texas is rich in Wolfcamp shale reserves and has witnessed a drastic expansion of unconventional natural gas development in the past decade. Texas has the largest number of shale gas wells since 2000 (EIA 2017b), and the most shale gas production until 2014, after which Pennsylvania became the largest shale producing state (EIA 2016). Therefore, Texas is the perfect area to study both short-term and long-term health effects from shale gas development.

We test the hypothesis that health care costs in counties with shale gas development are higher than that in counties without shale gas development. During our sample period January 2010 - June 2010, the patients were between 0 and 26 years old. Considering that infants and young children are more vulnerable to environmental risks because of their constantly growing and developing body organs and systems and they have little control over their environment, we stratify our population into 5 groups at 5-year intervals. There are very few patients between 25 and 26 years old, and we do not have county population for this age range (25 – 26) since it is not a 5-year interval, we drop these observations. In total, 191,763 patients are included to analyze the health care costs.

We focus on diseases that manifest in the short-term and referring to Colborn et al. (2011), we only include four groups of diseases in this study: circulatory, digestive, respiratory, and skin and sense organs. For circulatory and respiratory diseases, only acute diseases are considered, such as acute myocardial infarction, pneumonia and influenza, and asthma. We use the International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) Diagnosis Codes to identify and categorize the diseases. Table C.1 lists the ICD-9-CM codes used to define each health condition included in this study. Two sets of measurements are used to quantify health care costs: hospitalization rate and hospital charges. Besides per capita total hospital charges, we also examine per capita total non-covered charges as it represents out-of-pocket costs, the net costs to patients.

The rest of the paper proceeds as follows. Section 2 describes the genetic matching algorithm used to match counties with shale gas development with those without shale gas extraction and identify the causal effects of shale gas development. In addition to comparing counties with and without shale gas development, we also match shale boom counties with non-boom counties, where boom is defined as a minimum 400 million cubic feet of shale gas production during our sample frame. Finally, we conduct sensitivity tests of our results to check for hidden bias. Section 3 details our data sources along with a brief descriptive analysis. Section 4 reports our empirical results. And Section 5 concludes with our major findings and future research extensions.

4.3. Method

4.3.1 Matching Estimation

We are interested in estimating the causal effects of shale gas development on human health care costs in Texas. In this paper, we use a binary variable to indicate shale gas development – whether a county has shale gas extraction activity/boom or not, thus, the causal effect can be referred to as “treatment effect”. Treatment effect can be estimated using regression models, matching estimators, and instrumental variables in the absence of an experiment. Since shale gas development is not endogenous to health care costs, we can use regression models or matching estimators. Both regression and matching methods assume the only source of omitted variable or selection bias is the set of observed covariates and response variable is independent of the treatment conditional on observables. In practice, regression estimates can be understood as a type of weighted matching estimator (Angrist 1998). Unlike regression, however, in the matching case, treatment effects are constructed by matching individuals with the same covariates instead of through a linear model for the effect of covariates. The conditional independence assumption is also weaker, in that the effect of covariates on Y need not be linear. Thus, we choose a matching technique to identify the causal impacts. The impact of shale gas development on health care costs for counties with shale gas extraction is the most relevant quantity in this study, i.e., the average treatment effect on the treated (ATT), we then frame our discussion with a matching estimation of this effect.

There are two common approaches of matching: propensity score matching (Rosenbaum and Rubin 1983) and multivariate matching based on Mahalanobis distance (Cochran and Rubin 1973; Rubin 1979, 1980) which is a multi-dimensional generalization of the idea of measuring how many standard deviations away a point P is from the mean of a distribution D. Propensity score matching match treated and untreated observations on the estimated probability of being treated (propensity score), normally the predicted value from a logistic regression. It minimizes the discrepancy along the propensity score and achieves good balance of the matching covariates when sample size is large (Rosenbaum and Rubin 1983). In our case, it would be a good balance of the socio-demographics and economic status between counties with shale gas development and those without. Multivariate matching based on Mahalanobis distance minimizes the distance between individual coordinates of the observed variables X. If X consists of more than one continuous variable, multivariate matching estimates contain a bias term which does not asymptotically go to zero at rate $\sqrt{n}$.

Genetic matching (GenMatch) is a generalization of propensity score and Mahalanobis distance matching and maximizes the balance of observed covariates between treated and control groups (Sekhon and Grieve 2011; Diamond and Sekhon 2013). The algorithm uses a genetic algorithm to optimize balance as much as possible given the data. Applying Genetic Matching to an economic evaluation of a clinical intervention ─ Pulmonary Artery Catheterization, Sekhon and Grieve (2011) show that Genetic Matching achieves better covariate balance than propensity score matching, it gives different estimates of incremental effectiveness and cost-effectiveness compared to propensity score matching. They further conduct Monte Carlo simulations and find that Genetic Matching reduces bias and root mean squared error, compared to propensity score matching.

GenMatch is based on the idea that if Mahalanobis distance is not optimal for achieving balance in a given dataset, one should be able to search over the space of distance metrics and find something better (Sekhon 2011). GenMatch generalizes the Mahalanobis metric by including an additional weight matrix:

$$d(X_i, X_j) = \{(X_i - X_j)^T (S^{-1/2})^T W S^{-1/2} (X_i - X_j)\}^{1/2} \qquad (2)$$

where W is a $k \times k$ positive definite weight matrix and $S^{1/2}$ is the Cholesky decomposition of S which is the sample covariance matrix of X. The weight matrix W is a diagonal matrix, and a variety of standardized statistics are used as balance metrics and are optimized without limit to choose the diagonal elements of W. The default standardized statistics are paired *t* tests and nonparametric Kolmogorov–Smirnov test.

Conceptually, GenMatch attempts to minimize the largest observed covariate discrepancy at every iteration by maximizing the smallest *p* value at each step. We also include the propensity score estimated from a logistic regression as one of the covariates to match on as this will improve the balance of the weight on each of the covariates. After finding the optimal weight matrix estimated by *GenMatch* package in R, we use *Match* to estimate ATT by matching each treated unit to the two best nearest neighbors with replacement.

We further conduct a sensitivity analysis for the matching estimate. All matching estimators retain the strong assumption that observable covariates account for the selection process into the treatment and control conditions. Estimates of treatment effects based on matching are unbiased if there are no unobserved confounders and if all relevant covariates have been included in the matching model. Therefore, a common concern is that our matching process fails to account for some relevant but unobservable covariates. In other words, the concern is that treated and control subjects were not comparable prior to treatment with respect to these unobserved covariates, and had they been measured and controlled by adjustments, then the conclusions about treatment effects would have been different. We use the sensitivity tests for matched data developed by Rosenbaum (1995) to examine the extent to which inferences about a treatment effect vary over a range of plausible assumptions about unmeasured pretreatment differences.

Rosenbaum sensitivity analysis relies on the sensitivity parameter Γ which measures the degree of departure from random assignment of treatment or zero bias. Let π_j be the probability of treatment for county j, then the odds that county j has shale gas extraction activity is $\frac{\pi_j}{1-\pi_j}$. Similarly, the odds that another county k is a shale gas developing county is $\frac{\pi_k}{1-\pi_k}$. Suppose the odds ratio of counties with the same values of $\boldsymbol{X}$ (income, area, population and its composition) was at most: $\frac{1}{\Gamma} \leq \frac{\pi_j/(1-\pi_j)}{\pi_k/(1-\pi_k)} \leq \Gamma$ for all j and k with $\boldsymbol{X_j} = \boldsymbol{X_k}$**.** A value of one for Γ implies that the odds ratio of treatment (county with shale gas extraction) is the same and the study is free of hidden bias. If $\Gamma = 2$, then two counties with the same values of $\boldsymbol{X}$ could differ in their odds of receiving treatment by as much as a factor of 2. One uses several different values of Γ to show how inferences might change if hidden bias were present. There are two tests used to test the sensitivity of p-value and point estimate respectively - *psens* and *hlsens* commands from the *rbounds* package in R, e.g. how the p.value and the treatment effect changes with an increasing amount of bias. We choose 2 as the Γ for the Wilcoxon Signed Rank P-Value test, and 1.5 for Hodges-Lehmann Point Estimate test given our data.

4.3.2 Models

We are interested in the human health care costs of shale oil and gas development, such as potential impacts from air pollution, water contamination, noise and light pollution and earthquake shocks. Following Peng et al. (2016), we explore the impacts on county-level hospitalization rates. Additionally, we examine the impact of shale gas development on per capita total charges and total non-covered charges. Scholarly articles have found a variety of health conditions associated with shale gas development (McKenzie et al. 2012; Bamberger and Oswald 2015; Casey et al. 2016; Finkel 2016). According to Colborn et al. (2011), more than 75% of the chemicals from shale gas development could affect skin, eyes and other sensory organs, the respiratory system, the gastrointestinal system, and the liver. These disease categories would likely to be expressed upon immediate exposure. In this study, we only analyze the costs for illnesses that are most likely associated with fracking and would manifest in short term given we have a short time frame – January 2010 to June 2010. We use 2010 International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) diagnosis codes to identify the main diagnosis for each inpatient admission, and then only examine health conditions related to skin and sense organs, circulatory, digestive and respiratory systems. It takes one to three months to get a well ready to start production and most of the acute diseases occur during the drilling stage, while drilling intensity is proportional to production intensity, we can expect production volume to be a good measure of recent drilling activity and properly reflects its consequences on health care. If there is any short lag for the acute diseases to be realized, our estimate should be able to capture this appropriately by using production volumes. We assume that patients have been living in the current county for at least seven months by the time they are hospitalized because it takes at least one month to drill the well and we have six-month data on shale oil and gas production and hospitalization.

Peng et al. (2016) has shown that shale gas development has different impacts (magnitude and category) on different age groups from a Pennsylvania sample, therefore, we stratify our sample into 5-year-old interval groups. During our study period, the inpatients were all between 0 and 26 years old. We do not have information on county population for 25 and 26 years old since the data was reported by 5-year-old interval. Hence, we conduct our analysis for five age groups: 0-4, 5-9, 10-14, 15-19, and 20-24.

Considering that we generally respond only or more strongly to severe environmental pollution, we also investigate the health impacts of shale boom where boom counties are defined as counties with at least 400 million cubic feet of shale gas produced within our sample frame January - June 2010. 400 million cubic feet is approximately the median of our county-level gas production for counties with positive production. We tried 300 and 700 as the cut-off level, and the results are qualitatively comparable. Compared with counties with low or no fracking activity, we expect to find larger and more significant treatment effects for boom counties.

We first estimate the propensity score through a logistic regression where we regress whether the county has active shale gas development or not on a list of covariates. Bartik et al. (2016) found that counties with high-fracking potential experienced marked increases in total income (4.4 – 6.9 percent), employment (3.6 – 5.4 percent), and salaries (7.6 – 13.0 percent) using a national shale play data. Jacobsen (2015) found that shale gas boom increased local wage rates in almost every major occupational category. Younger Americans are overall more concerned about climate change and more likely to oppose fracking (Swift 2015; Hodges 2016). Men are more likely to favor increased use of fracking (Kennedy 2015), white people in Texas are less supportive of fracking (Alcorn et al. 2017), and Latino population besieged by fracking in California are strongly resisting the activities (Sierra 2016). Thus, we include income, unemployment rate, gender, age, race, and ethnicity composition of the population in this regression. We then include the estimated propensity score as another covariate to match on, and population density to balance on.

4.4. Data

In Texas, there are 254 counties with 29 being shale gas producing counties, and 14 of them produced at least 400 million cubic feet of gas during January – June 2010. Data on production is reported by each oil and gas lease rather than individual well. In the case of an oil lease, reported monthly production includes production from all of the wells on the lease, and a single oil lease might include numerous oil wells. However, gas leases contain one gas well per lease. We obtained data on shale oil and gas well production from the Statewide Production Data Query System of the Online Research Queries on the Commission's website. This query system gives all the oil and gas leases within a specific district[32] and time period. However, the direct query does not report the county where a well is located. Fortunately, this information can be manually extracted by lease from the Oil & Gas Production Data Query Online System by the Commission[33]. This manual query process is extremely time-consuming, therefore, given time constraint, I only extracted data for all leases for the period of January 1st, 2010 to June 30th, 2010 which is the study period of this research. Figure 4.1 shows the counties with shale gas production and those with boom production in Texas, where we define a county to be a boom county if its shale gas production within our study period is more than 400 million cubic feet. We choose 400 million because it is approximately the median volume of gas produced in the gas counties. County area is not considered in choosing this value, but given that counties in Texas are very similar in terms of area, we do not think this will change our results significantly.

[32] There are 12 oil & gas districts created by the Railroad Commission of Texas in early 1930s for statistical purpose. Each district contains 10 – 33 counties and one county belongs to only one district. District boundaries are shown in Figure 4.2. Matching by district may address any spillover effects, however, given that we only have 12 districts, the matching would be undesirable, we only match by county in this paper.

[33] Complete and detailed information for the leases and wells are available for purchase from the Railroad Commission of Texas for $445 annually. This project is not funded by any grant, therefore, I extracted the well and production information by manually querying each oil and gas lease.

Hospital discharge visit data is from the Center for Health Statistics, Texas Department of State Health Services. This data contains patient-level information for inpatient hospital stays. It includes patient demographic characteristics, disease diagnosis codes, total charges, payment sources, and length of stay. Data for recent years are available for purchase for $6,000 annually for non-residents of Texas, and the most recent public use data is for year 2010, therefore, data for the first two quarters of 2010 are used for analysis in this study. To have a clean identification, only patients from the same county where the hospital is located are included. Patients might go to hospitals in counties that are different than their residency county, and this should be less of a concern if matching by a larger area (e.g. district) which is left for future.

Socio-demographic and economic status data are collected from various sources. County population and income data are extracted from the Regional Economic Accounts by Bureau of Economic Analysis. Labor force and unemployment data are from Local Area Unemployment Statistics Information and Analysis, Bureau of Labor Statistics. Age composition and ethnicity data are from Population Estimates 2010, Social Explorer.

Tables 4.2 reports the summary statistics of county characteristics that are potentially related to shale oil and gas development and public health conditions. Income and unemployment rate are not significantly different between fracking and non-fracking counties in our sample, however, counties with fracking activities are more populous with a 2.4 times population density and 1.74 times total population as that for their counterparts. There seems to be a significant difference in age and race composition of the population between the two groups. Fracking counties on average have a larger percentage of younger (less than 15 years old) and smaller proportion of older (more than 54 years old) population. The concentration of black population is also higher in fracking counties, but not white or Latinos.

Table 4.3 shows the T-test results of hospitalization rate and per capita total costs and total non-covered costs between fracking and non-fracking counties for people of all age groups. Interestingly, there is only a small and insignificant difference on the health care outcomes, regardless of the condition category. Comparing the outcomes by age group, we see similar results with a couple of exceptions in Table 4.4. In fracking counties, hospitalization rate of skin and sense organ diseases seems to be slightly smaller for patients between age 20 and 24, and the per capita total health care costs of circulatory diseases are marginally less for patients 15 – 19 years old. Considering that more intense fracking activity should lead to more severe health conditions, we further compare the outcomes between shale boom and non-boom counties by age group and the results are shown in Table 4.5. Although we do not see significant difference between the two groups for most of the acute diseases, we do see larger per capita health care costs for fracking counties on circulatory and respiratory diseases for patients 5 – 9 years old.

4.5. Results

4.5.1 Main Results

We estimate the treatment effects of shale gas development for two sets of models. The first set looks at whether a county is a shale gas producing county or not, while the second set focuses on whether the county is a shale gas boom county or not. We do not have information on the production level in any of the previous years, but considering that recent shale development should be more important in affecting local environment and public health, and we only examine health conditions that manifest upon immediate exposure, this should not be a big concern.

We present the results for both models side by side for all specifications. Before examining the results, we need to know how good the optimization processes by GenMatch are. Detailed results are available upon request, but in summary, GenMatch did produce a good balance for the weights of covariates. Before Matching, the minimum p.values were less than 0.05 for both models which can also be seen from the significant differences on the T-test of the variables. After matching, the minimum p.values are both larger than 0.1, indicating there is no significant difference between the treated and control groups in terms of the observed covariates used for the matching process.

Table 4.6 reports the matching estimators for hospitalization rate, per capita total costs and per capita total non-covered costs by disease category. Consistent with the descriptive analysis, we do not find much statistically significant difference of the health care outcomes between fracking counties and non-fracking counties. However, there are several exceptions. For respiratory diseases, we find a positive treatment effect of active shale gas development, but this effect becomes smaller and insignificant when we compare boom counties with non-boom counties. This might indicate that even shale development with a low intensity has large impact on the respiratory system. Skin and sense organ illnesses are more frequent in shale boom counties, by 2.7 more cases per 10,000 people.

Compare with non-fracking counties, fracking counties seem to have a significantly larger health care costs on digestive diseases only among the four acute disease types. Counties with fracking activities on average pay \$14 more per person on digestive diseases over the period of January – June 2010. Surprisingly, circulatory diseases were less frequent and less costly in shale boom counties by a margin of \$25 per person. Shale gas development did not seem to have caused a higher health care burden for patients which can be inferred from the insignificant average treatment effects on per capita total non-covered costs, irrespective of disease category.

It is possible that pollution and other negative externalities caused by shale gas development have a more pronounced effect on one age group than others. For example, people with pre-existing respiratory illness are more sensitive to air pollution, and are more likely than others to contract pneumonia. Therefore, we estimate the impacts by age group and results are shown in Table 4.7 respectively. Similar as the results in Table 4.6, we can see that shale gas development affects the health of all age groups, and the impacts are significant as long as there is extraction activity. The average effect of shale oil and gas production on hospitalization rate was generally not statistically significant, especially for respiratory and skin and sense organ diseases. Circulatory and digestive diseases were actually less frequent in fracking counties, especially for patients in the 0 – 4, 5 – 9, and 15 – 19 age group, by a factor of 0.14 to 4.47 cases per 1000 persons. Considering that the air pollution levels were not very different between fracking and non-fracking counties in our sample period shown in Table 4.1, this result might suggest that the major path that shale gas development affecting public health in Texas in early 2010 was not through air pollution but maybe water pollution and stress. Future research can examine water sources and pollution levels, and proportion of people with mental disorders in fracking and non-fracking counties to investigate the exact channels.

For per capita total costs and total non-covered costs, the pattern is slightly different although the effects of fracking or boom are consistently not significant for respiratory and skin and sense organ diseases for all age groups. Significant effects of shale gas development were only observed for circulatory and digestive diseases. Despite that the hospitalization rates of these two types of diseases for patients younger than 10 years old were lower in fracking counties, the per capita total costs were not significantly different than that for non-fracking counties and the per capita total non-covered costs were only marginally significant and small. We may infer from this result that the circulatory system and skin and sense organs of infants and young children in fracking counties were less likely to be infected by environmental pollution from shale oil and gas development, however, once they are infected, the conditions were more severe and costlier had they lived in a non-fracking county.

Shale oil and gas production incurs large and significant costs due to digestive diseases for children between 10 and 14 years old. Fracking counties on average pay $135 more for digestive diseases than counties with no fracking activity at all. The effect became smaller ($77 difference) when we compare boom versus non-boom counties. Per capita total non-covered costs for this age group and disease category is not significantly different, indicating no increased financial stress for patients themselves who live in counties with shale extraction activity. However, they actually had less stress in paying for circulatory diseases. Relative to non-boom counties, patients in boom counties had hospital visit bills $356 less on circulatory diseases than those in non-boom counties, but there was not a significant different in the bills patients themselves had to pay as can be seen from the insignificant coefficient in the per capita total non-covered costs panel. Finally, we find that circulatory diseases and health care bills were less concerned by people between 20 and 24 years old in fracking counties, as the hospitalization rate and per capita total costs were not significantly different and per capita total non-covered costs were $14 less than that for patients in non-fracking counties.

4.5.2 Sensitivity Tests

Given that we find similar patterns of the average treatment effects of shale oil and gas development on health care cost for both all population and by age groups, we only report Rosenbaum sensitivity tests for the impact of fracking on the three health care outcomes analyzed for all patients. Results are shown in Tables 4.8 and 4.9 for point estimate (treatment effects) and p-value, respectively. Test results by age groups and for the impact of shale boom on health care costs are available upon request.

The Hodges-Lehmann Point Estimate test provides Rosenbaum's bounds for the additive effect due to treatment. This can be roughly interpreted as the difference in medians across treatment and control groups (fracking and non-fracking counties). When Gamma equals zero, the study is free of bias, the lower bound equals the upper bound and are an estimate of the true median impact of fracking. If zero is included in the interval, then we cannot reject the null hypothesis that the true impact of fracking on the examined health care outcome is different from zero. From Table 4.8, we can see that the median difference in hospitalization rate for circulatory illnesses for all age groups is -0.195 case per 1000 persons if there is no hidden bias. However, if we increase Γ to 1.4, then the lower and upper bounds bracket zero. That is if the odds of one county being a shale gas county are 1.4 times higher because of different values on an unobserved covariate despite being identical on the matched covariates, our inference changes. The result for the skin and sense organ diseases is equally sensitive to hidden bias, however, those for the digestive and respiratory diseases are slightly more sensitive, especially for the digestive category where even a 0.1 times difference in the unobservables between fracking and non-fracking counties will change the inferential decisions.

For the per capita health care costs, the results seem to be quite sensitive to hidden bias for both total costs and total non-covered costs, regardless of the condition category. In general, if a fracking county is exactly the same as a non-fracking county but 1.1 times different in an unobserved variable, then out matching results will change, except the impact on total per capita costs for the circulatory diseases.

The Wilcoxon Signed Rank P-Value in Table 4.9 shows that in order for the p-value to change from being significant to insignificant or vice versa, we need a much larger increase of Γ, i.e. a larger difference in the unobservables between fracking and non-fracking counties. For instance, if the odds of one county being a shale gas county are at least 1.4 times higher because of different values on an unobserved covariate despite being identical on the observed variables, our inference on the impact of fracking on hospitalization rate will change. This is more apparent for total per capita cost and total per capita non-covered cost where even a 1.5 times difference in the odds of being a fracking county because of different unobservables will not change our results, particularly for health conditions related to digestive and respiratory systems, and skin and sense organs.

The sensitivity test for the treatment effects indicates that our results may suffer from hidden biases even if they are small, while the p-value sensitivity tests suggests that a large unobserved difference in a covariate is required to change our inference, such as a new bill that bans fracking, or technological advances that make production profitable in places that were not economically feasible previously, or people dramatically shift their perception and preference for fracking. Combining the two tests together, we can say that shale gas development had a significant treatment effect on the different health conditions, but the finding is sensitive to possible hidden bias due to unobserved confounders.

4.6. Conclusion

Shale oil and gas development has become increasing widespread due to advancement in technology, generating plentiful debate about the benefits of a relatively cleaner domestic fuel (Jacobsen 2015; Bartik et al. 2016) and the local negative impacts associated with the extraction technology (Muehlenbachs et al. 2015; Weingarten et al. 2015; Boslett et al. 2016). A big concern is that the pollution and other disamenities during the development process have potentially large impacts on human health, even in the long-run (Finkel 2016). Existing research mainly focus on Marcellus shale play in Pennsylvania with a few in Colorado. Our paper adds value to the literature by focusing on Texas and investigating the health care costs of major short-term health conditions that are likely caused or exacerbated by nearby shale oil and gas development during January 2010 - June 2010. Specifically, we test the hypothesis that health care costs in counties with shale gas development are higher than that in counties without shale gas development.

Considering that infants and young children are more vulnerable to environmental risks because of their constantly growing and developing body organs and systems and they have little control over their environment, we stratify our population into 5 groups at 5-year intervals. We focus on diseases that manifest in the short-term and only include four groups of diseases in this study: circulatory, digestive, respiratory, and skin and sense organs. Two sets of measurements are used to quantify health care costs: hospitalization rate and costs of hospital visit. Besides per capita total costs, we also examine per capita total non-covered costs as it represents out-of-pocket costs, the net costs to patients.

Using a genetic matching algorithm with estimated propensity score, we match counties with shale gas development with those without shale gas extraction and calculate the average health care impact of fracking. Results show that counties with fracking activities have higher hospitalization rate due to diseases of the respiratory system, and skin and sense organs. Per capital total costs in fracking counties were lower for circulatory diseases, but higher for digestive diseases. Analyses by age groups show insignificant differences in the outcomes between fracking and non-fracking counties for respiratory system, skin and sense organs in general. Age 10- 14 had higher total costs for digestive diseases, but not significantly higher for total non-covered costs. Age 20-24 had higher hospitalization rate for respiratory diseases, but most of the costs were covered by insurance, their out-of-pocket expense was actually lower than the average in non-fracking counties.

A sensitivity test is performed to check the robustness of the results to any relevant unobservables, since matching assumes that the only source of selection bias is from the observed covariates. It seems like our results are sensitive to hidden bias as a slight change in the odds of differential assignment to treatment due to unobserved factors will result in a change in the conclusion. This might be due to the fact that we only have a small number of counties with shale gas development and the patients are all very young. With a larger and more representative data, the matching algorithm can be improved and should produce more robust results.

Given the countervailing effects on the different physiological systems, future research should explore the heterogeneity in more detail. In the past decade, the use of hydraulic fracturing in extracting oil and gas has been widely expanded to 34 states throughout the nation, and the production in Texas has quadrupled. Thus, a spatial and longitudinal study in both Texas and nationwide would be of immense importance, and might potentially capture any spillover effects as the pollution from shale gas development could affect people from different administrative districts. Besides, future comprehensive analyses should also include diseases that manifest in the long-run as they are oftentimes the costliest.

4.7. References

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Table 4.1. AMCV Automated Gas Chromatography (autoGC) Levels in Year 2009 and 2010

chemicalname	2009	2010	Difference	p.value
1-Butene	0.33	0.34	0.02	0.5249
1-Pentene	0.03	0.03	0.00	0.8109
1,2,3-Trimethylbenzene	0.02	0.01	-0.01	0.0000
1,2,4-Trimethylbenzene	0.07	0.05	-0.01	0.0084
1,3-Butadiene	**0.08**	**0.07**	**-0.01**	**0.5234**
1,3,5-Trimethylbenzene	0.02	0.01	0.00	0.0000
2-Methyl-2-Butene	0.06	0.07	0.00	0.5241
2-Methylheptane	0.03	0.03	0.00	0.0935
2-Methylhexane	0.10	0.09	-0.02	0.0039
2,2-Dimethylbutane	0.06	0.05	-0.01	0.0551
2,2,4-Trimethylpentane	0.12	0.12	0.00	0.6806
2,3-Dimethylpentane	0.05	0.04	-0.01	0.0003
2,3,4-Trimethylpentane	0.05	0.04	0.00	0.7135
2,4-Dimethylpentane	0.03	0.03	-0.01	0.0002
3-Methylheptane	0.03	0.03	0.01	0.0023
3-Methylhexane	0.12	0.12	0.00	0.7778
Acetylene	0.66	0.66	0.00	0.9227
Benzene	**0.51**	**0.47**	**-0.04**	**0.1723**
cis-2-Butene	0.06	0.06	0.00	0.5439
cis-2-Pentene	0.04	0.03	0.00	0.2364
Cyclohexane	0.20	0.16	-0.03	0.0097
Cyclopentane	0.09	0.08	-0.01	0.0658
Ethane	9.59	9.81	0.22	0.7759
Ethylbenzene	**0.11**	**0.09**	**-0.02**	**0.0045**
Ethylene	1.53	1.78	0.25	0.0182
Isobutane	2.35	2.50	0.16	0.5654

Isopentane	2.12	1.94	-0.18	0.2461
Isoprene	0.12	0.14	0.02	0.2463
Isopropylbenzene	0.02	0.01	-0.01	0.0001
m/p Xylene	**0.28**	**0.24**	**-0.04**	**0.0684**
Methylcyclohexane	0.08	0.08	0.00	0.6330
Methylcyclopentane	0.19	0.18	-0.01	0.5715
n-Butane	3.11	3.18	0.08	0.7272
n-Decane	0.03	0.02	-0.01	0.0048
n-Heptane	0.10	0.12	0.02	0.0225
n-Hexane	**0.38**	**0.35**	**-0.02**	**0.3130**
n-Nonane	0.04	0.03	-0.01	0.0000
n-Octane	0.04	0.06	0.01	0.0001
n-Pentane	1.06	0.94	-0.12	0.1990
n-Propylbenzene	0.02	0.01	-0.01	0.0000
n-Undecane	0.03	0.02	-0.01	0.0015
o-Xylene	**0.10**	**0.08**	**-0.02**	**0.0050**
Propane	6.33	6.56	0.23	0.5874
Propylene	0.90	0.85	-0.05	0.6055
Styrene	**0.04**	**0.03**	**0.00**	**0.6967**
Toluene	**0.58**	**0.52**	**-0.06**	**0.1244**
Pm2.5 - Local Conditions	**9.72**	**9.68**	**-0.04**	**0.8812**

Note: The levels are average annual levels calculated using data measured by Texas Air Monitoring Information System (TAMIS), established by Texas Commission on Environmental Quality (TCEQ) at seven fixed-site monitors in the Dallas/Fort Worth region. The last column shows the p-value of a two-sample t-test of the mean.

Table 4.2. County-Level Summary Statistics of Socio-Demographics and Economic Status

Variable	Fracking Counties	Non- Fracking Counties	T-test for the Difference
Per Capita Income ($)	33022	33682	-0.45
	(6091)	(7486)	(0.65)
Household Median Income ($)	43451	41150	1.26
	(9798)	(9169)	(0.21)
Unemployment Rate (%)	8.30	7.94	0.85
	(2.18)	(2.16)	(0.39)
Population Density (persons/square mile)	237.31	90.38	2.40**
	(634.93)	(239.84)	(0.02)
Total Population (1000 persons)	211.04	87.21	1.74**
	(552.01)	(328.14)	(0.08)
Male (%)	49.79	50.73	-1.59
	(1.12)	(3.15)	(0.11)
Age Composition (%)			
Age 0 – 4	7.31	6.57	2.91**
	(1.28)	(1.28)	(0.00)
Age 5 – 9	7.37	6.74	2.78**
	(1.18)	(1.13)	(0.01)
Age 10 – 14	7.42	6.96	2.21**
	(0.98)	(1.06)	(0.03)
Age 15 – 19	7.42	7.06	1.65
	(1.28)	(1.09)	(0.10)
Age 20 – 24	6.65	6.17	1.07
	(2.30)	(2.29)	(0.29)
Age 25 – 34	12.39	11.84	1.18
	(1.48)	(2.45)	(0.24)
Age 35 – 44	12.11	11.75	1.14
	(1.46)	(1.64)	(0.26)
Age 45 – 54	13.53	13.86	-1.21
	(1.39)	(1.35)	(0.23)
Age 55 – 64	11.93	12.79	-2.00**
	(1.95)	(2.20)	(0.05)

Age 65 – 74	7.82	8.95	-2.18**
	(2.15)	(2.66)	(0.03)
Age 75 – 84	4.41	5.36	-2.92**
	(1.29)	(1.70)	(0.00)
Race Composition (%)			
White	87.77	90.15	-1.60
	(9.39)	(7.27)	(0.11)
Black	8.76	6.40	1.80*
	(8.58)	(6.38)	(0.07)
Native	0.96	1.05	-1.11
	(0.35)	(0.44)	(0.27)
Asian	1.12	1.00	0.35
	(1.66)	(1.75)	(0.73)
Multi-Race	1.32	1.33	-0.10
	(0.50)	(0.55)	(0.92)
Latino (%)	31.25	33.04	-0.40
	(27.24)	(22.32)	(0.69)

Note: In the first two columns, the first row for each variable displays the mean, with standard deviation shown in parentheses. The last column shows the t-statistic for the mean difference test with p-value in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 4.3. T-test of Health Care Outcomes between Fracking and Non-Fracking Counties, All Population

Variable	Fracking Counties	Non-Fracking Counties	T-test for the Difference
Hospitalization Rate (cases/1000 people)			
Circulatory	1.03	1.13	-1.02
	(0.34)	(0.56)	(0.31)
Digestive	4.84	4.69	0.27
	(3.10)	(2.79)	(0.79)
Respiratory	1.83	1.92	-0.52
	(0.67)	(0.90)	(0.60)
Skin and Sense Organs	1.07	1.14	-0.29
	(0.50)	(1.31)	(0.77)
Per Capita Total Costs (dollars)			
Circulatory	76.08	84.90	-0.94
	(31.36)	(49.20)	(0.35)
Digestive	62.09	68.00	-0.74
	(26.61)	(41.59)	(0.46)
Respiratory	130.78	126.46	0.28
	(85.77)	(78.53)	(0.78)
Skin and Sense Organs	24.84	26.41	-0.30
	(10.41)	(27.83)	(0.76)
Per Capita Total Non-Covered Costs (dollars)			
Circulatory	0.80	2.76	-0.92
	(2.82)	(11.42)	(0.36)
Digestive	0.32	1.45	-1.00
	(0.56)	(6.06)	(0.32)
Respiratory	0.30	2.08	-0.88
	(0.94)	(10.94)	(0.38)
Skin and Sense Organs	0.08	0.75	-0.91
	(0.18)	(4.00)	(0.36)

Note: In the first two columns, the first row for each variable displays the mean, with standard deviation shown in parentheses. The last column shows the t-statistic for the mean difference test with p-value in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 4.4. T-test of Health Care Outcomes between Fracking and Non-Fracking Counties, by Age Group

Variable	Age 0 - 4	Age 5 - 9	Age 10 - 14	Age 15 - 19	Age 20 - 24
Hospitalization Rate (cases/1000 people)					
Circulatory	-0.63	0.13	-0.57	-1.55	-0.02
	(0.53)	(0.90)	(0.57)	(0.12)	(0.98)
Digestive	-1.29	-0.84	1.02	0.35	-0.59
	(0.20)	(0.40)	(0.31)	(0.73)	(0.55)
Respiratory	-0.27	-0.42	-0.90	-1.11	0.14
	(0.79)	(0.67)	(0.37)	(0.27)	(0.89)
Skin and Sense Organs	-0.59	-0.38	-0.03	-0.29	-1.89*
	(0.55)	(0.70)	(0.98)	(0.77)	(0.06)
Per Capita Total Costs (dollars)					
Circulatory	-0.58	1.59	-0.86	-1.75*	1.52
	(0.56)	(0.11)	(0.39)	(0.08)	(0.13)
Digestive	0.81	-0.81	-1.15	-0.99	0.13
	(0.42)	(0.42)	(0.25)	(0.32)	(0.90)
Respiratory	-1.20	0.27	1.12	-0.12	-0.50
	(0.23)	(0.79)	(0.26)	(0.91)	(0.62)
Skin and Sense Organs	-0.56	-0.20	-0.26	-0.04	-1.37
	(0.58)	(0.85)	(0.79)	(0.97)	(0.17)
Per Capita Total Non-Covered Costs (dollars)					
Circulatory	.	-0.21	-0.37	-1.04	-0.81
	(.)	(0.83)	(0.71)	(0.30)	(0.42)
Digestive	-0.34	-0.29	-1.02	-1.00	-0.46
	(0.73)	(0.78)	(0.31)	(0.32)	(0.65)
Respiratory	-0.80	0.90	-0.75	-0.93	-0.70
	(0.43)	(0.37)	(0.45)	(0.35)	(0.49)
Skin and Sense Organs	-0.47	-0.72	-0.69	-0.79	-0.35
	(0.64)	(0.48)	(0.49)	(0.43)	(0.72)

Note: The first row for each variable displays the t-statistic from the t-test of the mean between fracking and non-fracking counties, with p-value of the test shown in parentheses below. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 4.5. T-test of Health Care Outcomes between Boom and Non-Boom Counties, by Age Group

Variable	Age 0 - 4	Age 5 - 9	Age 10 - 14	Age 15 - 19	Age 20 - 24
Hospitalization Rate (cases/1000 people)					
Circulatory	-0.45	0.66	-0.36	-1.81*	-0.02
	(0.65)	(0.51)	(0.72)	(0.07)	(0.98)
Digestive	-0.21	-0.19	1.20	0.57	0.40
	(0.84)	(0.85)	(0.23)	(0.57)	(0.69)
Respiratory	-0.68	-0.68	-0.13	-1.07	0.09
	(0.50)	(0.50)	(0.90)	(0.28)	(0.93)
Skin and Sense Organs	-0.30	0.65	0.25	-0.00	-1.27
	(0.76)	(0.52)	(0.80)	(1.00)	(0.21)
Per Capita Total Costs (dollars)					
Circulatory	-0.44	2.61**	-0.53	-1.28	0.36
	(0.66)	(0.01)	(0.59)	(0.20)	(0.72)
Digestive	1.50	-0.92	-0.44	-0.53	-0.19
	(0.13)	(0.36)	(0.66)	(0.60)	(0.85)
Respiratory	-0.52	-0.15	1.63	0.26	0.31
	(0.60)	(0.88)	(0.10)	(0.79)	(0.76)
Skin and Sense Organs	-0.30	0.40	0.28	0.08	-0.81
	(0.77)	(0.69)	(0.78)	(0.93)	(0.42)
Per Capita Total Non-Covered Costs (dollars)					
Circulatory	.	-0.32	-0.73	-0.78	-0.50
	(.)	(0.75)	(0.47)	(0.43)	(0.62)
Digestive	-0.29	-0.47	-0.72	-0.70	-0.40
	(0.77)	(0.64)	(0.47)	(0.49)	(0.69)
Respiratory	-0.57	1.70*	-0.49	-0.63	-0.47
	(0.57)	(0.09)	(0.62)	(0.53)	(0.64)
Skin and Sense Organs	-0.34	-0.52	-0.47	-0.55	-0.19
	(0.74)	(0.60)	(0.64)	(0.58)	(0.85)

Note: The first row for each variable displays the t-statistic from the t-test of the mean between fracking and non-fracking counties, with p-value of the test shown in parentheses below. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 4.6. Average Treatment Effects on the Treated: Total Hospitalization Rate and Total Charges, All Population

Variable	Disease Category	Hydraulic Fracking (HF)	Boom
Hospitalization Rate (cases per 1000 persons)	Circulatory	-0.22	-0.28*
		(0.14)	(0.15)
	Digestive	-0.16	-0.29
		(0.74)	(0.69)
	Respiratory	0.39*	0.12
		(0.23)	(0.14)
	Skin and Sense Organs	0.11	0.27*
		(0.17)	(0.16)
Per Capita Total Costs ($)	Circulatory	-13.49	-24.78*
		(12.57)	(12.76)
	Digestive	13.96*	0.12
		(7.48)	(5.54)
	Respiratory	2.76	-1.86
		(18.36)	(18.54)
	Skin and Sense Organs	2.70	9.24
		(5.62)	(7.10)
Per Capita Total Non-Covered Costs ($)	Circulatory	-0.68	1.02
		(2.19)	(0.98)
	Digestive	0.02	1.92
		(1.47)	(1.79)
	Respiratory	-2.06	4.10
		(3.01)	(4.02)
	Skin and Sense Organs	-0.33	1.87
		(1.09)	(1.36)

Note: Standard errors in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 4.7. Average Treatment Effects on the Treated: Total Hospitalization Rate and Total Charges, by Age Group

Disease	Age 0 - 4		Age 5 - 9		Age 10 - 14		Age 15 - 19		Age 20 - 24	
	HF	Boom	HF	Boom	HF	Boom	HF	Boom	HF	Boom
Hospitalization Rate (cases per 1000 persons)										
Circulatory	-0.01	-0.01	-0.14*	0.06	-0.76	-0.81	-1.67	-3.89**	-1.16	0.64
	(0.02)	(0.01)	(0.07)	(0.10)	(1.00)	(0.98)	(1.53)	(1.47)	(1.09)	(0.64)
Digestive	-4.47**	1.44	0.65	1.56	-0.08	-1.36	0.58	-4.15	1.65	-0.85
	(2.17)	(1.99)	(0.65)	(1.17)	(2.21)	(2.20)	(6.37)	(5.93)	(2.31)	(2.57)
Respiratory	0.06	0.16	0.74	0.26	2.77	1.65	1.01	0.66	2.04	-0.94
	(0.12)	(0.20)	(0.77)	(0.55)	(1.69)	(1.23)	(1.23)	(1.12)	(1.52)	(1.28)
Skin and	-0.29	0.36	0.26	0.49	-0.66	0.27	2.05	2.79	0.37	0.17
Sense Organs	(0.49)	(0.64)	(0.46)	(0.46)	(0.92)	(1.12)	(1.65)	(2.28)	(0.58)	(0.40)
Per Capita Total Cost ($)										
Circulatory	-5.14	-2.14	-2.86	1.36	-67.41	-59.46	-61.65	-356**	-102.10	56.16
	(4.55)	(2.10)	(3.93)	(4.63)	(84.91)	(84.90)	(139.72)	(138)	(81.68)	(44.89)
Digestive	-3.86	-24.58	-3.64	8.59	135.00**	76.79*	50.25	-19.40	41.76	-57.82
	(22.20)	(24.18)	(35.11)	(14.68)	(55.99)	(45.59)	(69.10)	(63.01)	(73.27)	(67.49)
Respiratory	-22.13	64.99	5.16	1.49	18.67	-35.28	45.51	-65.04	36.37	38.83
	(49.82)	(59.04)	(30.71)	(19.45)	(75.35)	(70.40)	(150.80)	(150.20)	(75.67)	(94.42)
Skin and	-9.07	-1.68	-6.23	12.02	-32.73	10.15	86.74	118.62	8.25	-1.27
Sense Organs	(9.83)	(11.21)	(10.83)	(11.82)	(25.73)	(28.23)	(69.15)	(114.55)	(15.74)	(8.16)
Per Capita Total Non-Covered Cost ($)										
Circulatory	0.00	0.00	0.04	0.07	-26.01**	0.17	25.84	14.71	-13.62**	-3.34
	(0.00)	(0.00)	(0.04)	(0.07)	(11.31)	(1.81)	(30.88)	(13.48)	(5.64)	(3.10)
Digestive	-0.01*	-0.01*	5.68*	1.06	1.21	10.71	-13.83	20.23	15.00	1.37
	(0.01)	(0.01)	(3.31)	(1.14)	(6.71)	(8.60)	(17.93)	(23.16)	(9.32)	(2.14)
Respiratory	-1.32	3.77	0.24	1.27	-12.69	9.46	-16.94	36.89	-5.78**	0.57
	(2.39)	(2.58)	(0.72)	(1.30)	(10.30)	(11.25)	(27.92)	(38.66)	(2.93)	(0.91)
Skin and	1.18	2.29	3.33	11.31	-6.82	11.29	-2.32	1.84	0.08	0.21
Sense Organs	(1.16)	(2.20)	(5.87)	(10.39)	(10.27)	(12.24)	(1.95)	(2.20)	(0.17)	(0.34)

Note: Standard errors in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 4.8. Hodges-Lehmann Point Estimate Tests, All Population

		Hodges-Lehmann Point Estimate							
		Circulatory		Digestive		Respiratory		Skin, Sense Organs	
	Gamma	LB	UB	LB	UB	LB	UB	LB	UB
Hospitalization Rate	1.0	-0.195	-0.195	0.060	0.060	-0.241	-0.241	0.103	0.103
	1.1	-0.295	-0.095	**-0.040**	**0.160**	-0.441	-0.041	0.003	0.203
	1.2	-0.295	-0.095	-0.040	0.160	**-0.541**	**0.059**	0.003	0.203
	1.3	-0.295	-0.095	-0.040	0.160	-0.641	0.159	0.003	0.203
	1.4	**-0.295**	**0.005**	-0.140	0.260	-0.641	0.259	**-0.097**	**0.303**
	1.5	-0.395	0.005	-0.140	0.260	-0.741	0.359	-0.097	0.303
Total Per Capita Cost	1.0	-9.977	-9.977	-0.041	-0.041	1.085	1.085	0.679	0.679
	1.1	-12.677	-7.077	**-1.141**	**1.559**	**-3.615**	**4.585**	**-0.121**	**1.479**
	1.2	-14.577	-4.877	-2.541	3.359	-6.315	8.285	-0.821	2.179
	1.3	-15.877	-2.677	-4.041	4.659	-9.515	11.785	-1.421	2.879
	1.4	-17.977	-1.077	-5.041	5.659	-12.615	14.385	-2.021	3.579
	1.5	**-19.677**	**0.523**	-5.641	6.859	-15.815	17.285	-2.421	4.179
Total Per Capita Non-Covered Cost	1.0	-0.259	-0.259	-0.032	-0.032	-0.007	-0.007	0.094	0.094
	1.1	**-0.359**	**0.041**	**-0.132**	**0.068**	**-0.107**	**0.093**	**-0.006**	**0.194**
	1.2	-0.359	0.041	-0.132	0.068	-0.107	0.093	-0.006	0.194
	1.3	-0.359	0.041	-0.132	0.068	-0.107	0.093	-0.006	0.194
	1.4	-0.359	0.041	-0.132	0.068	-0.107	0.093	-0.006	0.194
	1.5	-0.359	0.041	-0.132	0.068	-0.107	0.093	-0.006	0.194

Note: Treatment used for the tests is fracking, i.e. whether a county has hydraulic fracturing activity or not. Results for treatment being "boom" is available upon request. Gamma is Odds of Differential Assignment to Treatment Due to Unobserved Factors. LB and UB are respectively the lower and upper bound of the interval of p-values for a certain gamma value.

Table 4.9. Wilcoxon Signed Rank P-Value Tests, All Population

	Wilcoxon Signed Rank P-Value								
		Circulatory		Digestive		Respiratory		Skin, Sense Organs	
	Gamma	LB	UB	LB	UB	LB	UB	LB	UB
Hospitalization Rate	1.0	0.013	0.013	0.293	0.293	0.309	0.309	0.158	0.158
	1.1	0.006	0.028	0.194	0.409	0.207	0.427	0.094	0.246
	1.2	0.002	0.052	0.125	0.523	0.134	0.541	0.054	0.344
	1.3	0.001	0.085	0.078	0.626	0.085	0.644	**0.030**	**0.444**
	1.4	**0.000**	**0.128**	**0.047**	**0.714**	0.052	0.730	0.016	0.541
	1.5	0.000	0.179	0.028	0.787	**0.031**	**0.800**	0.009	0.629
Total Per Capita Cost	1.0	0.104	0.104	0.505	0.505	0.458	0.458	0.389	0.389
	1.1	0.058	0.173	0.381	0.628	0.337	0.584	0.275	0.513
	1.2	**0.031**	**0.255**	0.277	0.731	0.239	0.691	0.187	0.626
	1.3	0.016	0.346	0.195	0.811	0.164	0.778	0.124	0.721
	1.4	0.008	0.438	0.134	0.871	0.110	0.845	0.080	0.798
	1.5	0.004	0.527	0.090	0.914	0.072	0.894	0.051	0.856
Total Per Capita Non-Covered Cost	1.0	0.086	0.086	0.777	0.777	0.383	0.383	0.719	0.719
	1.1	0.056	0.126	0.698	0.842	0.290	0.484	0.634	0.794
	1.2	**0.036**	**0.171**	0.618	0.890	0.215	0.576	0.550	0.851
	1.3	0.024	0.221	0.539	0.925	0.157	0.658	0.471	0.894
	1.4	0.015	0.273	0.465	0.949	0.113	0.728	0.398	0.925
	1.5	0.010	0.326	0.397	0.965	0.081	0.786	0.334	0.947

Note: Treatment used for the tests is fracking, i.e. whether a county has hydraulic fracturing activity or not. Results for treatment being "boom" is available upon request. Gamma is Odds of Differential Assignment to Treatment Due to Unobserved Factors. LB and UB are respectively the lower and upper bound of the interval of p-values for a certain gamma value.

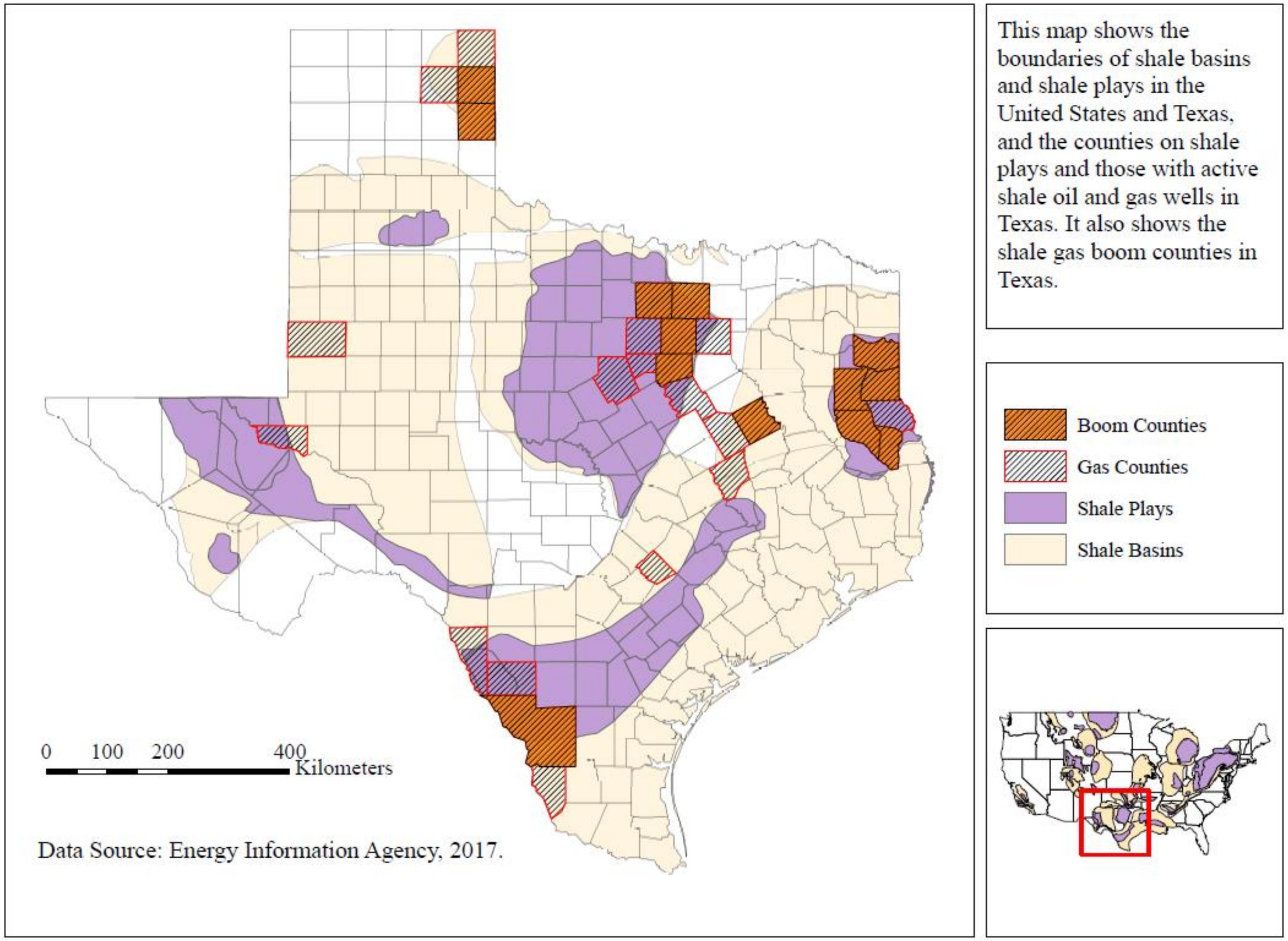

Figure 4.1. Shale Oil and Gas Map of Texas between January and June 2010

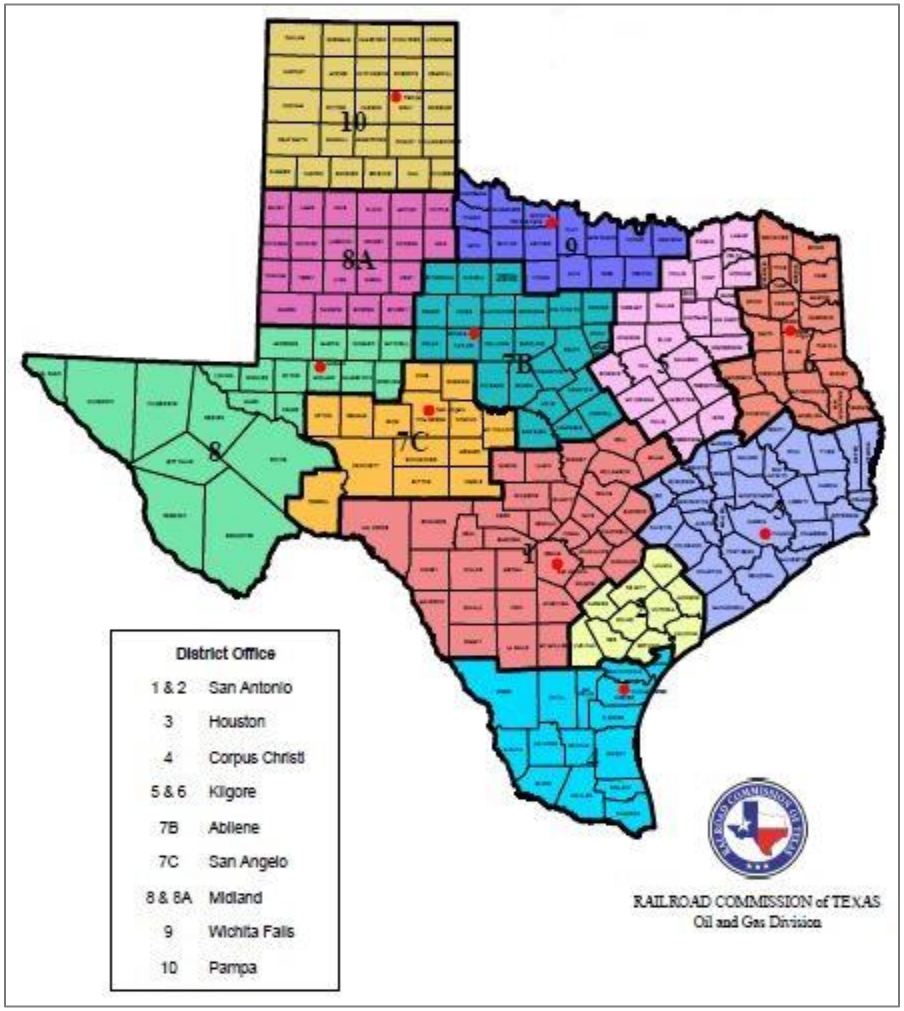

Figure 4.2. Oil and Gas Division District Boundaries of Texas

CHAPTER 5

CONCLUSION

During the past 25 years, there has been a dramatic increase in both the frequency and intensity of hydro-meteorological disasters worldwide. In the years to come, tropical cyclones are likely to become both stronger and more frequent, especially in the western North Pacific, where storms can devastate the heavily populated coastlines of Asian nations. The same holds true for the North Atlantic, where about 12 percent of the world's tropical cyclones spin each year (Emanuel 2013). The 2005 hurricane season in the U.S. had 27 named storms; 14 were hurricanes out of which three were category 5 – the most Category 5 hurricanes recorded in a single season, and Hurricane Katrina alone induced over $100 billion total losses (NOAA National Centers for Environmental Information 2006). Hill et al. (2009) estimate that for each billion ethanol-equivalent gallons of fuel produced and combusted in the U.S., the combined climate-change and health costs are $469 million for gasoline and $472–952 million for corn ethanol depending on biorefinery heat source (natural gas, corn stover, or coal) and technology.

Despite these large costs and potential risks of climate change, the concern reported by citizens and government officials in the U.S. has lagged behind (Jones 2014). Given that mitigating climate change is a global public good and greenhouse gas emissions from the burning of fossil fuels is the primary human activity affecting the amount and rate of climate change (IPCC 2007), it is necessary that public policies support and guide the direction of energy development in a path towards carbon neutrality. Currently in the U.S., there is much uncertainty about the direction of energy policy and even about the merits of a transition into a clean energy future. The two main policies of previous administrations - the Clean Power Plan and the Renewable Portfolio Standards - are highly contested and undergoing deep revisions from the new administration since January 2017. In the meantime, hydraulic fracturing and horizontal drilling techniques used to extract shale oil and gas have been accepted as an intermediate energy source and a bridge towards a renewable future and energy independence. However, studies have shown that there are potentially large local costs from this technology, such as earthquakes (Weingarten et al. 2015), water contamination (Muehlenbachs et al. 2015), air pollution (Annevelink et al. 2016), and subsequent health problems (Rasmussen et al. 2016).

Amidst the political and judicial turmoil facing climate change regulations, this dissertation examines the public perception of different energy development options and technologies in the United States. In its three essays, I investigate the perceived and realized impacts of a range of negative externalities resulting from non-renewable energy development. First, I examine the reactions of the stock returns of energy companies to new information about climate change in hurricanes, which can alter investors' beliefs about the companies' potential profitability and value. Then, I study the external costs of hydraulic fracturing in both housing and health care markets of the local communities where this activity takes place to investigate the distribution of welfare changes in the communities directly affected by fracking.

In the first essay, I estimate the abnormal returns of the stocks of leading energy companies in the U.S. after four notorious hurricanes. I used an event study methodology along with a regression approach including companies of differing carbon intensity (coal, oil, natural gas, and renewables) to detect the subtle differences among the perception of carbon-intensive sectors and cleaner sectors. Empirical results suggest that energy stock investors have not responded significantly to large hurricanes in the Atlantic seasons. However, after the most recent hurricane Sandy in 2012, they did seem to prefer equities in the renewable energy sector over those whose businesses are heavily dependent on coal.

By investigating a large number of companies with market power in each energy sector, we increase the internal validity of our results. The significant contrast of the abnormal returns between coal and renewable energy sectors provides a signal for fossil fuel dependent companies to care for climate change and take actions to reduce their carbon emissions now. In fact, on April 13, 2017, it was announced that ExxonMobil shareholders requested that beginning in 2018, the company publish an annual assessment of the long-term portfolio impacts of technological advances and global climate change policies. In times when the government ignores reality and attempts to undermine the efforts to combat climate change, calamitous and highly salient hurricanes might provide a signal and influence future climate policies.

The second and third essays in this dissertation focus on the environmental impacts of unconventional oil and gas development in the U.S., from the perspective of housing and health care market, respectively. The commercial use of horizontal drilling and hydraulic fracturing techniques in the United States has substantially increased domestic production of natural gas and oil since the mid 2000s (EIA 2017). This can boost US energy independence, increase local employment, residential and government revenue, local labor market competitiveness, and immigration. However, this technology has also caused various environmental and health concerns. One of the concerns is the recent dramatic increase of earthquake shocks in unconventional oil and gas producing areas in the Central and Eastern United States, particularly in Oklahoma. Weingarten et al. (2015) has found that 80% of the earthquakes of magnitude 3 and plus between 2009 and 2013 in Oklahoma were induced by wastewater injection, the primary option to process wastewater which is formed when producing shale oil and gas.

In the second essay, we identify the different impact categories associated with shale gas production and wastewater injection, and use a difference-in-difference hedonic model to estimate the impacts of induced earthquakes on housing prices in Oklahoma county, Oklahoma. Results show that properties with active injection wells within 2 km depreciated 2.15% after the magnitude 5.6 Prague earthquake in 2011. This devaluation is only observed for wastewater injection wells but not for shale oil and gas producing wells, suggesting that Oklahomans were able to distinguish the two types of wells and correctly relate earthquakes with the causes. The decline in property values shows that hydraulic fracturing and shale gas development could potentially cause economic losses offsetting the benefits, and thus, needs to be carefully and comprehensively assessed. In terms of welfare distribution and compensation, policy makers might enact a proportional tax on shale gas operators' operating revenue and use it to subsidize homeowners when they purchase earthquake insurance.

In addition to housing market impacts, a number of researcher in epidemiology have started to examine the link between hydraulic fracturing and public health conditions. Household surveys and longitudinal studies have shown that it is related with a variety of diseases, and respiratory symptoms are the most common. Jemielita et al. (2015) find that in Pennsylvania, cardiology inpatient prevalence rates were significantly higher for zip codes with higher number of wells and neurology inpatient prevalence rates were significantly associated with wells per square km. Peng et al. (2016) extend this research to the entire state of Pennsylvania and focus only on five respiratory conditions. They find significant associations between shale gas development and hospitalization rates for acute myocardial infarction, pneumonia, and upper respiratory infections.

The third essay in this dissertation focuses on Texas, the state with the most number of counties involved in fracking and most wells, and investigates the health care costs of major short-term health conditions that are likely caused or exacerbated by nearby shale oil and gas development: circulatory, digestive, respiratory, and skin and sense organs. Using a genetic matching algorithm, we match counties with shale gas development with those without shale gas extraction and calculate the average health care impact of fracking (shale boom) during January – June 2010.

Results show that all age groups combined, counties with shale gas development had a higher hospitalization rate for respiratory diseases, and boom counties had higher percentage of people with skin and sense organ diseases but lower percentage of patients with circulatory conditions. The per capita total costs are $13.96 higher for digestive diseases in fracking counties but $24.78 lower for circulatory diseases in boom counties. There is no significant impact of fracking on the total costs of other types of short-term diseases or any type of total per capita non-covered costs. Analysis by age group indicates that there is significant heterogeneity in the health care effects of shale gas development. A sensitivity analysis indicates that our results are sensitive to hidden bias. This might be due to the fact that we only have a small number of counties with shale gas development and the patients are all very young.

Through the lenses of environmental disasters, in the first two essays I exploit public perception of the negative impacts of energy development in the United States in the past 25 years, especially the recent 10 years. The results support that hurricanes in recent times have led to significant negative excess returns to carbon intensive energy stocks; and that earthquakes have lowered housing values adjacent to injection activity. These results are supportive of the hypotheses that the development and consumption of fossil fuels have resulted in negative externalities: climate change and seismicity risk. Regarding the former, the negative excess returns following hurricanes (one of the most salient impacts of climate change) are observed in carbon intensive energy stocks but not renewable energy. Regarding the latter, the seismicity risk associated with wastewater injection is found to be significant for houses located within 2 km away from an injection well but not in farther distances. It can help guide energy and climate policies that aim at sustainable development with the lowest costs, and equal and fair welfare distribution.

In the future, I should try to expand the scope of the studies in both time and space, and improve the fit of the models. With more recent large hurricanes, I may find more significant negative returns for carbon intensive energy stocks after the event, and by further exploring public's willingness to go green, I may be able to disentangle possible transmission mechanisms from hurricanes to stock markets – consumer demand for cleaner energy, or regulatory pressure for tighter legislation. For the housing market impacts of wastewater induced seismic risk, I may be able to disentangle the risk of earthquakes from the actual damage from earthquakes with details of the earthquakes, and particularly focus on recent frequent and large earthquakes. Also, I should examine separately the impact of being near an epicenter to being near an injection well to detect any misperception of earthquake risk, or the other disamenities associated with injection wells. The results of the third study are quite puzzling and sensitive to hidden bias. Future research should extend the time horizon to a long panel and examine the costs overtime to capture any potential unobservables that are time variant. Also, the sample should be expanded to include more geographic units to match at a larger level such as district to detect any spillover effect, and include patients from all ages which will give us a better picture and more accurate estimate of the costs to the entire population.

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