June 2017

The Impact of Environmental Policies and Innovation on the Investment in and Use of Natural Gas-Fired Combined Cycle Generators in the US Electricity Sector

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Recommended Citation

Stevens, Kelly Ann, "The Impact of Environmental Policies and Innovation on the Investment in and Use of Natural Gas-Fired Combined Cycle Generators in the US Electricity Sector" (2017). *Dissertations - ALL*. 751.
https://surface.syr.edu/etd/751

ABSTRACT

Developments over the past thirty years have contributed to increased natural gas generation in the US electricity sector. As a result, natural gas generation surpassed coal for the first time in history in 2016. In addition to low natural gas prices, developments with the natural gas-fired combined cycle generator (NGCC) have contributed to the rise of natural gas. In the 1990s, technological innovations led to substantial efficiency gains for NGCC, rendering these generators cleaner and more efficient than other widely available sources of power generation during that period. In the early 2000s, the US experienced the largest short-term increase in generation capacity in history, with over 70% of this new capacity installed as NGCC. Initially, much of the new NGCC capacity only provided power when energy demand was at its highest. Since 2003, NGCC utilization has nearly doubled, and NGCC is increasingly used to provide baseload power. The purpose of this dissertation is to scrutinize these developments with NGCC to better understand how energy and environmental policies influenced the time and location of capacity changes, how this capacity has been used, and the role of technology on both.

The first essay in this dissertation evaluates the impact of a government-sponsored research program on NGCC innovations in the 1990s. From 1992-2000, the Department of Energy partnered with two US turbine manufacturers, General Electric (GE) and Siemens Westinghouse Power Corporation (SWPC), in a cost-sharing program called the Advanced Turbine System to stimulate efficiency innovations for NGCC technology. Using data from the European Patent Office’s worldwide patent database (PATSTAT), I evaluate innovative activity in advanced turbine technology by the program participants and their competitors. Using a negative binomial model, I find GE increased the volume of their patents towards the end of the program and afterwards, while SWPC had higher patent citations for patents filed during the program relative to competitors. These observed changes in patenting activity merit further

investigation into why these changes took place, and how the resulting patents translated into commercialized technologies in the US and abroad.

The second essay evaluates the impact of policy anticipation on natural gas capacity growth during a time in which substantial natural gas capacity came online. I hypothesize that areas expecting nonattainment designations resulting from changes in the ozone and particulate matter National Ambient Air Quality Standards (NAAQS) rushed to complete installations before new environmental regulations took place in 2004 and 2005. I use EIA and EPA data from 1997-2009 to evaluate the role of policy anticipation on capacity investment with difference-in-difference models. My results show areas expecting nonattainment designations had more natural gas capacity growth than areas not facing nonattainment, on the order of 10% for ozone and 13% for particulate matter, per year. This study thus finds that substantial investment in environmental technology may take place in anticipation of policy changes.

The third essay considers how this new natural gas capacity is being used. Recent climate regulations aim to increase utilization of NGCC generators to offset coal generation and, consequently, reduce carbon emissions. There have been substantial increases in utilization for some NGCC generators in the last ten years, but most remain below baseload levels. This paper examines the factors that have driven NGCC utilization to date. I use a random-effects model to evaluate the relationships between environmental policies and natural gas prices on NGCC utilization. I find that both low natural gas prices and cross-state air pollution policies drive increases in utilization; however, the size of the impact by the environmental policies depends on the age of the plant. I use the estimates from this model for a counterfactual analysis which reveals the cross-state air pollution policies have had nearly three times the impact of low natural gas prices on utilization from 2003-2014.

The Impact of Environmental Policies and Innovation on the Investment in and Use of Natural Gas-Fired Combined Cycle Generators in the US Electricity Sector

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Submitted in partial fulfillment of the requirements for
the degree of Doctor of Philosophy in Public Administration

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June 2017

ACKNOWLEDGMENTS

I have many people to thank who supported me throughout this journey. I am deeply grateful to Peter Wilcoxen and David Popp who agreed to advise me throughout the PhD program and dissertation process. Pete exemplifies an extraordinary commitment to teaching, and I learned as much about energy economics as I did about teaching and advising through my regular interactions with him. I have long appreciated Pete and David's ability to think outside the box and withhold the answer, from which I benefitted greatly. They both allowed me room to pursue the research topics that interest me, and I appreciate their patience as I, sometimes slowly, learned the way. I consider myself particularly lucky because they are not only great academics, but truly great people.

I would also like to thank my other committee members – Harry Lambright, Sarah Hamersma, Inês Azevedo, and Sarah Pralle. I have learned so much from each of them in their different subject areas, and I am very grateful for their time and advice along the way. I am especially grateful to Inês for hosting me as a visiting student at Carnegie Melon University with the Engineering and Public Policy Department. CMU was my academic home away from home, and I benefitted from the exciting environment and research in EPP while living in Pittsburgh. Back at Syracuse, I am grateful to the staff and faculty members in the Center for Policy Research and Center for Environmental Policy and Administration for their helpful and friendly support over the years.

I am also thankful for Vice Admiral Robert Murrett, whom I had the privilege to work for as a teaching assistant for more than a few years at Syracuse University. Bob not only wrote many recommendation letters for me, but also served as another excellent example and mentor for teaching. I would also like to thank Paul Ruscher who continues to mentor and inspire me since my days working with him at Florida State University in meteorology.

The dissertation and PhD process can be rather lonely and frustrating at times, and I appreciate the many people that helped to make it a little less so. I am thankful for my talented, funny, and empathetic colleagues at Maxwell, such as Jung Eun Kim, Lincoln Groves, Zach Huitink, Qing Miao, Judson Murchie, and Tian Tang for their advice and friendship. I would also like to thank my friends in upstate New York for finding creative ways to celebrate the unfortunate weather, and my friends outside the area for allowing me an excuse to leave Syracuse for a visit. My in-laws have been wonderfully supportive throughout the relatively short, but busy time they have known me. My parents, Thom and Sharon, who traveled near and far to attend every soccer game, track meet, and marathon of mine that they could, continue to amaze me with their unwavering love and support. There were many twists and turns on my journey here, but the values and work ethic I learned from them are the source of my success. Finally, I want to thank my husband, John Hanley, who shared every burden and joy I experienced throughout this process without complaint. He continually inspires me to keep growing. I will always be grateful to this cloudy city for bringing the two of us together.

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CHAPTER ONE:

Introduction

Changes in technological innovation, resource availability and prices, national security, environmental concerns, and politics jointly create a complex and dynamic environment at the nexus of energy and environmental issues. As a result, periods of significant change are common in the energy and environmental sector. Multifaceted developments over the last thirty years have contributed to important developments for natural gas-fired power plants. While coal generation was once the dominant source of electricity in the US, in 2016 natural gas generation surpassed coal for the first time in history.[1] Since natural gas generation has lower direct emissions of conventional pollutants and carbon dioxide than coal, this substitution has had important consequences for the environment. The rise of natural gas generation is due in large part to hydraulic fracturing, which has been able to recover abundant domestic supplies of natural gas resulting in low natural gas prices since 2009. However, changes in natural gas generation technology, energy policy, and environmental policy have also played a part in the current natural gas revolution. Consequently, accounts focused solely on low natural gas prices[2] or President Obama's Clean Power Plan[3] for "killing" coal are mistaken. This dissertation focuses on several of these other developments contributing to the rise in natural gas generation.

The importance of factors other than natural gas prices can be seen in Figure 1. Figure 1 shows the efficiency of coal versus natural gas in the US electricity sector since the early 1950s,

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[1] EIA Today from April 20, 2017: https://www.eia.gov/todayinenergy/detail.php?id=30872

[2] Newsweek article October 8, 2016, "Coal industry is dying, no matter what a President Trump would do." Available at: http://www.newsweek.com/coal-industry-dying-no-matter-trump-507079

[3] Remarks by President Donald Trump signing the Executive Order to Create Energy Independence (March 28, 2017): https://www.whitehouse.gov/the-press-office/2017/03/28/remarks-president-trump-signing-executive-order-create-energy

calculated as a ratio of actual energy output to fuel energy input.[4] Until 2000, coal and natural gas efficiency were quite similar, but low. Average efficiencies for much of this time period hovered around 32%, meaning over two-thirds of the spent fuel was essentially wasted in electricity generation. Improved efficiency translates into lower emissions and lower costs as less fuel is lost in the process of making electricity. From 1950-1990, most natural gas generation came from steam-turbines and single-cycle gas turbines, with efficiencies around 30%.[5] However, in the 1990s, natural gas-fired combined cycle generators (NGCC), with efficiencies closer to 40-50%, became a more common source of natural gas generation. Beginning around 2000, net natural gas efficiency markedly improved while coal efficiency remained flat. This efficiency improvement for natural gas is primarily due to developments that increased the presence and use of NGCC for power generation in place of less efficient steam and single-cycle gas turbines.

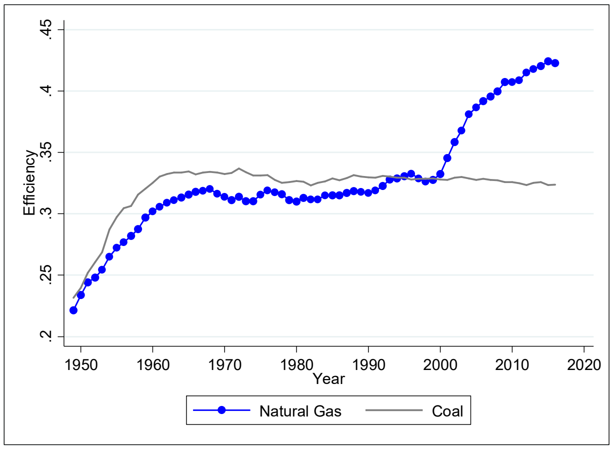

Figure 1: Average efficiency of natural gas compared to coal in the US on an energy output: energy input basis. Computed using data from the Energy Information Administration (EIA).

An NGCC unit includes both a gas turbine and heat recovery steam turbine that reuses the waste heat from the gas turbine to generate additional electricity (Figure 2). In a single-cycle

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[4] $Efficiency = \frac{Energy\ Output\ (kWh)}{Energy\ Input\ (kW\ \ )} = \frac{Net\ Generation\ (kWh)}{Fuel\ Consumed\ (ft^3)*heat\ content\ \left(\frac{BTU}{ft^3}\right)*\frac{1\ kWh}{3{,}412\ BTU}}$

[5] EIA Today April 20, 2017, available at https://www.eia.gov/todayinenergy/detail.php?id=30872.

gas turbine the exhaust heat from the gas turbine escapes and goes unused. In NGCC, the reuse of waste heat to generate steam for a steam turbine makes the system more efficient. This dissertation discusses the three main developments with NGCC contributing to the overall rise of natural gas efficiency compared to coal: (1) technological improvements of NGCC generators, (2) rapid increase in NGCC capacity from 2000-2004, and (3) increased utilization of this capacity for power generation.

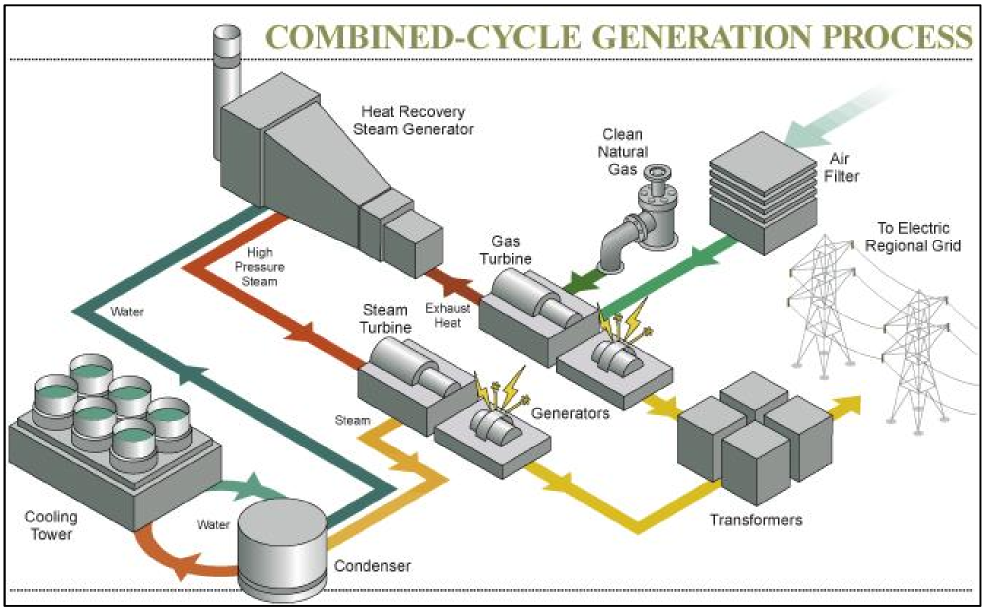

Figure 2: NGCC generation process, courtesy of Rolling Hills Generating.[6]

The first essay (Chapter 2) explores the technological innovation of NGCC power plants, which has rendered them much more efficient than conventional coal-fired generators. This chapter describes the history of NGCC innovation and evaluates the impact of a Department of Energy program on NGCC innovation in the 1990s. The program, called the Advanced Turbine System program was a cost-sharing partnership with two NGCC turbine manufacturers, General Electric (GE) and Siemens Westinghouse Power Corporation (SWPC), to create new NGCC plants to reach 60% efficiency. I find that changes in patenting activity by the program

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[6] Image source: http://insights.globalspec.com/article/2895/combined-cycle-power-plants-is-their-reign-assured.

participants varied by company: GE experienced a statistically significant increase in patenting towards the end of the program, while SWPC had patents with higher citations for a few years early in the program.

The second essay (Chapter 3) considers changes in NGCC capacity in the US. This component is the largest contributor to the increase in net efficiency for natural gas shown in Figure 1. From 2000-2004, the US experienced what has been called the natural gas capacity boom, a period with the largest short-term increase in generation capacity in US history. As a result, NGCC became the dominant source of natural gas generation, and it is significantly more efficient than single-cycle gas turbines or gas-fired steam turbines. Chapter 3 explores the impact of environmental policies on determining where this new NGCC capacity was built. This study finds that anticipation of new environmental regulations to meet more stringent air quality standards played a statistically significant role in determining where new NGCC generators were built during this period.

The last factor contributing to this rise in natural gas efficiency is driven by how much the new, more efficient NGCC generators are run. Chapter 4 considers the impact of low natural gas prices and environmental policies on NGCC utilization. Until recently, the average NGCC plant operated approximately 20-30% of the time, providing power only when energy demand was high. However, low natural gas prices and air pollution policies doubled NGCC utilization to about 50% by 2014. This chapter uses a random-effects model to measure the impact of environmental policies versus low natural gas prices on NGCC utilization, finding that cross-state air pollution policies had an effect three times the size of low natural gas prices on NGCC utilization. Chapter 5 summarizes the findings from Chapters 2-4, and the impacts these finding may have on the future for natural gas and directions for further research.

CHAPTER TWO:

Natural Gas Combined Cycle Innovations in the US: The Impact of the Advanced Turbine System Program

1. Introduction

In 2016, natural gas-fired generators provided just over 33% of all electricity generation in the US, surpassing coal-fired generation on an annual basis for the first time in history.[7] While the increased use of natural gas for generation is attributable to many factors, one important aspect is the technological improvements rendering natural gas-fired combined cycle generators (NGCC) relatively clean, efficient, and cheap. Efficiency improvements by advanced NGCC generators have been described as "the most important efficiency gains in electricity generation in modern times" (Newell, 2011). Since the inception of NGCC in the early 1940s, efficiencies of the system have vastly improved from 25% to 62% percent by 2016.[8] According to a Department of Energy (DOE) study by Michael Curtis (2003), an increase of a single percent point in thermal efficiency for a typical-sized NGCC plant (400-500 MW) can reduce operating costs by as much as $20 million over the life of the plant.

The Curtis study suggests that NGCC efficiencies increased substantially during the time period of the DOE's Advanced Turbine System (DOE-ATS) program from 1992-2000. The program was a cost-sharing, public-private partnership with two domestic natural gas manufacturers, General Electric (GE) and Siemens Westinghouse Power Corporation (SWPC), to improve performance of gas turbines and NGCC beyond the current technological limits at that time. DOE provided a total of $315 million and its private sector partners provided an

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[7] Which can be seen using Energy Information Administration's Electricity Data Browser, available at: http://www.eia.gov/electricity/data/browser.

[8] The1940s NGCC efficiency statistic is provided by Hirsch (1999), and the GE 7HA NGCC product line brochure provides the latest efficiency statistic, available at https://powergen.gepower.com/products/heavy-duty-gas-turbines/7ha-gas-turbine.html.

additional $155 million (National Research Council, 2001). The National Research Council (2001) argues that "DOE has been instrumental in accelerating the highly cost-shared development of gas turbines that have both high efficiencies and low NOx [nitrogen oxide] emissions." Curtis describes the innovations during the program as "breakthrough" and "transitional" for leading to the development of complex technologies significantly different from their predecessors (2003).

There are various reasons and means for government to sponsor research and development (R&D), and different degrees of success have been determined in the evaluation and review of these programs (David et al., 2000). DOE created the ATS program to overcome market failures created by deregulation of the electricity industry and low natural gas prices, which had been barriers to private R&D by domestic suppliers of electric generation equipment. A second objective was increased energy independence, amidst a renewed interest in energy security. Additionally, the program aimed to stimulate US competitiveness against foreign manufacturers by producing cleaner, more efficient, and lower cost gas turbines and NGCC generators (Curtis, 2003).

Curtis also states that interviews with industry members involved with DOE-ATS indicated that this type of research was not previously being done in the US, and that the program advanced turbine innovations by 5-10 years. He describes the program as a successful public-private partnership because the two turbine manufacturers commercialized turbines meeting the program objectives during or shortly after the program (Curtis 2003).

The focus on direct outputs by the program, in this case commercialized technology, does not address the common concern regarding public R&D programs, which is that they substitute for private R&D that would otherwise take place (David et al., 2000). Government programs such as this one are often derided as “corporate welfare,” with low social benefit but high private returns for the companies involved. Therefore, it is useful to study the innovative activity in this field before and after the program by the program participants *and* their competitors for a more informative determination of the program impact.

As a measure of innovation, I compare patenting activity by the two companies involved with the program to other firms patenting in these fields during the same period. Through econometric analysis using patent and citation counts, I evaluate the claims that the program advanced innovation for the participants relative to their competitors. I find that GE and SWPC responded somewhat differently to the program in terms of quantity and impact of their patents. GE increased their patenting towards the end and after the program, with little to no statistically significant increase in their citation counts. For SWPC, there were a few years during the program when the patents they produced had higher citations, but the patent quantity only increased relative to domestic patenting activity.

Additionally, this paper sheds light on the efficiency gains by NGCC generators by tracing the technological developments through patent research. The efficiency gains had important consequences when at the turn of the twenty first century their popularity exploded in what has been called the natural gas capacity buildout, the largest three-year period of capacity growth in US history (Figure 1) (Joskow, 2006).

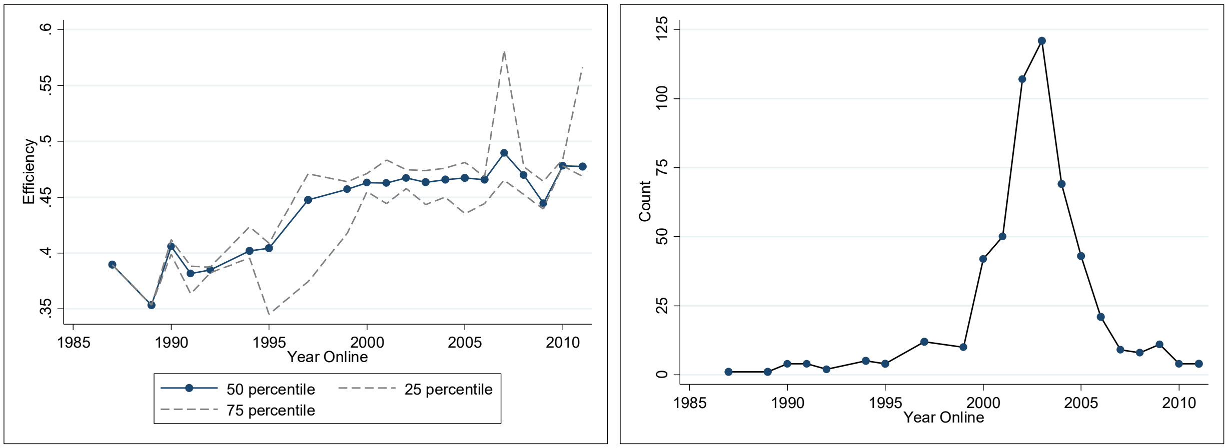

Figure 1: (left) Percentiles for NGCC plant efficiency based on a sample of NGCC plants in the US weighted by capacity. The chart is created using calculated plant efficiency using reported annual heat rates in EPA's eGRID for the years 2005, 2007, 2009, and 2012, and organized by the year the plant came online. It is important to note that there were a different number of plants and observations by year online, which is represented as the count of observations in the right graph.[9]

The paper proceeds with an overview of the existing literature on the DOE-ATS program, as well as a brief history on NGCC development and use. Section 3 describes the nature of patent research as an indicator of innovative success, and the hypotheses I develop to measure program success using the patent data. In Section 4 I describe the patent data and econometric method I use before presenting the results in Section 5. Section 6 summarizes the findings and directions for future research.

2. The DOE-ATS Program

2.1 The Motivation for DOE-ATS

2.1.1 Policy Changes

In the past, government has played an important role in promotion of new technologies through the innovation, adoption and commercialization stages to address common market

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[9] The spike in the 75 percentile efficiency for plants built in 2007 and 2011 were verified: the 2007 spike is from the Lake Side Power Plant in Utah, a Siemens Westinghouse design NGCC boasting 57% efficiency, while the 2011 spike is from the Kleen Energy Center NGCC with Siemens STG6-5000F combustion turbines, cited for reaching over 57% efficiency. These observations stand out primarily because there are fewer NGCC plants that came online after the natural gas buildout from 2000-2004.

failures. One approach is to stimulate or provide research and development funding through various means to overcome barriers to investment such as environmental externalities, market uncertainty, or free-riding on public benefit of knowledge creation (Popp, 2010). The 1992 Energy Policy Act (EPACT) authorized the DOE-ATS program as a collaborative, cost-sharing program with industry to stimulate US turbine manufacturing business, and to overcome market failures for the development of more efficient natural gas-fired generators.

Initially, gas turbines for electricity supply were developed as peaking units— to provide energy only when demand was at its highest— and were therefore small and infrequently used. While these systems could be made rather quickly and cheaply as compared to coal and nuclear power plants constructed in the 1950s-1970s, they were not very reliable or efficient, in part because they were only used for short periods of time (Hirsch, 1999). The introduction of opportunities for competition in electric generation through the Public Utility Regulatory Policies Act (PURPA) of 1978 changed that. Under PURPA, independent power producers (IPPs, or non-utilities) could now challenge the utility monopolies to provide power with what the Act designated as "qualifying facilities" (Hirsch, 1999). Specific types of efficient, small fossil-fuel generators or renewable power plants that met the definition of a qualifying facility were exempt from a selection of rules to which utilities were subject. This led to the development of the NGCC system, which exploits the waste heat from a gas turbine by using a heat recovery steam turbine for increased efficiency and power output. IPPs invested more heavily in these quickly built, low-cost natural-gas fired generators than did utilities, which benefitted from economies of scale in producing large coal and nuclear power plants for baseload power (Hirsch, 1999).

The 1990-91 Gulf War prompted Congress and the President to develop a series of energy policy initiatives seeking energy independence and promotion of domestic fuels. In October of 1992, Congress passed the Energy Policy Act (EPACT), refocusing attention to energy conservation and efficiency and enhancing what PURPA had set out to do. EPACT and several Federal Energy Regulatory Commission (FERC) orders opened transmission lines to competing generators, in accordance with President George H. W. Bush's preferred, market-based approach to energy regulation. Despite PURPA, many vertically integrated utilities still had a monopoly over power generation within their region. EPACT permitted exempted wholesale generators to operate and sell electricity into the grid without restriction, while FERC's orders included new requirements to make transmission information and access more available (Joskow, 2006). This new set of rules further encouraging competition meant utilities were subject to new incentives and optimization decisions as compared to their days of operating with little to no competition.

In addition to these federal energy policy changes, multiple states were choosing to go even further to encourage competition by adopting wholesale electricity deregulation. This involved a multi-year process of writing rules for restructuring and setting up electricity markets, which created uncertainty in the timing and effectiveness of the markets being designed (Craig & Savage, 2012). This had the overall effect of suppressing new capacity growth for several years as deregulation played out,[10] making electric equipment manufacturers more hesitant to invest in innovations for new technologies. Sanyal and Ghosh (2013) evaluate the impact of deregulation

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[10] The Annual Energy Outlook report for 1995 from the Energy Information Administration is available at: http://www.eia.gov/forecasts/aeo/archive.cfm.

on innovative activity by these upstream electric equipment manufacturers.[11] They find there was a significant drop in innovative activity, measured in patent counts, by the upstream electric equipment manufacturers following EPACT despite a boom in innovation for other technologies in different fields at that time. Additionally, they find that the quality of the innovations suffered as well from the introduction of downstream competition, supporting DOE's concerns about the impact of deregulation on R&D by manufacturers.

Moreover, natural gas prices were low following deregulation of the natural gas industry in the 1980s (Figure 2). While low prices made natural gas-fired generators more economically attractive to buyers, it also reduced incentives for R&D for efficiency improvements. Government[12] and industry believed natural gas prices would remain low for years, rendering natural gas-fired generators the technology choice for new capacity once investment resumed (Joskow, 2013; Curtis, 2003). However, natural gas prices began to rise as demand caught up with supply, requiring production from more expensive sources, imports from Canada, and additional pipeline infrastructure from 2000-2008. Natural gas prices dropped again with hydraulic fracturing and increased supply of unconventional natural gas in the US by 2009 (Joskow, 2013).

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[11] They evaluated manufacturers of boilers, flue gas desulfurization units, and low nitrogen oxide control burners. Some of these manufacturers, such as General Electric, also manufactured gas turbines, but the technology selection is different than the one in this study.

[12] The Annual Energy Outlooks for years 1992-1996, available at: http://www.eia.gov/forecasts/aeo/archive.cfm.

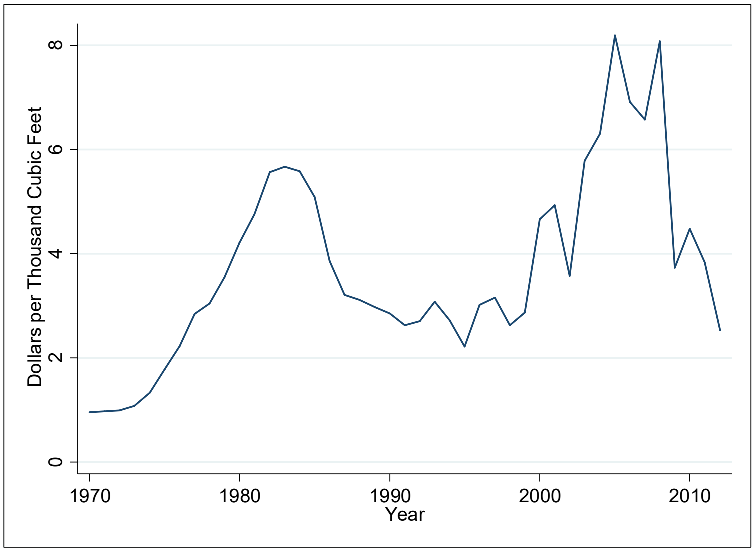

Figure 2: US natural gas wellhead price in dollars per thousand cubic feet, in 2010 dollars, using data from the US Energy Information Administration (EIA).

2.1.2 Gas Turbine Manufacturing

Gas turbines were originally designed in the 1930s for aircraft, and then adapted in the 1950s for power generation (Hirsch, 1999). There continues to be some spillovers between R&D work for jet engines to electric generators, as several companies that specialize in aerospace manufacturing also service or manufacture gas turbines for electricity generation (Bergek et al., 2008). Just prior to EPACT, an intense technology race for gas turbine manufacturing developed. From 1987-1991, US turbine manufacturer General Electric held the largest global market share at 28%, while Asea Brown Boveri (ABB) (Switzerland, 18%), Siemens (Germany, 19%), Mitsubishi (Japan, 13%), and Westinghouse (US, 5%) held much of the remaining market share (Bergek et al., 2008). Two smaller US turbine manufacturers had been bought out by foreign competitors: Combustion Engineering by ABB, and Allison Engine Company by Rolls-Royce (United Kingdom). Additionally, US anti-trust authorities blocked Westinghouse from selling their heavy electric business to ABB in 1988. These developments caused concern about the health of the US gas turbine manufacturers staying competitive in the US and international markets (Curtis, 2003).

The government also expected high demand for new natural gas capacity once regulatory uncertainty surrounding deregulation wore off. Energy demand had been steadily increasing, and the government wanted US manufacturers to be poised to provide more efficient generators once power producers resumed investing in capacity (Curtis, 2003). Following EPACT, DOE expected a rise of IPPs, who favored natural gas generators, and an emphasis on efficiency by utilities and non-utilities as competition reshaped industry dynamics. As noted earlier, this projection came true as new natural gas capacity soared from 2000-2004, with 70% of this new capacity in the form of NGCC generators.[13]

2.2 DOE-ATS

For the reasons discussed above, EPACT authorized the creation of the DOE-ATS program as a cost-sharing partnership with industry to improve performance of gas turbines beyond existing technological limits. The program specifically aimed to achieve: (1) an efficiency of 60% on a lower heating value basis in combined-cycle models, (2) NOx emissions of less than 10 ppm without end-of-pipe controls, (3) a 10% lower cost of electricity, and (4) state-of-the-art reliability, availability, and maintainability levels. These would be significant improvements over the 50-53% efficiency and 40-50 ppm NOx emissions for NGCCs then operating (Curtis, 2002). These technological developments would be socially beneficial by decreasing emissions and resource use, which aligned with EPACT's overall aim for energy security and environmental benefits.

Congress supported the program with appropriations totaling $315 million, while industry provided approximately $155 million in the composite (National Research Council,

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[13] See Chapter 3 of this dissertation on the natural gas capacity boom.

2001). The goal of this program was to develop utility- and industrial-scale gas turbines that were reliable and available to the market by the year 2000. The focus on the programs was to promote research and development of advanced gas turbine systems, stimulate and develop knowledge networks between industry and the public sector, and create an industry-led program. The ATS project included collaboration among universities, industry, and government laboratories.[14] All aspects of the project were competitively bid; however, General Electric (GE) and Westinghouse prevailed as the two companies to develop improved gas turbine systems from the DOE-ATS program through the final phase of the program, and were the only two companies with patents resulting directly from the program (Curtis, 2003). In 1998 Westinghouse divested its Power Generation business to Siemens, and the company became the Siemens Westinghouse Power Corporation (SWPC) until renaming the company Siemens in 2002. In the acquisition, Siemens inherited Westinghouse's NGCC designs and the advanced technology that was developed during the DOE-ATS program (Curtis, 2003). However, new contract clauses with the US government required SWPC to use these intellectual property rights to manufacture US goods (Curtis, 2003).

Each of these companies took different approaches during the innovative process with DOE-ATS. GE primarily relied on its own internal capabilities and knowledge from organizations within GE's company and mostly benefitted from the additional research funds provided by DOE-ATS. GE benefitted from the breadth and depth within its own company, which included GE Aircraft Engines, for research and development on gas turbines.

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[14] There is a long history of changes in R&D work supported by the government. Most pertinent in this study is the Technology Transfer Act of 1986 which established Cooperative Research and Development Agreements (CRADAS) for collaborative work between government laboratories and private industry. The terms of a CRADA allow the federal laboratory to assign private companies the rights to intellectual property resulting from joint work, while the federal government retains nonexclusive license to the intellectual property. For DOE-ATS, 93% of the patents directly resulting from the program were assigned to the private industry (Curtis, 2003). See Popp, 2006 for a longer discussion of changes in government R&D policy.

Additionally, GE had already begun work on advanced NGCC for international markets, which they believed would have more immediate demand (Curtis, 2003). By contrast, Westinghouse exited the aircraft engine industry in the 1960s, and relied on alliances and licensing agreements to acquire core capabilities for gas turbine technology. As a result, SWPC depended more heavily on universities, national laboratories and other government testing facilities for their innovative process with DOE-ATS (Curtis, 2003). According to Curtis (2003), the DOE-ATS program resulted in 55 new patents for the technology between 1995 and 2001, not including patents of spin-off technologies that may also contribute to increases in overall feasibility of new natural gas combustion units. These patents were identified through interviews and meetings with industry and government personnel involved with DOE-ATS. Curtis (2003) evaluates the citations by the DOE-ATS patents for evidence of collaboration, finding 14% of all citations in SWPC patents were self-citations to other SWPC[15] patents, while 71% of all GE's citations were self-citations, reflecting that GE relied more on its internal resources.

Innovations for NGCC generators take place in the system as a whole, subsystems (e.g. the gas turbine or steam turbine), or components of the subsystems (e.g. blades of a gas turbine). The result of the DOE-ATS program were improvements in four subsystems of the combined cycle unit, including closed-loop steam cooling, single crystal superalloy castings, thermal barrier coatings, and lean pre-mix dry low NOx combustors. Through interviews with members involved in the DOE-ATS program, Curtis (2003) reports that the closed-loop steam cooling was the most critically important development for reaching the goals of the program, as confirmed by his patent analysis showing 56% of GE and 43% of SWPC DOE-ATS patents were associated with the closed-loop cooling subfield.

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[15] Or Siemens or Westinghouse Patents before Siemens bought Westinghouse Power Corporation.

GE's first fully-integrated advanced NGCC unit was annonced in 1995, with the 7H frame at 60-hz for the domestic market, and 9H 50-hz deign for international markets (Table 1). The 480MW 9H frame was first installed in 2002 in South Wales, and the first US advanced system (7H) was installed in Scriba, NY in 2003.[16] SWPC tested a fully integrated system using the DOE-ATS developed models in a demonstration in 2004.[17] The fully integrated advanced NGCC line appeared in Siemens' H-series generators (SGT6-8000H), which was first annonced in 2007 and operational in 2013.[18] While fully integrated systems were later to arrive in the US market, the subsystem innovations were introduced in earlier, "conventional" NGCC systems by these companies. SWPC incorporated advanced technologies in their existing products (W501 D, F and G turbines) during and shortly after the DOE-ATS program. DOE reports that over 165 gas turbines in North America in the early 2000s employed the improved components from the DOE-ATS program in SWPC generators.[19] From 1999-2002, during the early portion of the natural gas capacity boom, GE's global market share increased to 54%, and Siemens/Siemens Westinghouse Power Corporation to 22% (Bergek et al., 2008).

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[16] Article in Modern Power Systems on the first installation of GE's 7H frame in the US: http://www.modernpowersystems.com/features/featurefirst-7h-turbines-go-to-heritage-station-scriba/

[17] Technical progress report prepared for DOE by SWPC in 2004: https://www.osti.gov/scitech/servlets/purl/828617

[18] Article in Power Engineering on NGCC projects in North America: http://www.power-eng.com/articles/2014/02/a-report-on-combined-cycle-projects-in-north-america.html

[19] Brief post from DOE on DOE-ATS success: https://www.energy.gov/fe/doe-technology-successes-breakthrough-gas-turbines

Table 1: NGCC designs by released by the companies involved with DOE-ATS, adapted from Watson, 1997 and Bergek et al., 2008.

	General Electric				**Siemens**				**Westinghouse**			
Year Announced	Model	Size (MW)	Efficiency (%)	First Order	Model	Size (MW)	Efficiency (%)	First Order	Model	Size (MW)	Efficiency (%)	First Order
1987	7F	230	53	1987								
1989									501F	230	54	1989
1990					V94.3	300	54	1992				
1994									501G	345	58	1997
1995	7G	350	58	none	V84.3A	245	58	1995				
1995	7H/9H	400/480	60	2004/ 1998								
1998					Adopts Westinghouse's 501F and 501G, now the F and G-Series							
2007					H-Series[20]	400	60.75%	2010				
2014	7HA/ 9HA[21]	346/446	63%	2014								

Today, fully integrated advanced NGCC make up less than 9% of the NGCC fleet in the US. The newer, conventional units with advanced NGCC technologies make up over 70% of the current fleet, with older, less efficient NGCC units about 21% of the fleet.[22] Recent capital cost estimates from EIA price advanced and conventional NGCC units as significantly less expensive than coal-fired plants in terms of overnight capital costs and operations and maintentance (O&M) costs, with advanced NGCC plants having slightly higher overnight capital costs but lower O&M costs compared to conventional NGCC. [23] Advanced NGCC comes out slightly

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[20] Siemens product information: https://www.energy.siemens.com/hq/pool/hq/power-generation/gas-turbines/SGT5-8000H/gasturbine-sgt5-8000h-h-klasse-performance.pdf. Article on Siemens plant performance: http://www.elp.com/articles/2010/06/fpl-picks-siemens-gas-turbine-for-two-plant-modernization-projects.html.

[21] Articles on GE plant performance: https://powergen.gepower.com/content/dam/gepower-pgdp/global/en_US/images/product/gas%20turbines/ha-timeline.jpg, and http://www.genewsroom.com/Press-Releases/Exelon-Orders-GE-H-Class-Gas-Turbines-World-Largest-Most-Efficient-for-US-Combined-Cycle-Power-Projects.

[22] ICF International report submitted to the Gas Turbine Association (March 29, 2013): http://www.gasturbine.org/docs/newdocs/YAGTP4602_GTA%20White%20Paper_041013%20final.pdf.

[23] EIA Updated Capital Cost Estimates for Utility Scale Electricity Generating Plants (November 22, 2016): http://www.eia.gov/analysis/studies/powerplants/capitalcost/.

ahead of conventional NGCC plants in levelized costs, giving them the lowest levelized cost of all generation technologies absent tax credits.[24]

3. Patent Research

In order to evaluate the claims by DOE that the program was successful outside of direct outputs measured in commercialized technology, I conduct a study using patent data. Patents have long been used as an indicator of innovation in empirical studies in place of, or as a complement to, aggregated R&D values. A patent places a temporary monopoly on an invention for the inventor as a means of encouraging innovation and technological progress (Griliches, 1990). It has been established that patent applications are an appropriate measure for R&D since they are usually filed early in the research process, thereby making patent data sorted by application date a useful indicator of R&D activity to measure innovative activity (Griliches, 1990).

The main advantage of using patent data over R&D expenditures is that patents contain disaggregated information about innovative activity. Patents include bibliographic information about the inventors and applicants, descriptive data on the patent coverage, technology classification data, as well as information about knowledge flows through evaluation of patent citations. Despite their usefulness, patents are an imperfect measure of innovative activity. Not all inventions may be patentable, and the propensity to patent and can vary across industries (Popp, 2005). In this case, I evaluate patents for the advanced turbine class primarily by gas turbine manufacturers; therefore, the differences in propensity to patent are less of a concern. A study by Bergek et al. (2008) on NGCC industry shakeouts determine patents are a relevant

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[24] "EIA Levelized Cost and Levelized Avoided Cost of New Generation Resources" in the Annual Energy Outlook 2017 (April 2017), available at https://www.eia.gov/outlooks/aeo/pdf/electricity_generation.pdf.

indicator to measure of R&D for NGCC technologies since they fall in the broader category of electrical equipment, with some of the highest propensities to patent.

3.1 Patent Counts

I use patent counts of unique inventions as an indicator of the quantity of innovative activity taking place for ATS technologies. Previous studies on environmental technologies find 1-3 year lags between the initiation of a program or policy and associated patenting response (Sanyal & Ghosh, 2013; Johnstone et al., 2010). Since the DOE-ATS report states there was a concern there would be a lack of this type of research in the 1990s, justifying government intervention, I expect to see low patent counts prior to or in the early years of the program. During the program or shortly after, I expect to see higher numbers of patents from the participants relative to non-participants in this field. This would indicate that innovative activity was higher for the participants, possibly as a result of DOE-ATS.

3.2 Patent Citations

Another common concern with patent data is that each patent may not hold the same value, therefore additional consideration must be taken to determine the relative contribution of each patent (Griliches, 1990). Frequently, researchers turn to the information contained in the patent citations to evaluate knowledge flows and approximate the impact of the patent. Patent citations credit previously existing knowledge that the new work builds upon, and delimit the scope of the patent’s claim. Evaluating citations contained within a patent (backwards citations) provides information about knowledge flows associated with the invention, while citations to the patent (forward citations) contain information on how useful the innovation was for producing additional knowledge (Trajtenberg et al., 1997).

Like the issues discussed with patent counts, each citation may not provide equal information about knowledge flows. Citations can be identified by the applicant, patent examiner, or lawyer of the innovator or applicant, and sometimes for strategic reasons. Further complicating matters, legal requirements and practices for identifying prior work can vary across different patent offices, and the United States Patenting and Trademark Office (USPTO) is the only patent office where the *inventor* has a legal duty to declare and cite any previous knowledge on which the innovation was built (Verdolini & Gaelotti, 2011). However, studies on citations to and from USPTO patents have determined a significant portion of the citations represent an important knowledge flow (Jaffe et al., 2000), and USPTO citations have been used to measure knowledge diffusion (Verdolini & Gaelotti, 2011) and patent importance (Popp, 2017). For these reasons, I use only the USPTO citation data for the citation analysis to determine the relative impact of the patents produced during the DOE-ATS program.

A survey of the patent citation literature by Jaffe and de Rassenfosse (2017) reports numerous studies confirming a relationship between citation counts and technological importance and economic value (defined in various but specific ways). Trajtenberg et al. (1997) find that university patents are associated with more basic research compared to corporate patents, and therefore hold a higher importance to future research measured through higher forward citation counts. To be regarded as basic means the innovation answered fundamental scientific questions, rather than focusing on specific technical issues associated with more applied research. Industry is more likely to work on applied innovations that solve problems with their specific technologies in efforts to commercialize them, while basic research will have a major impact on the field and be more fundamental to later work, and thus will have more citations (Trajtenberg et al., 1997). Curtis (2003) describes the innovative work in DOE-ATS as "breakthrough" and "transformational," but "generic" in a sense that the innovations add to technological understanding applicable to all turbine manufacturers. While the patents I evaluate in this study are from private industry, I hypothesize that the patents filed by the DOE-ATS program participants during or shortly after the program will have higher technological importance and therefore higher citation counts relative to earlier patents by the participants and patenting by non-participants.

4. Data & Method

4.1 Data

I use the Worldwide Patent Statistical Database (PATSTAT) maintained and distributed by the European Patent Office (EPO). PATSTAT is a comprehensive source of bibliographic patent data for over 100 patent offices, including the USPTO, and is a commonly used database for patent research (e.g. Lanzi et al., 2011; de Rassenfosse et al., 2013).

I begin by identifying patents representing unique inventions in advanced turbine technology beyond the 55 patents provided by Curtis (2002). This way, I can evaluate advanced turbine patenting activity taking place outside of the program, as well as before and after the program to evaluate the impact of the program on advanced turbine innovation. Additionally, Curtis (2003) states there were spin-off innovations that related to the research done in DOE-ATS but which were not a "direct" result of DOE-ATS and therefore not discussed in his research. I develop a search strategy similar to the one used by Lanzi et al. (2011) to identify the relevant International Patent Classification (IPC) codes, developed by the World Intellectual Property Organization and used to classify inventions. I identify common IPC codes in the DOE-ATS patents in each of the advanced turbine technology subfields, and verified that the code applies to NGCC technologies related to the advanced turbine subfield using the IPC definitions (Appendix A). I was able to verify some of these codes with previous literature on efficiency improving innovations in fossil-fuel technologies (Lanzi et al., 2011). The search using the chosen IPC codes identifies 43 of the 55 DOE-ATS patents.[25]

Inventors often seek patent protection in multiple countries, in which case a priority patent (first application filing) is duplicated and submitted for protection under another patenting authority. The application date of the priority filing is the priority date and assigned to the duplicate patents, which all fall in the same patent family. Patents that do not have any duplicates are referred to as solo patents (i.e. family size of 1). In order to count unique inventions only, I sort the patents by their families and keep the earliest patent (i.e. priority patent) based on the application date. I use the priority year of the patent as its date, since that marks when patenting protection begins if the patent is granted, and corresponds with the timing of the inventive activity (Griliches, 1990). I begin with over twenty-five thousand granted patents with a priority date between 1980-2008, which reduces to approximately fourteen thousand unique inventions (i.e. families).[26] I provide the descriptive statistics on the families in Table 2. To evaluate patenting activity occurring in the US only, I keep the patent from each family that was granted by the USPTO in a second dataset (approximately eight thousand unique inventions, as some families never sought protection in the US).

In order to assign patents to the appropriate companies, I use the applicant's "person data" provided in PATSTAT.[27] I identify 23 companies that appear most frequently in the extracted patent data. I merged together several companies based on an evaluation of the patent families and research on the companies to identify company mergers and subsidiaries, which results in 14 companies (Appendix B). In some cases, the innovations targeted at jet engines had

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[25] I excluded the thermal barrier coating technology subfield because the applications are broader and there are fewer common IPC codes among these patents.

[26] I choose to work with granted patent applications rather than all applications because the USPTO only began publishing information in 2001 on applications that were not granted (de Rassenfosse et al., 2013).

[27] This is akin to the USPTO's "assignee" data.

applications for NGCC turbines as well; therefore, there are some companies that focus on jet engines included in my dataset. Patents by companies that appeared infrequently in my dataset are placed in the group "Other." The descriptive statistics for these companies are provided for their patents granted anywhere in the world (Global) and just the US. Figure 3 is a plot of patent counts by the global and US datasets.

For the reasons discussed in Section 3, I sum forward citations for USPTO patents to other USPTO patents for the citation analysis. I remove self-citations, whereby a company cites its own patent, in order to focus on the external spillover benefit of a patent to determine its value (Jaffe et al., 1993). Otherwise, it is possible a patent may have higher citation counts due to the stock of patents that followed by that company. The citation statistics, based on individual patents, are reported in Table 2, and Figure 4 shows patent citation counts by the priority year.

Table 2: Descriptive statistics for the patent count and citation data for the global and US datasets.

	Global						US					
Group	**N**	**Mean**	**St. Dev.**	**Min**	**Max**	**% Self**	**N**	**Mean**	**St. Dev.**	**Min**	**Max**	**% Self**
Counts												
Aero[28]	29	59.4	39.4	23	159		29	36.3	21.8	16	109	
Alstom	29	25.4	18.5	2	57		29	16	12.7	1	44	
GE	29	80.5	59.6	10	198		29	66.6	50	8	185	
Japanese[29]	29	43.7	24.5	4	84		29	10.5	4	4	23	
Mitsubishi	29	32.1	29.7	0	119		29	8.1	11.6	0	43	
Other	29	178	69.6	101	367		29	84.4	32.6	49	187	
SWPC	29	30.3	18.7	8	70		29	20	11.7	4	43	
United Tech.	29	41.4	25.1	10	114		29	34.4	17.2	9	92	
All	232	61.4	61.6	0	367		232	34.5	35.4	0	187	
Citations												
Aero							1,048	11.3	12.2	0	132	7%
Alstom							461	9.7	10.2	0	94	8%
GE							1,914	13.3	14.1	0	117	25%
Japanese							302	15.4	17.1	0	119	8%
Mitsubishi							232	9.6	9	0	50	9%
Other							2,424	13.6	19.9	0	494	3%
SWPC							574	11.8	14	0	95	9%
United Tech.							988	14.6	16.1	0	158	15%
All							7,943	12.9	16	0	494	12%

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[28] For the purpose of the descriptive statistics only, the Aero group represents four aerospace manufacturing companies with smaller contributions to the dataset: Honeywell, MTU, Rolls-Royce, and SNECMA.

[29] For the purpose of the descriptive statistics only, the Japanese group represents four Japanese gas turbine manufacturing companies: Hitachi, IHI Corp., Kawasaki Heavy Industries, and Toshiba.

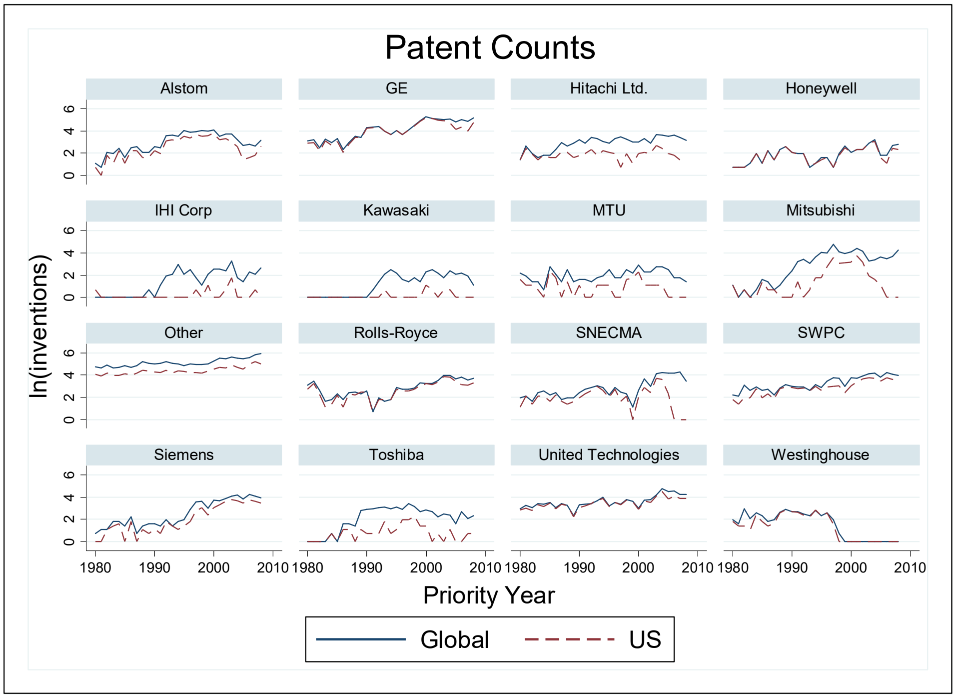

Figure 3: Patent counts (*inventions*) for the global and US datasets. SWPC is the combination of Siemens and Westinghouse patents before they merged (1998).

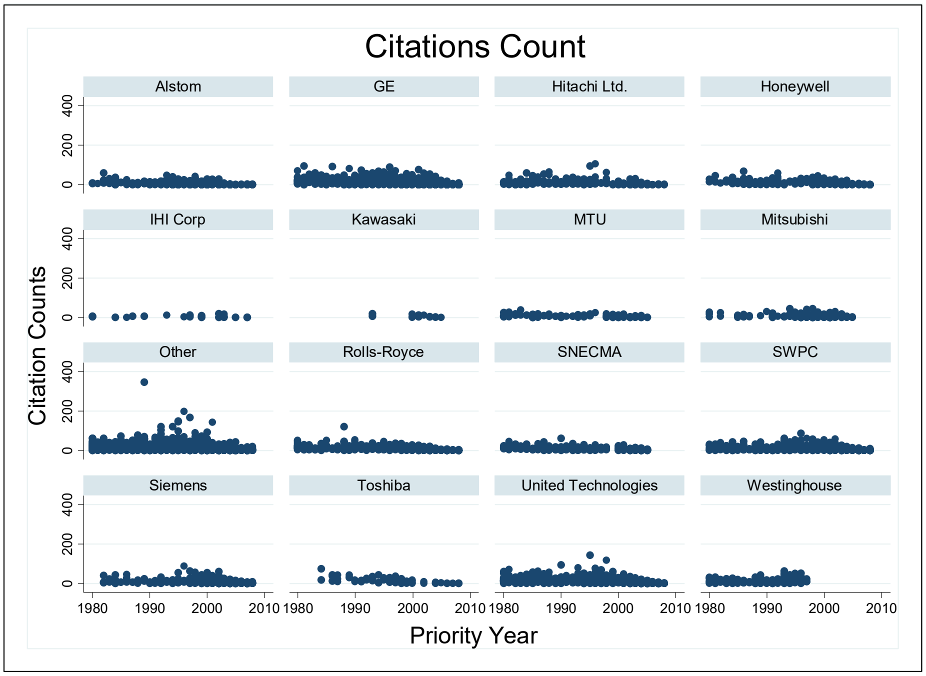

Figure 4: Citation counts per patent by each company by priority year. SWPC is the combination of Siemens and Westinghouse patents before they merged (1998).

4.2 Model

I use a fixed-effects model, where the coefficients of interest are the interaction of a participant dummy (assigned to GE and SWPC) with individual year dummies ($\delta_{jt} \cdot year_t \cdot participant_j$) from 1988-2008 to evaluate the difference in participant patenting compared to non-participants in each year before, during, and after the DOE-ATS program. This way, I am implicitly imposing no effect from 1980-1987. Since the program is eight years long, I am interested in seeing how patenting responds to the program in each year of the program. There is a possible lag in the timing between initiation of a program and patenting that can vary among policies (Sanyal & Ghosh, 2013). While the 55 DOE-ATS patents were issued from 1995-2001, the DOE report on the program does not state the time period it may have taken for spin-off technologies associated with DOE-ATS work to be patented. Moreover, previous studies have found that policy impacts on patenting counts for environmental technologies have diminishing returns (Popp, 2005), which will be easier to evaluate with this approach. The trade-off of evaluating each year to determine a temporal signature is that I lose degrees of freedom and, potentially, the significance of the coefficients.

Since I am using count data as my dependent variables with overdispersion (mean < variance), I use a negative binomial model. A negative binomial model uses a Poisson process, which is flexible in the error structure compared to ordinary least squares estimation which assumes a conditional normal error structure. The Poisson process allows transformation of the predicted outcome, letting nonlinear relationships be linearized between the dependent variable and predictors. A negative binomial is more appropriate than a Poisson model in this case because it also accounts for overdispersion by way of an additional error parameter (Coxe et al., 2009; Allison, 2009). However, the fixed-effect in a conditional negative binomial regression applies to the distribution of the dispersion parameter rather than controlling for time-invariant parameters (Allison, 2009). Therefore, I use the unconditional maximum likelihood negative binomial model with dummy variables for the individual fixed-effects and clustered robust standard errors by company, which Allison (2009) recommends as an appropriate alternative to the fixed-effects conditional negative binomial model (equation 1). In a second model, I use the same specification but separate interactions for each company that participated in the program to determine if the program affected the participants differently (equation 2). The participants in this case are GE, Westinghouse (from before the acquisition), and SWPC (Siemens alone before the acquisition, SWPC after the acquisition).[30]

$$inventions_{jt} = \beta_1 + \delta_{jt}\left(year_t \cdot participant_j\right) + \alpha_t + \alpha_j + \epsilon \qquad \text{(eq. 1)}$$

$$inventions_{jt} = \beta_1 + \delta_{kt}(year_t \cdot company_k) + \alpha_t + \alpha_j + \epsilon \qquad \text{(eq. 2)}$$

$j = company$
$t = time\ (year)$
$k = participant\ company$
$participant\ (0, non-participant; 1, participant)$
$\alpha_j = company\ fixed-effect$
$\alpha_t = year\ fixed-effect$
$\epsilon = error$

For patent citations, I use the same structure as the patent count models, but my unit of analysis in this case is each patent. The dependent variable is the number of citations (excluding self-citations) the patent received. The year fixed-effects controls for the amount of time each patent has to be cited, as well as the number of patents afterwards (i.e. opportunities for a

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[30] In the participant models (eq. 1 and 3), SWPC represents all patents from Siemens, Westinghouse, and SWPC as one company.

citation).[31] This model also has company fixed-effects and clustered robust standard errors at the company level.

$$citations_{it} = \beta_1 + \delta_{jt}(year_t \cdot participant_j) + \alpha_t + \alpha_j + \epsilon \qquad \text{(eq. 3)}$$

$$citations_{it} = \beta_1 + \delta_{kt}(year_t \cdot company_k) + \alpha_t + \alpha_j + \epsilon \qquad \text{(eq. 4)}$$

$$i = patent$$

I run these regressions on patent counts and citations for all unique patents authorized across the world, versus those authorized only in the US.[32] Since the program was designed to stimulate innovation in the US, the dataset for patents authorized in the US only represents the patents that sought US protection. The global dataset, however, represents all innovative activity in the ATS field, including activity by foreign companies that may not seek US patent protection.[33]

5. Results

The model coefficients and confidence intervals displayed in the figures in this section (and Tables in Appendix C) have been transformed to incidence-rate ratios (IRR), which is the exponentiated version of the negative binomial coefficient (e^{β}). The IRR is interpreted as the predicted multiplicative effect on the incidence rate, which for patent counts is how many unique inventions were patented in a year by the company. For example, in subgraph A of Figure 5, the coefficient for the year 1990 interaction for participants in the US data set is 2.75. This means that participants patented 2.75 times more than non-participants in that year. Using IRR, a coefficient of 1 (rather than 0), indicates no effect. For citations, the IRR represents the

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[31] Additionally, year fixed-effects control for universal parameters for each year that may affect firm's investment behavior, such as anticipation of low natural gas prices or decreases in coal R&D which may also increase NGCC innovation.

[32] In addition, I could evaluate the non-US patents to determine if there were universal impacts to all patents outside of the US.

[33] However, the global dataset does not include country fixed-effects that would control for natural gas R&D programs outside the US that took place during this time. I do not include country fixed-effects because I do not have many companies from the same country.

multiplicative effect on how many citations the average patent for the participants (or each company) received. I first discuss the results of the count and citation analyses in detail separately, then summarize with a discussion of what the collective results signify in section 5.3. Full tables of the results are in Appendix C.

5.1 Count Results

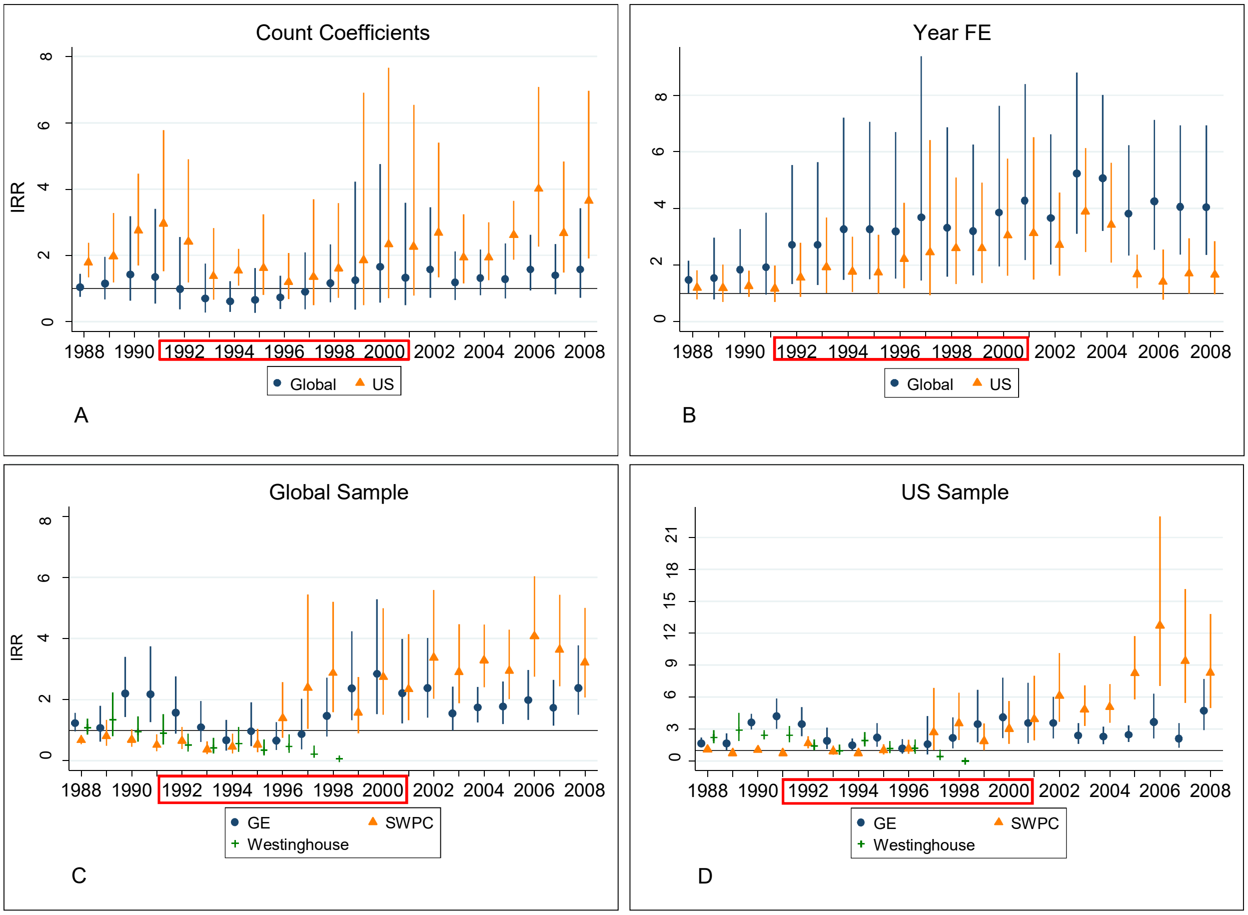

Figure 5: The coefficient results from the models with 95% confidence intervals, represented as incidence-rate ratios, with the years of the program outlined in red. Top figure (A) is the joint treatment effect for the program participants, while the bottom figures (C & D) represent coefficients for participant companies separately. In the top figures, the coefficients are from the global and US authorized datasets. Subgraph A displays the treatment effect, while subgraph B contains the year fixed-effects coefficients. On the bottom, subgraph C is the treatment coefficients for the global dataset, while subgraph D is for the US authorized dataset.

After removing a linear trend in turbine patenting for the global and US datasets (subgraph B), there are no significant treatment effects in the global dataset (subgraph A) at the 95% confidence level, however subgraph C shows more statistically significant treatment effects when each company is separately represented in the global dataset. GE experienced higher patenting activity relative to non-participants in 1990 and 1991 before the program began in the global dataset, while Westinghouse had higher patenting activity during this time only relative to US patenting (subgraph D). Patenting by both companies tapers off in the early years of the program and are mostly statistically insignificant, except for 1994 in the US dataset only. GE was more of a global company than Westinghouse (Bergek et al., 2008), therefore the fact that Westinghouse pre-program increase in patenting does not show up in the global data is not all that surprising. Prior to 1998, the SWPC coefficient in the individual company subgraphs (C & D) represents patenting activity by Siemens before the acquisition of Westinghouse, which is not statistically significant in the global or US dataset until after the acqusition of Westinghouse. For the US dataset, this is expected, as Siemens did not seek US patent protection as frequently as they did after the acquisition of Westinghouse.

Towards the later years of the program (1998-2000) SWPC (Siemens + Westinghouse now) and GE both appear to begin to increase their patenting activity relative to the global dataset (subgraph C). However, the statistically significant coefficients for SWPC are more of a reflection of the low patenting activity by Siemens in the 1980s, pre-Westinghouse acquisition, which are the base years for the treatment coefficients. In subgraph A, the participants include GE and SWPC, and these coefficients are not statistically significant for the joint effect in the global dataset. In subgraph C, the statistically significant increase in patenting for SWPC is a reflection of the increased patenting from adding Westinghouse, since I separated Westinghouse out before the acquisition to focus on the impact of DOE-ATS on the only two participants at that time – GE and Westinghouse.[34] Therefore, SWPC patenting in the company subgraphs is relative to their patenting in the 1980s as just Siemens, and not a proper comparison to draw conclusions from for SWPC after the acquisition of Westinghouse. For example, the magnitude of the spike in SWPC patenting activity in 2006 in the US dataset (subgraph D) indicating they had 12 times more patents than non-participants is largely reflective of low patenting activity in the US by Siemens during the base years of 1980-1988. Based on subgraph A, the joint effect of the participants on the US patenting was statistically significant, confirming SWPC patenting was higher after the program in the US relative to Siemens+Westinghouse patenting in the 1980s, just not 12 times higher (subgraph D).

For GE, the increasing patenting rates towards the end of the program to after the program peak at 2.87 times higher than non-participants in the global dataset, and 4.1 times as high in the US dataset in 2000. It is not surprising that GE, a US company, has a higher coefficient for the US dataset. Both companies continue to have high patenting activity following the program, but for GE to a lesser degree, and SWPC for the reasons mentioned above. GE's peak in 2000 gradually decreases and levels out, which may be evidence of diminishing returns from the DOE-ATS program.

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[34] Appendix D contains model results without separating out Westinghouse from SWPC for verification.

5.2. Citation Results

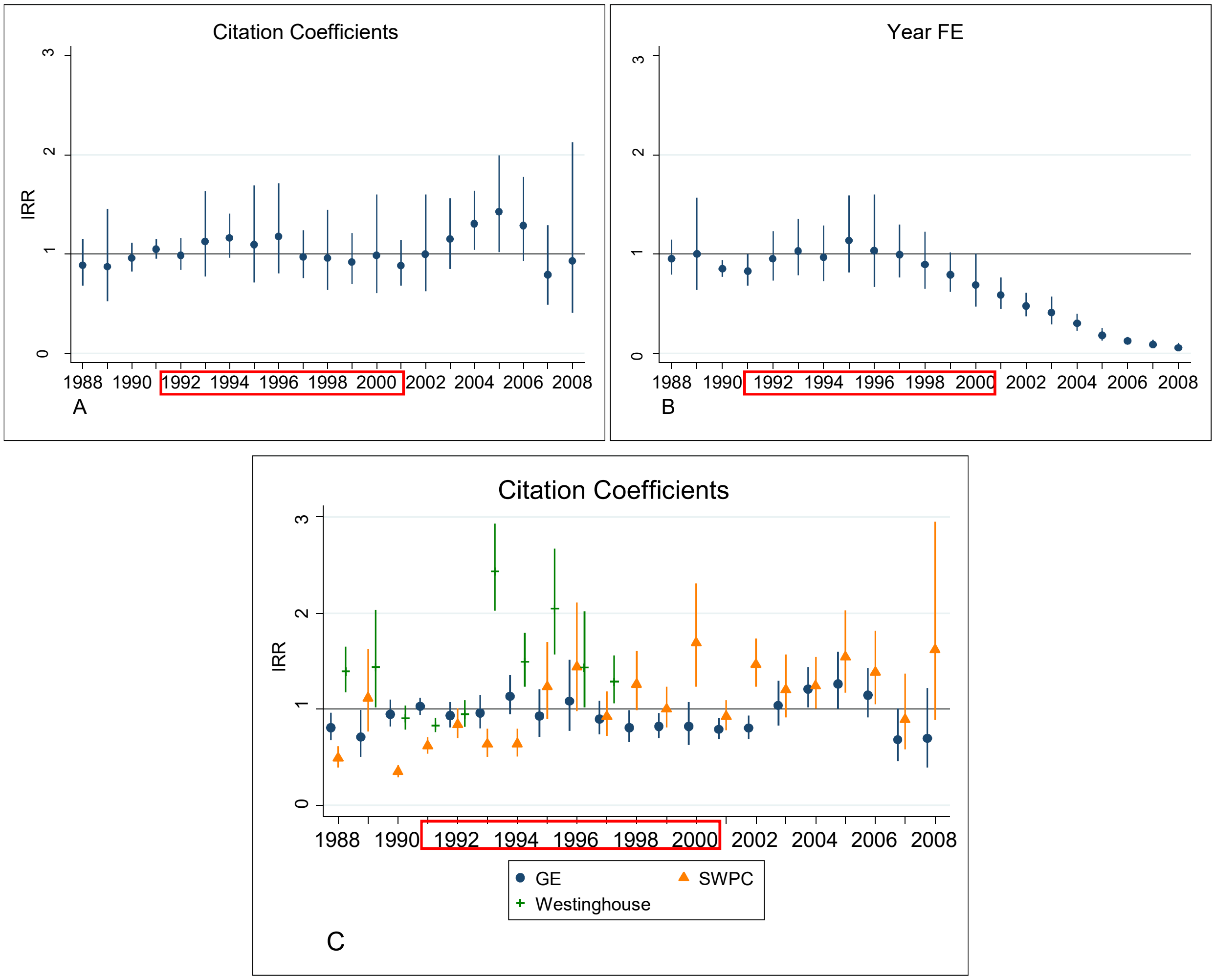

Figure 6: The coefficient results from the citation models with 95% confidence intervals, represented as incidence-rate ratios, and the years of the program outlined in red. Top figures (A & B) are from the models with the joint effect for the program participants, while the bottom figure (C) contains coefficients for participant companies run separately. The citation models were run on data from the US only.

In subgraph A of Figure 6, the participants (joint) 2004-2005 were the only two years with statistically significant higher citations than non-participants, on the order of 1.3-1.4 times the average non-participant citations received. The individual company treatment coefficients (subgraph C) show the post-program increase was shared between GE and SWPC. There is less of a concern comparing post-acquisition SWPC patents to pre-acquisition Siemens patents, since the impact on citations may not be as severe as the impact on patent counts when a company size grows. SWPC had a couple other years post-program with higher citations, and higher citations in 1998 and 2000 after merging with Westinghouse. Westinghouse was the only company with higher citations during the program, from 1993-1997. The citation rate in 1993 was 2.47 times the citing rate of non-participants in that year. The Curtis (2003) report states that Westinghouse participated in more alliances and government collaborations during DOE-ATS, which may explain why their patents were cited more. These results are all after removing a year fixed-effect (subgraph B), which clearly shows growing truncation from 1999-2008 due to less opportunity for newer patents to receive citations.

5.3 Combined Results

Overall, the program did not have a uniform impact on the participants. There were a few years when the joint coefficient for patent counts are statistically significant, but that only occurs relative to US patents only. Program participants increased their patenting relative to non-participants patenting in the US several years after the conclusion of the program, from 2002-2008. Since these coefficients are not significant in the global dataset, it indicates that foreign companies were also pursuing advanced turbine innovations during this period, and the DOE-ATS participants were not doing more patenting relative to companies that were not pursuing US patent protection. However, it is unclear if the program was focused on participant's activity relative to the US market only. If so, this could indicate the program was successful since it increased domestic patenting activity for the participants in the years following the program.

There are only two years in the joint citation analysis with statistically significant coefficients, 2004-2005, also several years after the conclusion of the DOE-ATS program, which is not expected since the DOE-ATS report concludes commercialized technologies were demonstrated at the conclusion of the program, not several years afterwards (Curtis, 2003). More coefficients are significant in the analysis of each company separately for the counts and the citations. However, there are only a few recognizable patterns that may be associated with the DOE-ATS program for each company. First, it does appear GE and Westinghouse had higher patenting activity in the years right before the program, GE relative to the globe and Westinghouse relative to the US only. Additionally, Westinghouse's patents in 1988 and 1989 had higher patent citations. This does not fit the description of the program in the DOE-ATS report that "this type of research was not taking place at this time," (Curtis, 2003) however it is unclear if "at this time" meant before the program or during the early years of the program.

In the early years of the program, Westinghouse had lower patenting activity compared to the global patenting, while GE's patent counts were slightly higher than non-participants compared to US patenting only. Again, there is no clear effect in the early years of the program on patent counts. In terms of impact, Westinghouse did have higher impact patents (i.e. higher citations) from 1993-1997, but this was not true for GE, and more research would need to be conducted to conclude why.

Towards the end of the program (1998-2000), GE increased their patenting activity relative to the global dataset, and SWPC increased their patenting relative to the US dataset. This peaks for GE in 2000, while SWPC continued to grow relative to US patenting, which is probably more a reflection of Siemens acquisition of Westinghouse and the new, legal requirement for SWPC to manufacturer US goods with Westinghouse's intellectual property developed during DOE-ATS that Siemens inherited. Citations were no higher for GE after the program, with the exception of a small increase from 2004-2005, while SWPC had several years with higher citations between 2000 and 2006. Overall, this analysis shows the program contributed to increased patenting activity by GE towards the later years of the program, and it also contributed to higher impact patents by Westinghouse in the early years of the program.

6. Conclusion

This study adds to the existing literature regarding the impact of a government-sponsored cost sharing program on advanced turbine innovations for NGCC generators in the US. The results of a patent analysis show few joint impacts on program participants in the years before, during, and after the program which ran from 1992-2000. The individual company analyses reveal a greater number of statistically significant effects for companies involved with the program, however there are few clear patterns indicative of the impact of the DOE-ATS program. There are several suggestive results which require more investigation, possibly of a qualitative nature, to confirm.

Patent quantity was higher in the participants, particularly GE, but also for Westinghouse relative to US patents only, in the years before the program. This would indicate that there was not a lack of this type of research in the years before the program by the program participants in the US. As the program started, patent counts actually decreased for the participants but citations increased in the early years for Westinghouse only. Johnstone et al. (2010) show firms will focus more on research that is closer to being commercially ready than on basic research (which can be more risky). Yet, the DOE-ATS research was described as transformational, with generic applications to all turbine manufacturers (Curtis, 2003). The lower patent count but higher citation rate for Westinghouse could indicate it was moving from more applied research pertaining to its specific technologies, to more basic research associated with DOE-ATS with a broader impact on the field.

Towards the later years of the program, the opposite occurred for GE: GE increased its patent counts from 1998-2000, but had lower citation counts than non-participants at this time. It is possible that GE moved closer to commercialization towards the end of the program, resulting in higher patent counts with lower citations. SWPC increased its patenting activity in the US and global datasets after the acquisition of Westinghouse (1998), and had a few years during and after the program with higher citations. But, impact in the US is in part due to low patenting in the US before acquiring Westinghouse, which certainly changed once SWPC was legally required by new contract clauses with the US government to use the intellectual property rights from DOE-ATS to produce US goods.

Westinghouse and GE released new NGCC models in 1994 and 1995, respectively, which may explain the pre-program increase in patenting. But, under the same argument, they did not release their next NGCC models until 2007 (SWPC) and 2014 (GE), despite having increases in patenting from 1998-2000. This activity may be associated with incremental improvements to their mid-1990s models during this time, as they were each experiencing some problems with and modifying the DOE-ATS technologies (Bergek et al., 2008; Curtis, 2003). Additionally, in 2003 and 2004, the global and US year fixed-effects have a positive deviation from the linear trend; this may suggest that GE and SWPC were first to market, 4-6 years ahead of competitors as their patenting activity started increasing around 1998-1999. Accordingly, GE increased its global market share from 28% in 1987-1991, to 54% from 1999-2000. For Siemens, its market share increased from 19% in the early 1990s, to 22% after acquiring Westinghouse. Again, additional work will need to be done to confirm the hypotheses formed from the patent analysis, since no clear patterns associated with the program are found.[35]

Another area of future research on NGCC innovation should consider programs and developments related to NGCC ramp-speed, which has increased in advanced generators over

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[35] Future work with more specific data on installed NGCC models and license agreements would be useful for further evaluation on what patent applications led to installed technology.

time.[36] The fast start-up and shut-down times for NGCC makes it a good complement to intermittent renewable sources of generation, such as wind and solar. Johnstone et al. (2010) find renewable policies have had a positive impact on renewable innovation, therefore it would be interesting to evaluate if renewable policies have also contributed to ramp-speed innovations for NGCC post-DOE-ATS. There are renewed calls for government involvement to invest in another round of advanced turbine innovations, as there is a concern Japanese manufacturers are further ahead of the US in developing even faster ramp-speed technologies.[25] Lessons learned from the DOE-ATS program can be useful in developing future programs for NGCC technological change.

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[36] Report on Competitiveness of US Gas Turbine Manufacturers, prepared by ICF International for the Gas Turbine Association (March 29, 2013): http://www.gasturbine.org/docs/newdocs/YAGTP4602_GTA%20White%20Paper_041013%20final.pdf.

Appendix A: IPC Codes

IPC Codes	Definition
Cycles:	
F01K 21/04	Using mixtures of steam and gas; Plants generating or heating steam by bringing water or steam into direct contact with hot gas (direct-contact steam generators in general
F01K 23/02,04,06,08,10*	Plants characterized by more than one engine delivering power external to the plant, the engines being driven by different fluids, the engine cycles being thermally coupled
F02C 3/20, 22, 24, 26,28, 30, 32, 34, 36*	Gas-turbine plants characterized by the use of combustion products as the working fluid, using a special fuel, oxidant, or dilution fluid to generate the combustion products
F02C 6/10,12*	Plural gas-turbine plants; Combinations of gas-turbine plants with other apparatus, supplying working fluid to a user, e.g. a chemical process, which returns working fluid to a turbine of the plant
F02C6/	Combinations of gas-turbine plants with other apparatus
F02C6/02	Plural gas-turbine plants having a common power output
Compressor	
F01D 25/24	Casings (modified for heating or cooling)
Combustor	
F23R 3/28, 34,00	Generating combustion products of high pressure or high velocity, e.g. gas-turbine combustion chambers, continuous combustion chambers using liquid or gaseous fuel
Closed loop steam cooling	
F01D 25/24, 12	e.g. Steam Turbines, component parts, for cooling (casings or general)
F01D 5/18	Blades, hollow blades; heating or cooling means on blades
F01D 5/08	Blade carrying members for heating or cooling
F02C 7/08	Gas turbine plants, features, component parts, heating air supply before combustion
F02C 7/12, 16, 18	Gas turbine plants, component parts, cooling of plants
Seals	
F01D 5/02, 06	Steam engines, steam turbines, blades, members, rotors
F01D 11/00, 08	Minimalizing internal leakage of working fluid, for sealing space between rotor blade and stator
Removable inner turbine shell	
F01D 25/14	Steam turbines, component parts, casings modified
Single Crystal	
F01D 5/00	Non-positive-displacement machines and engines: blades

*also in Lanzi et al.

Note: I eliminated the thermal barrier coating subfield, as there are fewer common IPC codes in this subfield and the technical applications are fairly broad.

Appendix B: Company Information

Company	Company Focus	Group	Country	Founded	Pertinent Mergers	Note
General Electric	Turbine manufacturer	Participant	US	1892	Nuovo Pignone (Italy, 1994)	GE bought Nuovo Pignone in 1994, now GE subsidiary.[37]
Siemens/Siemens Westinghouse Power Corporation (SWPC)	Turbine manufacturer	Participant	US	1847	Westinghouse Power Corporation (1998)	Siemens bought Westinghouse Power Corporation in 1998, temporarily renamed SWPC before going back to Siemens in 2004.[38]
Alstom	Turbine manufacturer		France	1928	Asea Brown Boveri (ABB) (2000) Combustion Engineering (US, 1989)	ABB formed from a merger between ASEA (Sweden) and BBC Brown Boveri Ltd. (Switzerland) in 1987. In 1999, ABB and Alstom merge their power generation business.[39] Bought by ABB in 1989.[8]
Hitachi	Turbine manufacturer	Japanese	Japan	1910[40]		
Honeywell	Aerospace	Aero	US	1885	AlliedSignal (US, 1999)	AlliedSignal acquired Honeywell in 1999 but chose to retain Honeywell name for recognition.[41]
IHI Corp.	Turbine manufacturer	Japanese	Japan	1853[42]		
Kawasaki Heavy Industries	Turbine manufacturer	Japanese	Japan	1896		Kawasaki Gas Turbines entered the market in 1976.[43]
Mitsubishi Heavy Industries	Turbine manufacturer	Japanese	Japan	1891[44]		
MTU	Aerospace	Aero	Germany	1909	DaimlerBenz MAN Turbo-machinery DaimlerChrysler (1998)	Parent company[45] Parent company Daimler-Benz merges with Chrysler to form DaimlerChrysler[46]
Rolls-Royce	Aerospace	Aero	UK	1906	Allison Gas Turbine Division (US, 1994)[47]	This segment of the business was acquired by Siemens in 2014, therefore I do not include this merger in my dataset.[48]
SNECMA	Aerospace	Aero	France	1945		Acquired by Safran in 2005, which I do not include as a merger because I did not have many patents by Safran and the merger was late in my database.[49]
Toshiba	Turbine manufacturer	Japanese	Japan	1939		
United Technologies	Aerospace		US	1929	Pratt & Whitney (US)	Subsidiary[50]

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[37] Reuters: Reuters: http://www.reuters.com/article/us-ge-oilandgas-idUSBRE98I0J920130919

[38] Siemens Company history: Siemen's company history: https://www.siemens.com/history/en/news/1097_siemens-westinghouse.htm

[39] ABB company history: http://www02.abb.com/

[40] Hitachi company information: company information: http://www.hitachi-america.us/products/business/isd/generators/

[41] Honeywell company history: https://www.honeywell.com/who-we-are/our-history

[42] IHI Corp. company history: https://www.ihi.co.jp/en/

[43] Kawasaki company history: http://www.kawasakigasturbines.com/index.php/company_background/

[44] Mitsubishi Heavy Industries company history: https://www.mhi.com/company/

[45] MTU company history: http://www.mtu-report.com/History/MTU/What-does-the-T-in-MTU-stand-for. Acquired by Rolls-Royce in 2011, which I do not include because this was well after my dataset ends in 2008. Primarily focused on aerospace and automotive, but manufactured in gas turbine and compressors for power generation as well.

[46] Daimler company history: https://www.daimler.com/company/tradition/company-history/1995-2007.html

[47] GM history: https://history.gmheritagecenter.com/wiki/index.php/Allison_Engineering-Allison_Transmission

[48] Rolls-Royce company history: company history: https://www.rolls-royce.com/about/our-story/rolls-royce-history-timeline.aspx

[49] Safran company history: https://www.safran-aircraft-engines.com/. Full name: Société nationale d'études et de construction de moteurs d'aviation

[50] Pratt & Whitney and United Technologies company history: http://www.utc.com/Who-We-Are/Pages/At-A-Glance.aspx#pratt-whitney; Bergek et al. (2008) states Pratt & Whitney and Siemens worked together in the 1990s, but they did not share any patents in my database.

Appendix C: Full Model Results

Table C1. Results from Global and US count regressions for participants.

	Global		US	
	Coeff.	St. Dev.	Coeff.	St. Dev.
Treatment Effect				
1988	1.044	(0.173)	1.787***	(0.263)
1989	1.154	(0.313)	1.970**	(0.512)
1990	1.418	(0.585)	2.751***	(0.677)
1991	1.353	(0.636)	2.962**	(1.011)
1992	0.986	(0.480)	2.412*	(0.873)
1993	0.694	(0.329)	1.377	(0.505)
1994	0.607	(0.215)	1.542*	(0.276)
1995	0.654	(0.302)	1.621	(0.574)
1996	0.734	(0.239)	1.194	(0.336)
1997	0.895	(0.388)	1.353	(0.694)
1998	1.168	(0.412)	1.607	(0.655)
1999	1.248	(0.776)	1.854	(1.243)
2000	1.655	(0.892)	2.336	(1.415)
2001	1.331	(0.672)	2.264	(1.226)
2002	1.578	(0.632)	2.685**	(0.957)
2003	1.185	(0.354)	1.935*	(0.510)
2004	1.32	(0.340)	1.939**	(0.431)
2005	1.28	(0.399)	2.610***	(0.445)
2006	1.570+	(0.412)	4.008***	(1.163)
2007	1.398	(0.368)	2.675**	(0.807)
2008	1.572	(0.623)	3.646***	(1.204)
N	406		406	
Pseudo R2	0.199		0.229	
Year FE	X		X	
Company FE	X		X	
Clustered St. Errors	X		X	

Standard errors in parentheses

+ p<0.10, * p<0.05, ** p<0.01, ***p<0.001

Table C2: Count model results for company fixed-effects and treatment effects for each company.

	Global		**US**	
	Coeff.	SD	Coeff.	SD
GE	1.987**	(0.434)	1.804***	(0.305)
1988	1.223	(0.154)	1.671***	(0.238)
1989	1.067	(0.287)	1.639*	(0.387)
1990	2.204***	(0.491)	3.619***	(0.369)
1991	2.174**	(0.605)	4.212***	(0.711)
1992	1.569	(0.453)	3.460***	(0.674)
1993	1.091	(0.326)	1.890*	(0.487)
1994	0.674	(0.235)	1.470*	(0.268)
1995	0.958	(0.338)	2.193**	(0.545)
1996	0.666	(0.216)	1.18	(0.337)
1997	0.871	(0.375)	1.597	(0.787)
1998	1.467	(0.463)	2.180*	(0.700)
1999	2.368**	(0.702)	3.439***	(1.165)
2000	2.841***	(0.901)	4.100***	(1.352)
2001	2.207**	(0.667)	3.542***	(1.323)
2002	2.379**	(0.635)	3.567***	(0.956)
2003	1.550+	(0.354)	2.392***	(0.479)
2004	1.739***	(0.291)	2.269***	(0.411)
2005	1.771**	(0.348)	2.465***	(0.391)
2006	1.989***	(0.409)	3.643***	(1.024)
2007	1.737*	(0.373)	2.111**	(0.564)
2008	2.381***	(0.559)	4.716***	(1.180)
SWPC	0.437***	(0.090)	0.278***	(0.042)
1988	0.674***	(0.077)	1.084	(0.153)
1989	0.808	(0.205)	0.733	(0.163)
1990	0.686+	(0.143)	1.036	(0.090)
1991	0.520*	(0.136)	0.739*	(0.107)
1992	0.648	(0.177)	1.663**	(0.290)
1993	0.367***	(0.105)	0.908	(0.215)
1994	0.460*	(0.155)	0.734+	(0.122)
1995	0.535+	(0.182)	0.998	(0.234)
1996	1.397	(0.437)	1.178	(0.314)
1997	2.389*	(1.005)	2.681*	(1.285)
1998	2.878***	(0.872)	3.537***	(1.075)
1999	1.571	(0.446)	1.860+	(0.604)
2000	2.739**	(0.840)	3.020***	(0.954)
2001	2.346**	(0.684)	3.924***	(1.429)
2002	3.374***	(0.869)	6.108***	(1.578)
2003	2.903***	(0.640)	4.836***	(0.948)
2004	3.280***	(0.518)	5.078***	(0.908)
2005	2.944***	(0.567)	8.254***	(1.487)
2006	4.077***	(0.816)	12.73***	(3.832)
2007	3.639***	(0.745)	9.387***	(2.597)
2008	3.216***	(0.726)	8.299***	(2.159)
(cont.)	Coeff.	SD	Coeff.	SD
Westinghouse	0.948	(0.201)	0.595***	(0.092)
1988	1.087	(0.132)	2.196***	(0.312)
1989	1.342	(0.350)	2.913***	(0.658)
1990	0.949	(0.205)	2.421***	(0.221)
1991	0.899	(0.243)	2.416***	(0.381)
1992	0.513*	(0.143)	1.425+	(0.263)
1993	0.423**	(0.124)	0.955	(0.236)
1994	0.565+	(0.194)	1.943***	(0.338)
1995	0.352**	(0.122)	1.166	(0.276)
1996	0.465*	(0.148)	1.193	(0.324)
1997	0.220***	(0.094)	0.418+	(0.201)
1998	0.0699***	(0.022)	2.9e-10***	(0.000)
N	435		435	
Pseudo R2	0.221		0.247	
Year FE	X		X	
Company FE	X		X	
Clustered SE	X		X	

Standard errors in parentheses

+ p<0.10, * p<0.05, ** p<0.01, ***p<0.001

Table C3: Citations model results for participants.

	US	
Effect	Coeff.	St. Dev.
1988	0.886	(0.118)
1989	0.871	(0.228)
1990	0.957	(0.074)
1991	1.046	(0.049)
1992	0.984	(0.082)
1993	1.123	(0.214)
1994	1.161	(0.112)
1995	1.096	(0.243)
1996	1.173	(0.226)
1997	0.969	(0.121)
1998	0.957	(0.201)
1999	0.917	(0.130)
2000	0.985	(0.243)
2001	0.88	(0.115)
2002	0.997	(0.240)
2003	1.15	(0.179)
2004	1.305*	(0.150)
2005	1.423*	(0.244)
2006	1.284	(0.212)
2007	0.791	(0.197)
2008	0.929	(0.392)
N	7,943	
Pseudo R2	0.0724	
Year FE	X	
Company FE	X	
Clustered St. Errors	X	

Standard errors in parentheses

+ p<0.10, * p<0.05, ** p<0.01, ***p<0.001

Table C4: Citation model results for company fixed-effects and treatment effects for each company.

	US	
	Coeff.	St. Dev.
GE	1.956***	(0.150)
1988	0.806*	(0.073)
1989	0.708*	(0.122)
1990	0.949	(0.071)
1991	1.028	(0.045)
1992	0.934	(0.067)
1993	0.96	(0.089)
1994	1.134	(0.103)
1995	0.929	(0.125)
1996	1.083	(0.186)
1997	0.898	(0.088)
1998	0.806*	(0.084)
1999	0.819*	(0.067)
2000	0.82	(0.112)
2001	0.790**	(0.057)
2002	0.803**	(0.061)
2003	1.037	(0.118)
2004	1.211*	(0.106)
2005	1.264+	(0.152)
2006	1.145	(0.130)
2007	0.683+	(0.136)
2008	0.693	(0.200)
SWPC	1.550***	(0.159)
1988	0.492***	(0.056)
1989	1.116	(0.214)
1990	0.350***	(0.032)
1991	0.618***	(0.043)
1992	0.840+	(0.080)
1993	0.636***	(0.074)
1994	0.638***	(0.072)
1995	1.235	(0.202)
1996	1.438+	(0.281)
1997	0.925	(0.118)
1998	1.261+	(0.157)
1999	1.002	(0.107)
2000	1.691***	(0.269)
2001	0.922	(0.081)
2002	1.465***	(0.127)
2003	1.199	(0.164)
2004	1.245*	(0.137)
2005	1.543**	(0.215)
2006	1.384*	(0.194)
2007	0.893	(0.195)
2008	1.618	(0.496)
(cont.)	Coeff.	St. Dev.
Westinghouse	1.131	(0.092)
1988	1.393***	(0.121)
1989	1.440*	(0.254)
1990	0.906	(0.063)
1991	0.832***	(0.038)
1992	0.946	(0.072)
1993	2.437***	(0.230)
1994	1.491***	(0.142)
1995	2.047***	(0.278)
1996	1.436*	(0.251)
1997	1.285*	(0.127)
N	7943	
Pseudo R2	0.0736	
Year FE	X	
Company FE	X	
Clustered SE	X	

Standard errors in parentheses

+ p<0.10, * p<0.05, ** p<0.01, ***p<0.001

Appendix D: Company Results for GE and SWPC Only

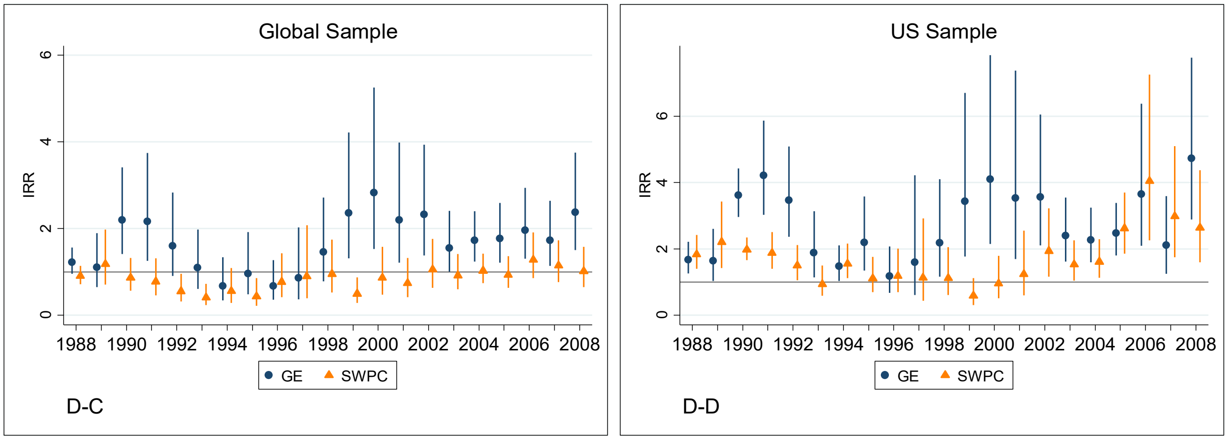

Figure D1: Subgraphs D-C and D-D display subgraphs 5-C and 5-D from the main text without separating out Westinghouse from SWPC patents for the count results.

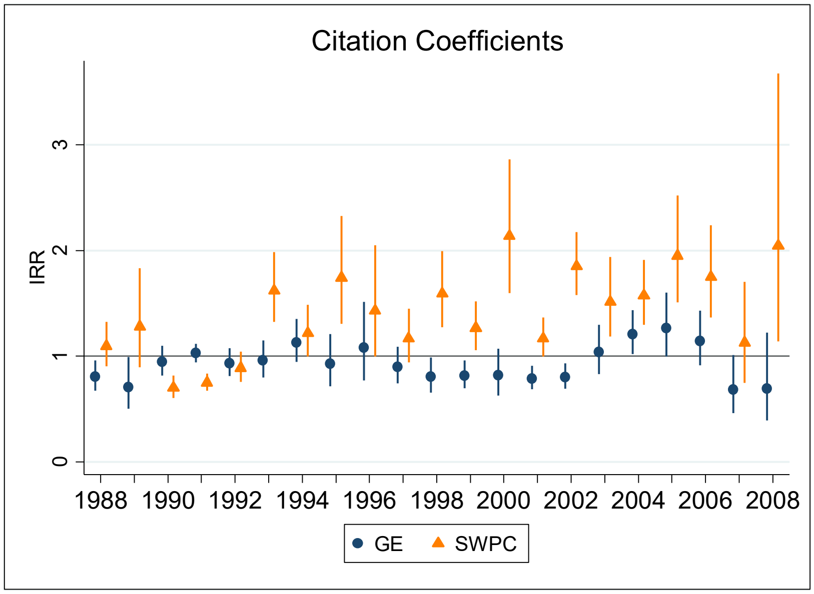

Figure D2: Citation coefficients similar to Figure 6-C in the main text but without separating out Westinghouse from SWPC patents for the citation results.

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CHAPTER THREE:

Policy Anticipation and Capacity Investment: Air Quality Standards and the Natural Gas Capacity Boom

1. Introduction

Natural gas capacity in the US electricity sector experienced unprecedented growth from 2000-2003 (Figure 1 & 2), with a surge of new and expanded electric generation units, particularly utilizing natural gas combined cycle gas turbine technology (NGCC). This represents a large, sudden investment in natural-gas fired power plants, which typically require a long planning and pay-back period. Research has cited numerous reasons for the early 21st century uptick in natural gas capacity including changes in technology feasibility, fuel prices, energy demand, domestic supply of natural gas, storage capacity, natural gas transportation infrastructure, and energy and environmental policies (Joskow, 2006 & 2011; Kaplan, 2010; Levi, 2013; Rao, 2012). Since investment decisions for capacity installation require planning time, it is also possible *anticipation* of impending policy changes influenced this capacity growth, which has not been considered in previous study of the natural gas capacity boom.

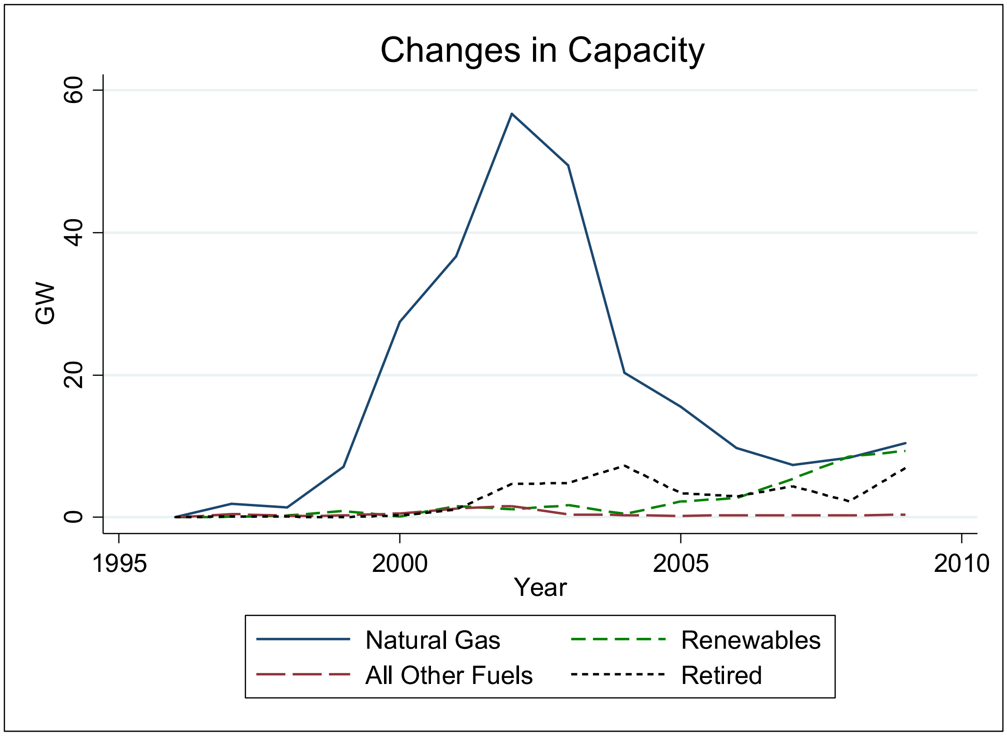

Figure 1: Increases in US natural gas, renewables, and all other fuels versus total capacity retired from 1997-2009 in GW/year.

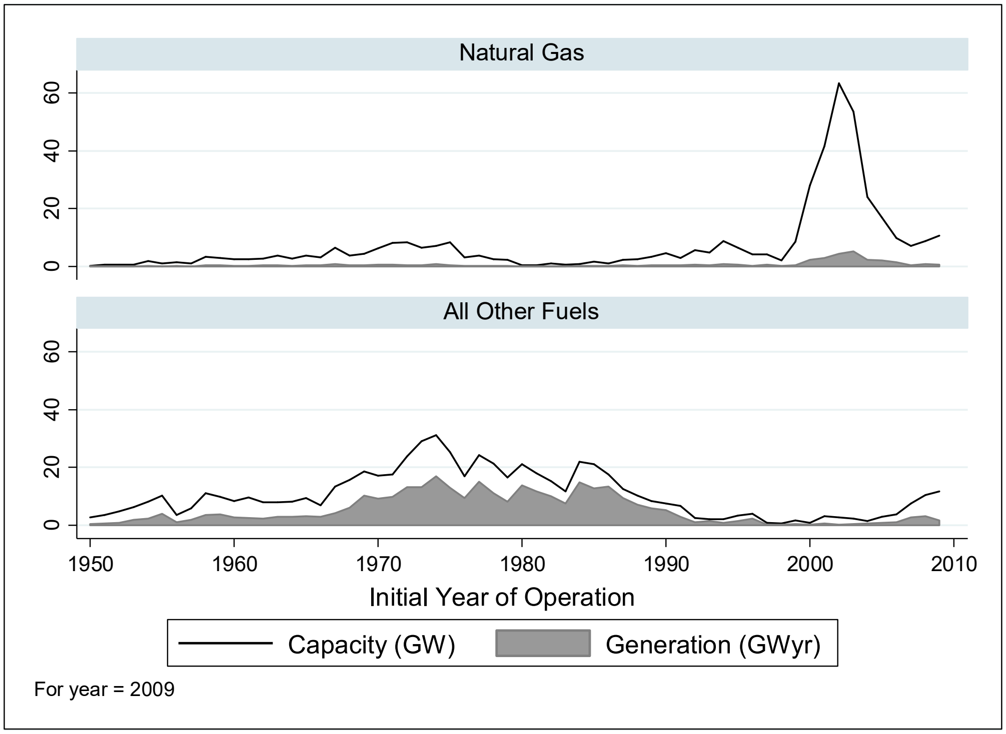

Figure 2: Changes in natural gas capacity versus all other fuels for existing power plant sector in 2009.

In 1997, the US Environmental Protection Agency (EPA) changed the format of the ozone and particulate matter (PM) National Ambient Air Quality Standards (NAAQS), effectively raising the stringency of the standards (Bell & Eliss, 2003), resulting in hundreds of counties being designated as nonattainment. Areas not meeting the NAAQS and designated as nonattainment are subjected to stricter construction regulations requiring emissions offsets and the most stringent air pollution control standards (Bachman, 2007; Frey, 2012). The normal time period between promulgation of new NAAQS and nonattainment designation is typically four years; however in this case designations did not take place until 2004 for ozone and 2005 for PM due to both expected and unexpected delays.

Since power plants must have permits to emit air pollution, there is reason to believe that areas expecting stricter building regulations may have rushed to complete planned capacity installations before new environmental regulations took place. Previous studies have considered the role of regulation on technology adoption and diffusion (Ishii, 2011; Popp, 2010; Frey, 2012), finding a strong link in both cases. Other studies have estimated the costs of regulatory uncertainty in the environmental sector as a result of regulatory delays, leakage, or other sources of inefficiencies (Bosetti & Victor, 2011; Reinelt & Keith, 2007). Absent the many sources of regulatory uncertainty regarding pollution policy, such as low credibility, politics, or market volatility, these studies find decision-makers choose to invest in cleaner technologies while anticipating environmental regulations. According to this literature, emitters in areas that anticipate new regulations with more certainty act sooner and more aggressively than other areas. The NAAQS have existed since the 1970 Clean Air Act Amendments, with the earliest reviews of these standards beginning in 1975 (Bachman, 2007). This established process for making nonattainment designations occurs with higher amounts of predictability than implementation of newer environmental policies, such as those aimed at reducing carbon emissions. The well-communicated, long lead time leading up to policy implementation provided investors plenty of time to act as well.

Prior studies of the natural gas capacity boom generally considered the influence of various technological and energy policy factors without quantifying the effects (Joskow 2006 & 2011; Rao, 2012; Levi, 2013). Or, studies look at characteristics of the firm (e.g. size, age, etc.) and ownership (e.g. independent power producer, or public-owned utility) that may influence electricity capacity installation decisions (Frey, 2012; Rose & Joskow, 1990). This study uniquely decomposes the boom in natural gas capacity empirically, specifically considering the role of policy anticipation that is in effect in some areas but not others in the presence of controls.

In order to study the role of policy anticipation on natural gas capacity growth, I use several difference-in-difference models. The pre-policy period, the time after the new standards were announced but before nonattainment designations were issued, is the time period of interest. The technology adoption decision in this case includes the decision to build a power plant, which type of plant (and thus, the fuel source) to build, how large the plant should be, and where it should be located. The format of this study addresses whether any new natural gas capacity was built using a linear probability difference-in-difference model, as well as the quantity of how much natural gas capacity was built using a continuous difference-in-difference model. I find that areas expecting nonattainment were more likely to build natural gas capacity before the designation, and built a total of 45-74% more natural gas capacity than areas not expecting nonattainment.

The growing complexity of the environmental regulatory process, decreased budgets for environmental institutions, and increased frequency of court challenges contribute to longer implementation periods for environmental policy (Rosenbaum, 2013). In an environment with frequent regulatory delays, policy anticipation may become more important in investment decisions. This paper begins with a background on NGCC technology and the natural gas capacity boom. Following this, a brief description of changes in the NAAQS is presented and theory on how policy anticipation and other controls influenced investment decisions. After a description of the models and data, the results of these models are presented and discussed.

2. Background

2.1 Natural Gas Capacity Boom

The natural gas capacity building boom peaked in 2002 with about 56 GW of new capacity installation, which is approximately 5% of the total US capacity as of 2009 (Figure 1). The adoption curves (Griliches, 1957) for different technologies based on the 2009 fleet of power plants shows a variety of “S” curves, none as sharp and pronounced as the recent adoption of new natural gas capacity (Figure 3).

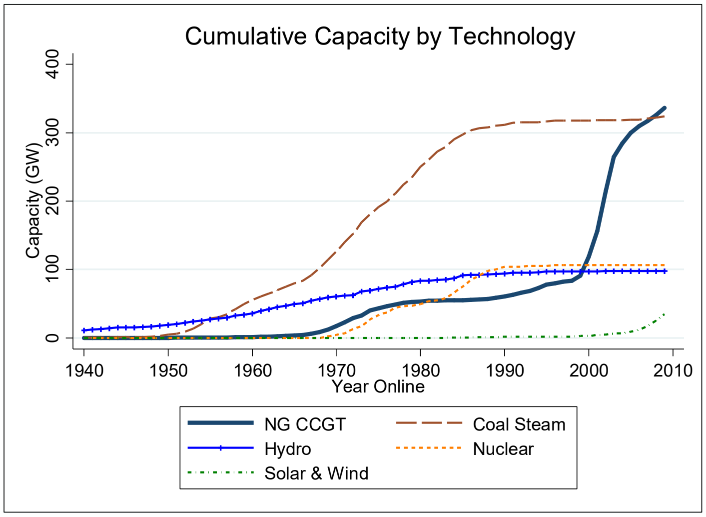

Figure 3: Cumulative capacity of different technologies by installment year based on 2009 fleet of power plants.

New installations of natural gas capacity came from both NGCC and single-cycle gas turbine (GT) units during the 2001-2003 boom in natural gas capacity across the country (Figure 4). NGCC units include both a gas turbine and heat recovery steam turbine that reuses the waste heat from the gas turbine for high efficiency generation. Due to lower levels of impurities in natural gas compared to coal, and high thermal conversion efficiency of NGCC plants,[51] NGCC generators produce up to 60% less carbon dioxide (CO_2), 80-90% lower nitrogen oxides (NO_x), and negligible amounts of particulate matter (PM) and sulfur dioxide (SO_2).[52] NGCC units are typically larger than GT generators and built to support both peaking and baseload operations, and approximately 70% of the new natural gas capacity that came online from 2001-2003 was installed as a NGCC unit.

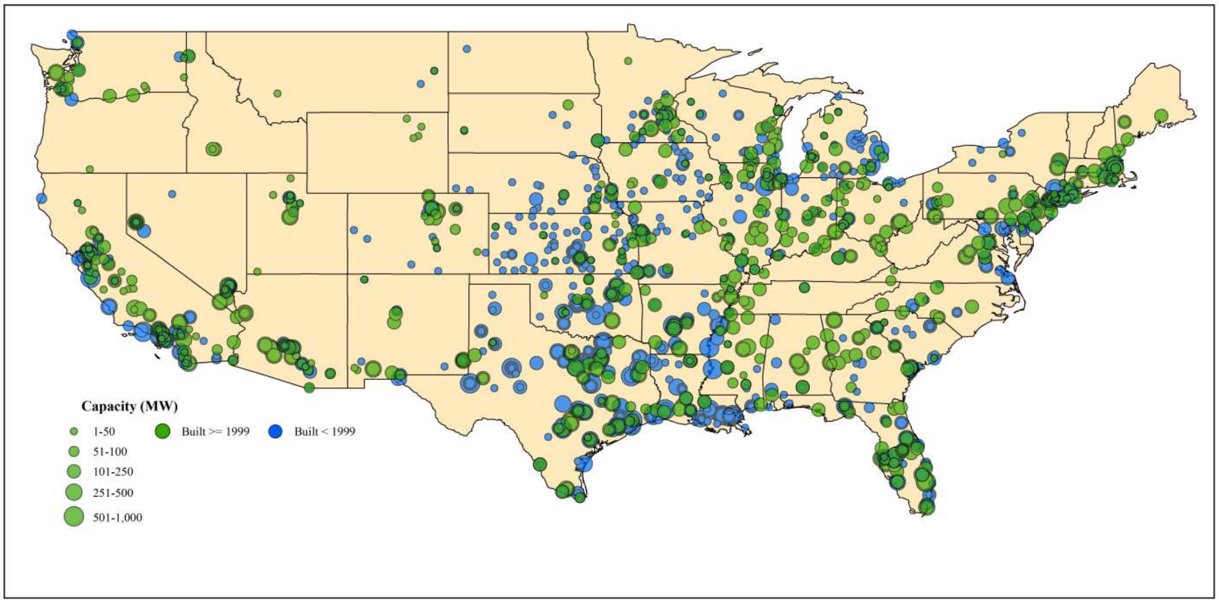

Figure 4: Map of natural gas generators in the US, with those installed before 1999 in blue, and from 1999-2009 in green, sized by capacity of the generation unit.

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[51] It should be noted that recent literature argues the lifecycle methane emissions of unconventional natural gas burned in a NGCC ultimately leave a higher greenhouse gas footprint than coal generation due to hydraulic fracturing extraction methods for shale gas (Howarth 2014). EPA and others continue to conduct more research to understand the impact of upstream methane emissions on the lifecycle CO_2 emissions reductions from NGCC.

[52] Nitrogen dioxide is a precursor to ozone, and both NO_x and SO_2 are precursors to particulate matter (PM).

NGCC plants can be built relatively quickly and cheaply, requiring about half the time and capital cost of a typical coal-fired plant. The EIA reports in 2010 that the overnight capital cost for conventional NGCC plants was $978/kW, compared to a single unit advanced pulverized coal plant at $3,167/kW (in 2010 dollars).[53] In the 2000Annual Energy Outlook,[54] the EIA projects that natural gas would far outpace coal in new capacity due to lower capital costs, shorter construction lead times, higher efficiencies, and lower emissions. In most cases, the decision to build a power plant includes a proposal by a firm, approval by a Public Utility Commission, a permitting process, and a 2 year lead time for NGCC plant construction process before the plant is operational.[55]

2.2 NAAQS Changes

The NAAQS serve as one of the primary means for controlling air quality through the use of standards for criteria pollutants to protect public health and welfare. In accordance with the 1977 Clean Air Act Amendments, EPA must review the NAAQS every five years to keep these standards appropriately protective in light of current scientific research. In 1997 following court-ordered reviews of the NAAQS, EPA moved from a 1-hour time averaging standard to an 8-hour standard for ozone, and added $PM_{2.5}$ as a criteria pollutant, resulting in new nonattainment areas for ozone and PM.[56]

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[53] The EIA report, "Updated Capital Cost Estimates for Electricity Generation Plants" (2010) is available at: http://www.eia.gov/analysis/studies/powerplants/capitalcost/archive/2010/pdf/updatedplantcosts.pdf.

[54] The 2000 EIA Annual Energy Outlook is available at: http://www.eia.gov/outlooks/archive/aeo00/pdf/0383(2000).pdf.

[55] The EIA report, "Updated Capital Cost Estimates for Electricity Generation Plants" (2010) is available at: http://www.eia.gov/analysis/studies/powerplants/capitalcost/archive/2010/pdf/updatedplantcosts.pdf.

[56] US EPA "Table of Historical Ozone National Ambient Air Quality Standards (NAAQS)" available at: https://www.epa.gov/ozone-pollution/table-historical-ozone-national-ambient-air-quality-standards-naaqs, and "Particulate Matter (PM) Standards – Table of Historical PM NAAQS" available at https://www3.epa.gov/ttn/naaqs/standards/pm/s_pm_history.html.

Projects in nonattainment areas, or areas that are not meeting the NAAQS, are subjected to stricter construction and operation standards, which particularly impacts construction of new electric utility or industrial sources (Bachmann, 2007). Specifically, new sources in nonattainment areas must follow Nonattainment New Source Review procedures and meet Lowest Achievable Emissions Rates - the most stringent air pollution control standard in the Clean Air Act short of banning construction.

Designations resulting from the revisions to the ozone and PM standards in 1997 did not take place until 2004 and 2005, respectively, due to several bureaucratic steps in the policy process and court challenges. After promulgation of new NAAQS, states are required to collect three years of monitoring data before submitting a nonattainment recommendation to the EPA Administrator following specific guidance from EPA.[57] Once EPA receives a recommendation from a state, EPA responds with its designation, which it cannot finalize for at least forty days, giving states time to challenge the designation. In addition, President Clinton issued a memorandum with the promulgation of the 1997 standards that provided supplementary guidance on implementation of the new standards. This granted EPA and the states even more time before designations were finalized to allow additional flexibility and reduce economic burdens on states and firms. Litigation of both standards further delayed actual attainment designations (Bachman, 2007). Investors and state regulators could have expected at least three to four years from promulgation of the standards to final designation, and in this case faced even more time.

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[57] EPA guidance indicates that metropolitan statistical areas that have design values exceeding the new standards are considered nonattainment. These “design values” are based on three year averages of air quality, therefore states have up to three years to collect monitoring data for their nonattainment recommendations. Thus, air quality from 1998-2000 needed to be collected before states could submit a recommendation for ozone nonattainment.

Regulators and industry first officially become aware of anticipated changes in the NAAQS with the NAAQS proposals appearing in the Federal Register in December 1996. States maintain air quality monitoring continuously, and know at any point in time if they are meeting the NAAQS based on most recent design values. In the case of $PM_{2.5}$, while new monitoring instruments were required, modeling predictions and PM_{10} measurements provided states adequate estimates of anticipated levels. Further, since designations are based on three year averages, in the first year collecting data states can reasonably project if they will have nonattainment areas. This is well communicated to regulated industry through websites, workshops, and outreach events by state agencies and regional and Federal EPA offices. Therefore, investors and regulators are typically able to anticipate nonattainment designations. Areas that were designated nonattainment under the new 1997 ozone and $PM_{2.5}$ standards are below in Figure 5.

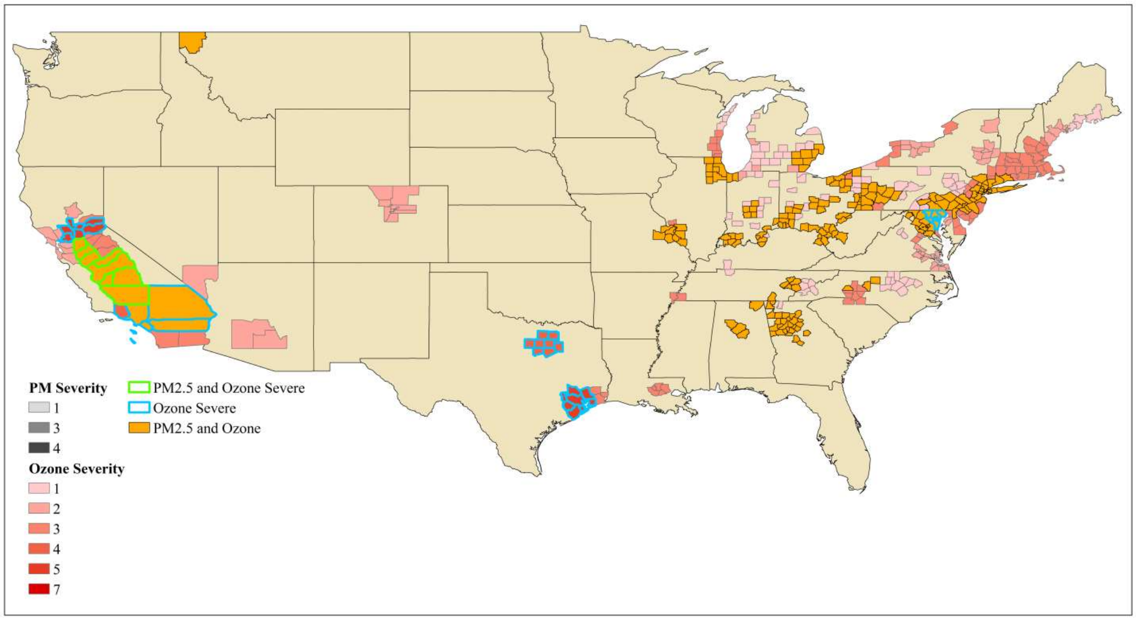

Figure 5: Areas that were designated as nonattainment for PM2.5 and ozone, ozone only, or PM2.5 only based on the 1997 standards and severity of nonattainment.

In addition to designating an area as nonattainment, the EPA also classified these areas based on the severity of nonattainment. More offsets are mandated in areas with severe nonattainment; to facilitate achievement, they receive later compliance dates. With respect to the 1997 standards, EPA designated areas based on seven classification levels for ozone, and three classification levels for PM, seen in Table 1 and Figure 5.

Since ozone and PM share some precursor pollutants, many of the areas with PM nonattainment also experienced ozone nonattainment. Table 1 shows how many counties designated nonattainment for each classification level were also designated nonattainment (of any classification) of both pollutants for the 1997 NAAQS.[58] There were more ozone nonattainment areas in general, with about 40% of all ozone nonattainment areas also designated nonattainment based on $PM_{2.5}$. Of the $PM_{2.5}$ nonattainment areas, 85% of them were also designated nonattainment for ozone, with all “serious” $PM_{2.5}$ nonattainment classifications also designated nonattainment for ozone.

Upon promulgation of the standards in 1997, areas knew reasonably well if they would have difficulty meeting the standards. Therefore, firms in areas that anticipated nonattainment designations may have been more likely to build new electric capacity before the more stringent building regulations became effective. Further, firms in areas with existing, “dirty” capacity

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[58] EPA used Clean Air Act § 172 (42 U.S.C. §85(I)(D)(1) (1)) to designate all nonattainment areas with a 1-hr ozone design value of less than 0.121 ppm as a “general” ozone nonattainment area, which had similar requirements to a “moderate” classification. EPA then classified all areas above the 1-hr threshold as marginal, moderate, serious, severe, or extreme with the associated requirements. However, the use of the 1-hr design value to determine if an area was “general” or “classifiable” nonattainment for the 8-hr standard was vacated by the D.C. Circuit Court in 2006 after initial designation, and the remaining subpart 1 “general” nonattainment areas were classified as moderate nonattainment areas in 2012. These areas remained nonattainment as long as the 8-hr design value was exceeding the 1997 standard, only the classification was revoked. Hence, these areas are titled as “Former Subpart 1” nonattainment areas. $PM_{2.5}$ “general” nonattainment classifications were not formally challenged in court, however were also redesignated to “moderate” classification in 2011.

may have been more likely to build new, cleaner capacity in anticipation of tighter operating regulations.

Table 1: Count of counties designated nonattainment by different classification levels for the 1997 ozone and $PM_{2.5}$ standards.

	Ozone		**$PM_{2.5}$**	
Class	**Count**	**Also PM**	**Count**	**Also Ozone**
1. Former Subpart 1	136	56	106	89
2. Marginal	75	8	0	0
3. Moderate	181	96	94	81
4. Serious	16	6	8	8
5. Extreme	9	9	0	0
6. Severe 15	17	3	0	0
7. Severe 17	2	0	0	0
Total	436	178	208	178

2.3 Other Factors

Outside of the technological advantages of NGCC and regulatory changes, there are several other factors to consider while evaluating changes in capacity. One could expect an overall increase in capacity with growing electricity demands, particularly in areas with growing population or industry. For example, the EIA Energy Outlook in 1995 hypothesized that the information technology boom of the 1990s and increased sales of appliances would lead to increased energy demand in certain areas.[59] However, the immense peak in construction of one specific fuel-technology combination, as seen from 2001-2003 with NGCC, is rare. EIA data shows that recently retired capacity (from 2001-2009) is about 8% of total new capacity installations (from 2001-2009) (Figure 1).[60] This shows that the majority of new capacity installations were not likely stemming from a need to replace retired capacity.

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[59] EIA's Energy Outlook in 1995 is available at: http://www.eia.gov/outlooks/archive/aeo95/pdf/0383(95).pdf.

[60] I conducted sensitivity tests that included a variable for concurrent and lagged retirements. Since this value is small during the pre-policy period of interest, it did not have a significant impact on the results. Further, closer examination in the EIA-860 data time series reveals multiple units once designated retired come out of retirement or are moved to standby and then later retired. For these reasons I do not include a retirement variable in the analysis.

In addition to changes in electricity demand, factors regarding the supply of fuel may also impact new capacity installation. Over time, prices of natural gas have been volatile, and generally growing since late 1990s until more recent declines (Figure 6). Rao (2012) shows that new NGCC plants become competitive with coal plants when natural gas prices are below $7.40 per million metric British thermal unit (MMBtu), and between $10.00 and $12.80 supposing a carbon penalty.[61] The average citygate price of natural gas was $6.15 MMBtu[62] from 1998-2004, and below $7.40 per MMBtu for most of this time period.

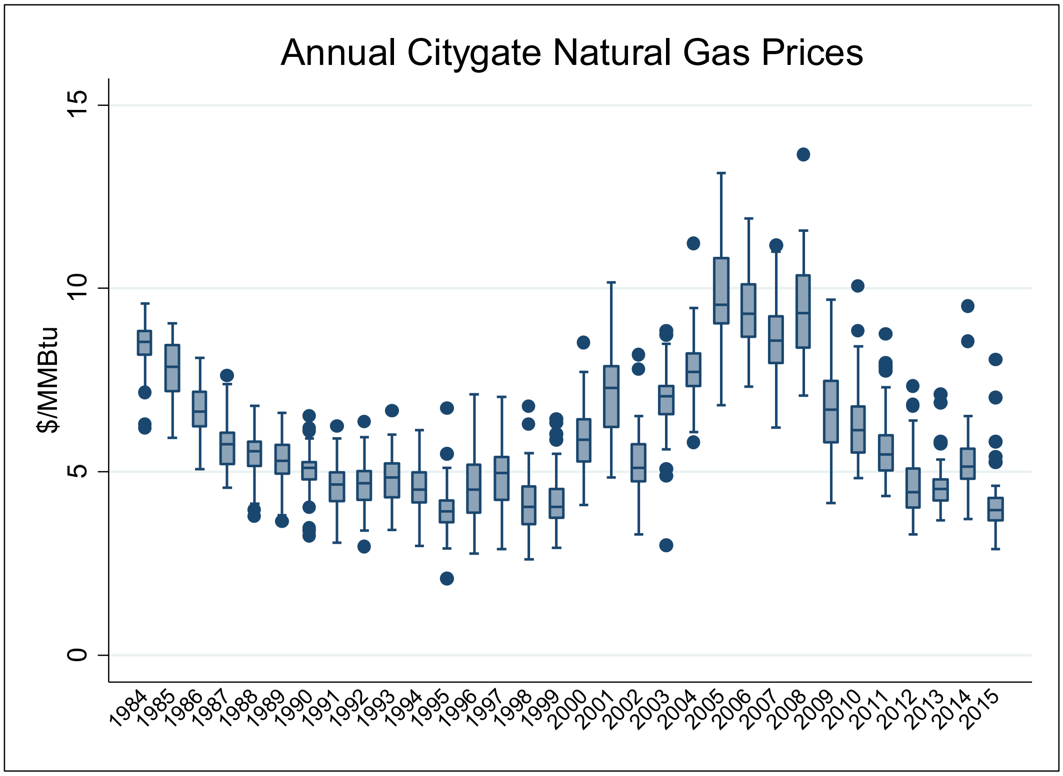

Figure 6: Box-plot of state-averaged annual citygate natural gas prices for the states included in this analysis (i.e. all states except Alaska and Hawaii) in 2010 dollars.

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[61] These numbers are based on the average price for plants with various capacity and capacity factors from the original report cited in Rao (2012) from Wynne, Broquin, and Singh's 2010 *Bernstein Report* titled, "US utilities: Coal-fired generation is squeezed in the vice of EPA regulation; who wins and who loses?"

[62] Based on the annual, national average citygate price of natural gas in 2010 dollars, available at: https://www.eia.gov/dnav/ng/ng_pri_sum_a_EPG0_PG1_DMcf_m.htm.

In addition to low natural gas prices in the 1990's, natural gas prices were forecasted to stay low through the early 2000s, further incentivizing investment in natural gas power plants. In the 1995 Annual Energy Outlook (AEO),[63]the EIA predicted that natural gas prices delivered to the electricity sector would remain around \$2-\$3 in 1995 dollars per MMBtu through 2015. It cites Federal and State initiatives for increased competition in the natural gas market would keep prices low, and assuming slow economic growth would stabilize gas prices and higher production.

Natural gas availability also has an influence on the choice to construct more natural gas facilities. Recent changes in extraction technology – namely horizontal drilling and hydraulic fracturing – have led to large changes in the estimated natural gas reserves available at lower prices (Shahidehpour, 2005). However, the shale gas revolution generally began in 2007, years after the 2000-2003 natural gas capacity buildout, and is therefore not being considered in this study as a potential factor in the early 2000s capacity boom.

Natural gas generation also requires storage and transportation infrastructure. Previous studies have found that transmission of natural gas has become easier as electricity infrastructure has improved over time (Shahidehpour, 2005). A dense network of pipelines supplies natural gas for home heating and power plant purposes across the country. According to my calculations using EIA and eGRID data, about 26% of new natural gas capacity in the boom years went into areas that had no natural gas generating capacity before. This suggests these areas may have experienced improvements or expansions of natural gas pipelines which allowed natural gas capacity to be built in the area for the first time. However, most of the new capacity (74%) went into areas with preexisting natural gas-fired generation units that therefore already had large-capacity pipelines in the area.

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[63] The EIA AEO for 1995 is available at: http://www.eia.gov/outlooks/archive/aeo95/pdf/0383(95).pdf.

Additionally, restructuring of the electricity industry took place around the time period of the natural gas boom. From 1997-2004 multiple states passed legislation to deregulate their electricity markets. However, to different degrees, some states either halted or even reversed their deregulation efforts after complications in California and international markets following deregulation. There are competing theories as to how deregulation or market restructuring may impact capacity investment. Critics of rate-of-return regulation in traditional markets (absent competition) argue utilities have the incentive to invest in higher cost capacity under the likelihood that rate increase requests would be approved, also known as the Averch-Johnson effect (Averch-Johnson, 1962). This is one argument for why deregulation, and the introduction of competition, would help lower costs in the electric utility sector and could lead to less new natural gas capacity in deregulated areas. Recent work by Knittel et al. (2015) finds restructured markets had reduced investment in NGCC, post-restructuring, compared to traditional markets due to the absence of long-term contracts. They find this reduced NGCC capacity has limited the ability for fuel-switching between coal and natural gas plants as natural gas prices started dropping in 2009.

However, opposing theories argue that deregulation decentralized capacity planning decisions, which may have led to rapid construction of capacity. In interviews with plant managers, plants in deregulated areas were less likely to believe their competitor's plans for capacity growth. In general, they were optimistic other plants would not be able to accomplish their full construction goals, and would pursue larger capacity gains of their own in attempts to grab a larger piece of the potential profit (Kadoya et al., 2005). As mentioned in the section on natural gas capacity, NGCC plants can be constructed faster and are more suitable for peaking purposes than a traditional coal or nuclear plant. For these reasons, it is possible that more

NGCC plants were constructed to take advantage of higher spot-market prices during peaking operations when energy prices are at their highest in competitive markets (Ford, 2002).

Previous literature largely concludes that deregulated areas will have more new natural gas capacity installation since they may attract more independent power producers (IPPs) (Ishii, 2011)—which were responsible for 80% of the new capacity installations during this time (Joskow, 2006)—and were thus subject to decentralized capacity planning (Ford, 2009; Kadoya et al., 2005). However, other studies have found conflicting results leaving it possible that deregulated states were less likely to invest in new capacity following Averch-Johnson (Frey, 2012). For these reasons, I include a control for states with wholesale market competition in the models. In Appendix B I explore the impact of regulatory evolution on natural gas capacity growth further with additional analysis.

This section describes the many different factors that may affect new natural gas capacity investment. Research has generally stated that changes in technology feasibility, population, industry, retirements, fuel prices, market restructuring, and transportation infrastructure have contributed to this boom in natural gas capacity installation. These factors are included as other independent variables in this study or more generally controlled for using fixed-effects, described further in the next section.

3. Analysis

3.1 Data and Descriptive Statistics

I use several datasets with information on power plants and area characteristics to construct a strongly balanced panel for 1997-2009. I primarily depend on Energy Information Administration (EIA) generator and plant data reported in EIA 860 forms for capacity and plant characteristics. Additionally, I used EPA's Emissions & Generation Resource Integrated Database (eGRID) to determine which plants are in the power sector. While the dataset covers

1996-2009, the dependent variable is the change in natural gas capacity, therefore the regression dataset runs from 1997-2009 (Table 2). I removed generators that were not recorded as "operating" in the EIA data. This removes plants that were under construction, out of service, planned, retired, on standby, or operating under test conditions. Further, plants identified as combined heat and power plants were removed from the dataset since they typically do not dispatch to the grid.

The ozone and PM nonattainment data and nonattainment severity information are from the EPA Green Book. The state citygate price of natural gas is provided by EIA, and population change from 2000 and 2010 at the county level is from US Census data. Gross domestic product (GDP) data is from the US Bureau of Economic Statistics and is the real GDP in chained 2009 dollars.

Table 2: Descriptive statistics and definitions of variables.

Variable	Description	Units	Equation	Obs.	Mean	Std. Dev.	Min	Max
ln NG cap change	Difference in the logs of natural gas capacity year to year	ln(MW)	ln(NG cap_t) - ln(NG cap_{t-1})	13,656	0.082	0.62	-0.223	7.795
NG build	= 1 if new NG capacity was built in the area that year, 0 otherwise			13,656	0.044	0.204	0	1
NG cap change	Difference in natural gas capacity year to year	MW	(NG cap_t) - (NG cap_{t-1})	13,656	18	130	-359	4,428
preOzone*Ozone	interaction variable for ozone DID		preOzone * Ozone 1997 treated	13,656	0.079	0.269	0	1
prePM*PM	interaction variable for PM DID		prePM * PM 1997 treated	13,656	0.044	0.204	0	1
Ozone 1997 treated	=1 if the area was designated nonattainment for ozone 1997, 0 otherwise			13,656	0.157	0.364	0	1
PM 1997 treated	=1 if the area was designated nonattainment for PM 1997, 0 otherwise			13,656	0.075	0.263	0	1
preOzone	=1 if year is 1998-2003, 0 otherwise			13,656	0.5	0.5	0	1
prePM	=1 if year is 1998-2004, 0 otherwise			13,656	0.583	0.493	0	1
Ozone NAA	=1 when any ozone nonattainment for any ozone standard, 0 otherwise			13,656	0.115	0.318	0	1
PM NAA	=1 when any PM nonattainment for any PM standard, 0 otherwise			13,656	0.073	0.26	0	1
Restructure	=1 in the year state introduced wholesale market competition, 0 otherwise			13,656	0.571	0.494	0	1
Pop change percent	Percent change in population 2010-2000	%	(pop_{2010} - pop_{2000})/pop_{2000}	13,656	0.062	0.1	-0.499	0.547
ln(NG P)	Natural log of annual average Citygate natural gas price in real 2010 dollars	ln($ chained 2010)	ln(NG $P)_{t-3}$	13,656	1.759	0.307	1.38	2.27
ln GDP change	Difference in the logs of GDP in chained 2009 dollars	ln($ chained 2009)	ln(GDP_t) - ln(GDP_{t-1})	13,656	0.021	0.027	-0.097	0.113
ln(initial cap)	Natural log of initial nameplate capacity for all generation types, 0 if there was no initial capacity	ln(MW)	ln(Total nameplate)	13,656	4.196	2.651	0	9.474
Severe	=1 if ozone or PM nonattainment classification serious, extreme, or severe			13,656	0.008	0.089	0	1
Total nameplate	Total nameplate capacity for all generation types	MW		13,656	781	1,563	0	17,153

3.2 Empirical Model

To measure the impact of nonattainment anticipation on capacity investment, I use a difference-in-difference (DID) model to examine variation in capacity growth during the pre-policy period between areas expecting nonattainment designations following the new NAAQS and those that did not. The DID model compares the average gain from before and after a policy takes place in the treated group with a control group. A typical DID model is interested in the difference after the policy takes place; however, since the anticipation of nonattainment is the policy variable of interest in this study, I am focusing on the pre-policy period when the effect is expected to take place. A DID is ideal in this case because multiple groups and time periods are present in this dataset in order to identify a causal effect. I also include a linear probability model (LPM) version of the DID to analyze the probability of any new natural gas capacity being built in a zone, versus how much new natural gas capacity was built in the regular DID model.

The unit of analysis in this study is census-based electricity "zones" of roughly 780 MW capacity (Table 2). The zones are based on 2009 census Core Based Statistical Areas (CBSAs)[64] of metropolitan and micropolitan areas (Figure 7). Each facility is assigned to a zone based on the CBSA it falls in, or if it does not fall within the boundaries of a CBSA, which CBSA it is closest to. If facilities are outside of the state containing the CBSA it is closest to, I create a new zone for that CBSA with the state the facilities reside in. The zones are further delineated for those facilities that reside within the boundaries of the CBSA or outside of the boundaries of the CBSA since they may behave differently. Therefore, the zones are CBSA-state areas for facilities that are either inside or outside the boundaries of the CBSA.[65] There are 1,138 zones

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[64] Previously known as metropolitan statistical areas, or MSAs.

[65] For example, there are several facilities with the closest CBSA the Dothan, Alabama metropolitan area that fall within the state boundaries of Alabama, Georgia, and Florida. Therefore, the Dothan metropolitan area will have

each year that remain fixed throughout the dataset. These zones are not as fine as county level jurisdictions, but not as coarse as state jurisdictions, and I attach the relevant policies to each zone. The standard errors are clustered at the CBSA level since the same CBSA is connected to several zones in some cases.

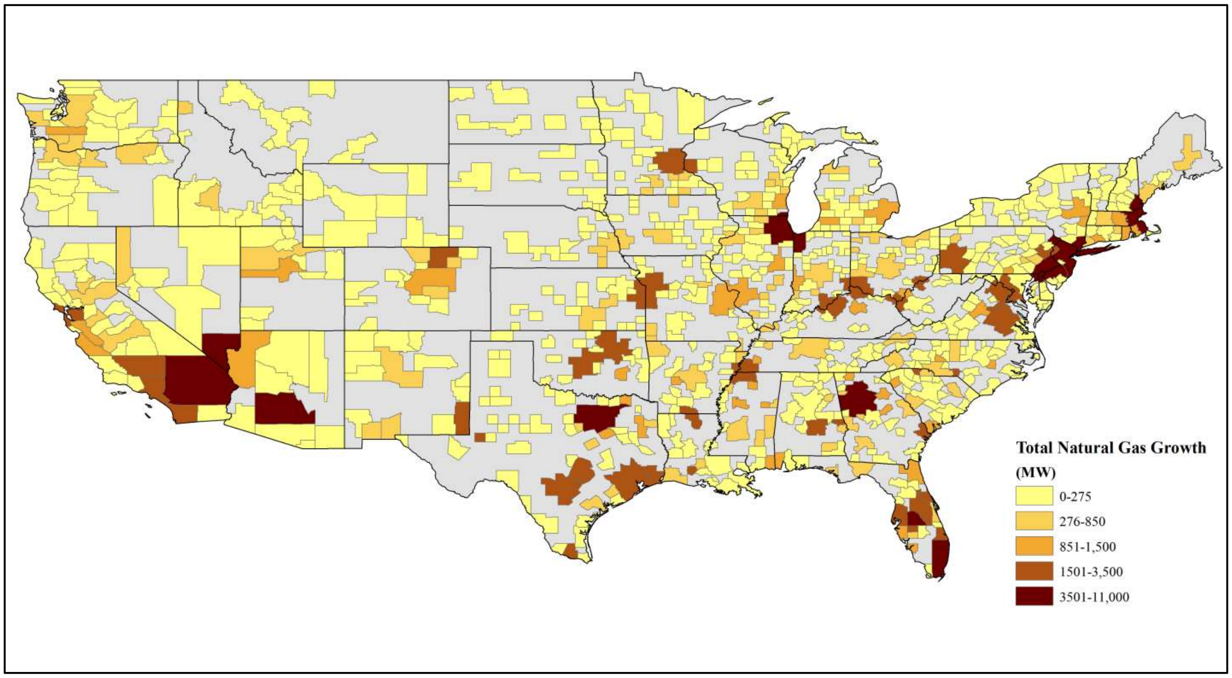

Figure 7: Changes in natural gas capacity from 1997-2009 aggregated by CBSA.

The dependent variable in the DID is the difference in the natural log of natural gas capacity from one year to the next (*ln NG cap change*). The dependent variable in the LPM DID model (*NG build)* is a dummy variable, coded as 1 if the zone built any natural gas capacity in that year, 0 otherwise. The DID model (equation 1) includes state (α_s) and year fixed-effects (θ_t) to control for all unobservable stationary statewide and time effects.[66] For example, other policies, or changes in demand from sources not included in the model can be controlled using

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four zones: in Alabama and in Dothan metropolitan area, in Alabama but not within Dothan metropolitan area, in Georgia but not within Dothan metropolitan area, and in Florida but not within Dothan metropolitan area.

[66] Sensitivity tests were conducted using individual fixed-effects. The interaction variables remained significant and of similar magnitudes, however further information on the other control variables was lost, therefore these results are not included in this study.

these area and time fixed-effects. The model also includes robust and clustered standard errors based on nearest metropolitan area to address heteroskedasticity and potential correlations among the errors within a region. The variables *preOzone*Ozone* and *prePM*PM* are the interaction variables of interest ($\delta_0(treat_i \cdot prepolicy_t)$) indicating the observations took place during nonattainment anticipation (e.g. *preOzone,* 1998-2003 for ozone and 1998-2004 for PM) and in areas that were eventually designated nonattainment (e.g. *Ozone 1997 treated*). The inclusion of these variables in the model captures possible differences between the treated and control groups after the pre-policy period, while the time period dummy controls for other unobservable factors that may have caused a difference in the pre-policy period absent the policy.

$$y_{it} = \beta_0 + \delta_0(treat_i \cdot prepolicy_t) + \gamma_1 treat_i + \gamma_2 prepolicy_t + cX_{it} + \alpha_s + \theta_t + \epsilon \quad \text{(eq. 1)}$$

I also include a model testing the different levels of classification of nonattainment to see if firms in areas with higher pollution levels built (or were more likely to build) more natural gas capacity than in areas with lower pollution levels. In order to test this, I run the LPM DID with the same controls but with an additional "severe" variable indicating which *preOzone*Ozone* and *prePM*PM* were also above moderate classification (i.e. serious, extreme, or severe). I use the LPM version of the DID because there are a limited number of observations fitting this "severe" criteria, and it is statistically simpler to determine if building occurred at all versus how much in a continuous model.

There are several control variables included to address other factors that might contribute to changes in natural gas capacity (cX_{it}). The *Pop change percent* variable is the percentage change in population for the counties of each CBSA from 2000 to 2010. *Restructure* follows

Craig and Savage (2013) conventions of coding all states with access to wholesale markets (i.e. "partial competition") as 1, beginning in the year the state adopted the initiative to restructure, leaving states with traditional markets coded 0 (Appendix A). The $ln(NG\ P)_{t-3}$ variable is the annual state average citygate price of natural gas at a three year lag.[67] I ran sensitivity tests on several different lags of natural gas prices from concurrent to six year lags. The overall R-squared measure of fit, and DID interaction coefficients of interest did not change with the different lags of natural gas prices, indicating that any year of lagged natural gas prices is orthogonal to the interaction variables. Therefore, I decided to use the three year lag price (*t-3*) which represents the price of natural gas when the decision to build new capacity was typically being made. The *ln GDP change* variable is the difference in the natural log of gross domestic product from one year to the next for each state to control for changes in industrial activity. On average, nonattainment areas have a larger capacity than areas with no nonattainment designations resulting from the 1997 standards, as they are typically more metropolitan areas. For this reason, I include a control for initial capacity (*ln*(*initial cap)*). I also include a variable controlling for nonattainment status based on previous NAAQS standards for each pollutant (e.g. $ozoneNAA_{it}$). All of the variables are described further in Table 2.

Bertrand et al. (2004) demonstrate that DID standard errors can be biased due to autocorrelation. I test for autocorrelation with a Lagrange-Multiplier test which shows there is no first-order autocorrelation. I also use a simple test suggested by Bertrand et al. (2004) that averages all pre- and post- policy variables and runs the DID on just these two time periods to eliminate autocorrelation. These results (not included) contain very similar coefficient values, and all interaction variables remain significant at the 94% confidence level, which further indicates autocorrelation is not an issue in the original model.

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[67] However, it is possible that sub-state variation in natural gas prices could matter as well.

4. Results & Discussion

Table 3 contains the results from the DID regressions with the interaction variable *preOzone*Ozone* and *prePM*PM* as the main variables of interest. Model 1 is the LPM DID model with the binary *NG Build* variable as the dependent variable. Model 2 is the continuous DID with *ln NG cap change* as the dependent variable. Model 3 is the same LPM in model 1 but with an additional variable (*Severe*) indicating if the nonattainment area was classified as serious to severe nonattainment.

The results of the LPM DID show areas anticipating ozone nonattainment, during the pre-policy period (1998-2003) are 5% more likely to build any new natural gas capacity than other areas, while areas anticipating PM nonattainment are 8% more likely to build natural gas capacity, *per year*. Each of these interaction variables is significant at the 99% confidence level or above. At the 95% significance level, the same DID interaction variables are significant in the continuous DID (model 2) showing areas anticipating ozone nonattainment would have built 10% more natural gas capacity, while areas anticipating PM nonattainment built 13% more natural gas capacity than other areas, *per year*. Over the six year period anticipating ozone, and seven year period anticipating PM nonattainment, this would mean these areas built 45% and 58% more natural gas capacity, respectively, than areas not anticipating new nonattainment designations.[68]

As seen in Table 1 and Figure 5, multiple areas faced both ozone and PM nonattainment simultaneously. By summing the coefficients from model 1 for *preOzone*Ozone* and *prePM*PM*, I find that areas anticipating both ozone and PM nonattainment built 23% more natural gas capacity than other areas per year, for a cumulative growth of 74% more natural gas

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[68] This was calculated using the following derived equation to measure how much lower natural gas capacity would have been absent nonattainment: $\%\Delta y_n = e^{-ny} - 1$, where n is the number of years for accumulation, and y is the interaction coefficient for the policy.

capacity. Using the average natural gas capacity growth during this time of 18 MW per year (Table 2), areas expecting both ozone and PM nonattainment built approximately 93 MW more new natural gas capacity from 1998-2003 than average, which is on the order of adding an additional medium-sized generating unit or small-sized power plant.

The larger coefficient for the PM interaction in all models indicates PM nonattainment anticipation had a greater impact on natural gas capacity growth than ozone nonattainment anticipation. While NGCC reduces ozone precursor emissions to 5% of NO_x and less than 1% of SO_2 emissions of coal-steam combustion, it produces only negligible amounts of PM, closer to 0.01% of coal-steam PM emissions. This large advantage of NGCC in PM reductions to ozone precursors may explain why the coefficients on PM interactions are larger than ozone. The additional year of anticipation (2004) before designations may also contribute to this difference.

Looking beyond the interaction variables in the DID models, restructured areas were 3% less likely to build new natural gas capacity per year in the LPM model confirming the findings from Frey (2012). This supports the hypothesis behind the Averch-Johnson effect suggesting deregulated areas would experience less capacity growth absent rate-of-return regulation. The citygate price of natural gas at a three year lag is only significant in the continuous DID, indicating as natural gas prices increased three years prior, natural gas capacity increased. The increase in natural gas price in the early 2000s was in part due to the increased demand caused by the natural gas capacity buildout, but also due to several cold winters and limited supply of natural gas from decreased drilling and exploration while natural gas prices bottomed out in the late 1990s (Neumann & von Hirschhausen, 2015). Intuitively, one would expect low prices of natural gas preceding the boom, which was the case in the late 1990s. However, the rapid increase in prices in the early 2000s was generally unexpected (Neumann & von Hirschhausen, 2015), therefore plans to complete or undertake new building projects may have continued as planned despite the sudden uptick in prices.

The results also show changes in GDP are not significantly related to changes in natural gas capacity, but areas with a growing population were more likely to have new natural gas capacity built. The initial capacity variable is significant in the LPM and continuous DID, with a positive coefficient in the LPM and negative coefficient in the continuous model. This shows that areas with larger initial capacity were more likely to build (as expected). However they had relatively less natural gas capacity growth, probably because these areas already contained a substantial amount of capacity.

Adding the *Severe* variable to indicate if areas expecting nonattainment during the pre-policy period had higher levels of pollution in model 3 does not lead to considerably different results from the LPM in model 1. The *Severe* variable is statistically insignificant in model 3, which is likely due to the limited number of areas at this higher severity level (10% for ozone, and 3% for PM, Table 1). The coefficients on the interaction variables (*preOzone*Ozone* and *prePM*PM*) slightly decrease from model 1 upon adding the *Severe* variable. In the case where there is greater variance in the severity of nonattainment, perhaps as NAAQS continue to be tightened in later revisions, this type of analysis may provide more insight. Despite very low R-squared values, all three models pass an F-test indicating the models are statistically significant overall.

Table 3: Results of LPM (I) and regular DID (II), and LPM DID with nonattainment severity (III).

	(I) NG Build		**(II) ln NG cap change**		**(III) Severe**	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Interaction:						
preOzone*Ozone	0.0480***	(0.0143)	0.0986*	(0.0389)	0.0466***	(0.0139)
prePM*PM	0.0807**	(0.0249)	0.125*	(0.0549)	0.0783**	(0.0280)
Treated:						
Ozone 1997 treated	0.00165	(0.0973)	0.353	(0.2049)	0.00173	(0.0973)
PM 1997 treated	0.0323	(0.0506)	0.244*	(0.1065)	0.0325	(0.0506)
Pre-policy Period:						
preOzone	0.013	(0.0135)	0.0147	(0.0282)	0.0139	(0.0134)
prePM	-0.0422*	(0.0205)	-0.038	(0.0285)	-0.0411	(0.0211)
Controls:						
Ozone NAA	0.0369*	(0.0143)	0.0366	(0.0314)	0.0356*	(0.0141)
PM NAA	0.0459**	(0.0159)	0.0296	(0.0239)	0.0446**	(0.0170)
Restructure	-0.0254***	(0.0074)	-0.0437	(0.0263)	-0.0255***	(0.0074)
Pop change percent	0.160***	(0.0343)	0.131*	(0.0606)	0.159***	(0.0339)
ln(NG P)	0.0831	(0.1669)	0.757*	(0.3522)	0.0834	(0.1669)
ln GDP change	0.0226	(0.0957)	0.068	(0.2665)	0.022	(0.0958)
ln(initial cap)	0.00349**	(0.0011)	-0.0123***	(0.0025)	0.00351**	(0.0011)
Severe					0.0165	(0.0560)
Constant	-0.193	(0.3741)	-1.554	(0.7919)	-0.193	(0.3741)
R^2	0.0645		0.0244		0.0645	
N	13,656		13,656		13,656	
State FE	X		X		X	
Year FE	X		X		X	
Robust SE	X		X		X	
Cluster (CBSA)	X		X		X	

Standard errors in parentheses
* $p<0.05$, ** $p<0.01$, *** $p<0.001$

5. Conclusion and Policy Implications

This study finds that areas anticipating nonattainment designations from the 1997 ozone and $PM_{2.5}$ NAAQS changes had 45%-74% more total natural gas capacity growth than other areas during the natural gas capacity boom, depending on the pollutant or combination of pollutants. Firms in these areas essentially rushed to build planned capacity—using the technology of choice at the time—to avoid building restrictions imposed by nonattainment designation. Firms in areas expecting nonattainment had sufficient policy certainty to act quickly, with the additional incentive of shortening the time spent in nonattainment. Thus, anticipation of stricter environmental regulations affects adoption of new energy technology. Because the NAAQS are frequently revised and debated, this study may have relevant implications for capacity changes going forward.

Although these results show that anticipated NAAQS changes had a statistically significant impact on NGCC capacity growth, the overall share of the capacity growth they explain is small. It is possible that anticipation of other policies, in addition to the NAAQS, contributed to the large natural gas capacity increase. During this time period, certain countries anticipated implementation of the Kyoto Protocol, the first international agreement to commit countries to greenhouse gas emissions reductions to address climate change.[69] The Kyoto Protocol was adopted by 192 nations in 1997, and took effect in 2005. The US, however, dropped out of the international agreement in 2001 and was the only country to sign the Protocol without ratifying it.[70] Since NGCC has lower emissions of carbon dioxide than other fossil fuel technologies, it is possible NGCC growth was also related to anticipation of new greenhouse gas emissions reductions resulting from the Kyoto Protocol. Future work with international capacity data should also consider the impact of the Kyoto Protocol more specifically, which is controlled for in this study using year fixed-effects and not specifically considered.

Anticipation of renewables policies are not included in this study because renewable capacity during the 2001-2003 capacity boom was only 2% of the total new capacity installed, and therefore were not as viable an option when choosing which type of fuel to install as it may

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[69] The United Nations Framework Convention on Climate Change: http://unfccc.int/kyoto_protocol/items/2830.php.
[70] The United Nations Framework Convention on Climate Change, ratification status: http://unfccc.int/kyoto_protocol/status_of_ratification/items/2613.php

be today. State and local policies regarding climate change and greenhouse gases may have also played a role in the natural gas capacity boom that are not directly analyzed in this study, but also captured by the state and year fixed-effects. These are more likely to have assisted in more recent capacity changes (i.e. post- natural gas capacity buildout) since implementation of regional and state greenhouse gas emission reductions plans and trading schemes began well after the natural gas construction boom,[71] or are scheduled to begin in future years.[72] Further study on natural gas capacity change could include more controls to consider "state greenness," or the proclivity of a state to adopt cleaner generators. These are generally controlled using the state fixed-effects, but could be more specifically analyzed.

The US EPA Clean Power Plan supported increased use of this existing natural gas capacity to displace coal generation. In 2015, 56%[73] of US natural gas capacity was used to produce approximately 30% of total electric generation,[74] leaving excess gas-fired capacity available to replace coal generation. Lafrancois (2012) calculates that US electricity sector CO_2 emissions could be reduced by as much as 42% if existing NGCC capacity was utilized at a higher, but still technically feasible, rate (approximately 75%). Areas that increased natural gas capacity earlier are, in most cases, better equipped to decrease coal generation as natural gas prices have fallen in recent years.

As the US considers more aggressive ways of reducing carbon dioxide emissions, policymakers are looking to grow other sources of non-coal generation, such as wind and solar

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[71] The Regional Greenhouse Gas Initiative (RGGI) began greenhouse gas emissions trading in 2008 (http://www.rggi.org). California's AB 32 started a greenhouse gas emissions cap-and-trade system in 2012 (http://www.arb.ca.gov/cc/capandtrade/capandtrade.htm).

[72] EPA's Clean Power Plan compliance dates are scheduled to start in 2022.

[73] EIA Today, April 4, 2016, "Average utilization for natural gas combined-cycle plants exceeded coal plants in 2015," available at: https://www.eia.gov/todayinenergy/detail.cfm?id=25652.

[74] EIA Today, March 16, 2016, "Natural gas expected to surpass coal in mix of fuel used for U.S. power generation in 2016," available at: http://www.eia.gov/todayinenergy/detail.cfm?id=25392.

generation. This study may suggest not only the appropriateness of policy in this case, but also the effectiveness of past policies on changes in capacity and energy infrastructure investments. Additionally, the ability of NGCC to quickly start-up and shut-down compared to other fuel sources makes it a good complement to intermittent renewable technology (Neumann & von Hirschhausen, 2015). For this reason, increasing capacity of NGCC may also mean an increased use of renewables, another strategy outlined in EPA's Clean Power Plan. Areas that already experienced this rapid growth of natural gas capacity may be better able to increase their generation from renewable resources, since natural gas generation complements renewable generation—particularly while natural gas prices are low (Fell & Kaffine, 2014).

This study provides more evidence for, and understanding of, the role of uncertainty and anticipation of policies in energy investment, pertinent in a regulatory environment with changing expectations and regulatory delays. In February 2016, the US Supreme Court stayed the EPA's Clean Power Plan, and in 2017 new EPA Administrator Scott Pruitt initiated a formal review of the Clean Power Plan adding more uncertainty as to whether the rule will eventually take effect. While a large proportion of states are choosing to continue planning for the eventual implementation of the Clean Power Plan, some states have halted their efforts to comply with the rule. Since states have individualized carbon emissions targets, it will be interesting to evaluate how states' differing predictions about the Court's decision and the fate of the review and varying levels of preparation affect compliance and carbon abatement. In the world of finance, banks are already moving away from financing coal-fired power plants and projects in the US as these investments and the future of coal become more risky.[75]

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[75] Corkery, M., 2016. As Coal's Future Grows Murkier, Banks Pull Financing. The New York Times (March 21, 2016), A1.

The purpose of this study is to begin to look at the role of policy anticipation in influencing the pre-shale natural gas capacity boom. This study finds evidence that energy and environmental policies, with variations across space and time, led to different construction outcomes. As a result, more information is provided on the nature of the areas that invested in new natural gas capacity. Investment decisions and policy changes require multiple years of planning; considering the role of policy evolution – from anticipation to implementation – adds to what is known about investment choices. From changes in nonattainment status, I find that anticipation of new environmental policies plays a significant role in shifting or spurring capacity growth. Lessons from the natural gas capacity boom thus suggest how expectations concerning future environmental regulations can incentivize investment in cleaner energy technology.

Appendix A

Table A1: Restructuring coding based on Craig & Savage (2013).

State	Access to wholesale markets	Year
Alabama	No	
Alaska	No	
Arizona	No	
Arkansas	Yes	2004
California	Yes	1998
Colorado	No	
Connecticut	Yes	1997
Delaware	Yes	1997
District of Columbia	Yes	2002
Florida	No	
Georgia	No	
Hawaii	No	
Idaho	No	
Illinois	Yes	2002
Indiana	Yes	2002
Iowa	Yes	2002
Kansas	Yes	2004
Kentucky	Yes	2002
Louisiana	Yes	2004
Maine	Yes	1997
Maryland	Yes	1997
Massachusetts	Yes	1997
Michigan	Yes	2002
Minnesota	Yes	2002
Mississippi	Yes	2004
Missouri	Yes	2002

State	Access to wholesale markets	Year
Montana	Yes	2002
Nebraska	Yes	2004
Nevada	No	
New Hampshire	Yes	1997
New Jersey	Yes	1997
New Mexico	Yes	2004
New York	Yes	1999
North Carolina	Yes	2002
North Dakota	Yes	2002
Ohio	Yes	2002
Oklahoma	Yes	2004
Oregon	No	
Pennsylvania	Yes	1997
Rhode Island	Yes	1997
South Carolina	No	
South Dakota	Yes	2002
Tennessee	Yes	1997
Texas	Yes	1997
Utah	No	1997
Vermont	Yes	1997
Virginia	Yes	2002
Washington	No	
West Virginia	Yes	2002
Wisconsin	Yes	2002
Wyoming	No	

Appendix B: Testing Deregulation

In a previous version of this paper, I tested for the impact of anticipating deregulation in addition to nonattainment anticipation with several different control variables and models (Table B2). This appendix describes how and why earlier models on natural gas capacity growth differed and the relevant results. I did not include anticipation of deregulation in the final version of this paper because the relationship with natural gas capacity growth was not as theoretically well-grounded as that with nonattainment anticipation. Additionally, my results did not show much significance regarding the impact of deregulation, in any stage of policy development. The previous version of the model used a probit instead of the linear probability model used in the final version. I decided to use the LPM in the final model because the probit coefficients were more difficult to interpret, and DID models (which I use in the final version of the paper) were developed using linear models, not non-linear ones. Additionally, the results were not considerably different between the two binary choice models.

The previous version did not have as many controls, and relied on a time trend instead of a year fixed-effect. Additionally, the delineations of new versus expanded capacity (described more below) was not very informational. However, the ozone pre-policy period was significant, which encouraged me to continue finding a more appropriate model to test the impact of nonattainment anticipation.

I used an OLS model with state fixed-effects (α_s) to control for unobserved trends particular to the state, such as state industrial and economic activity (equation B1). I also used a probit model to focus just on the decision to build natural gas capacity to test if the relationships vary from the OLS model. In each model, a time trend ($\theta_1 t + \theta_2 t^2$) is included to control for other time-varying effects not included in this study. Standard errors are also robust to address heteroskedasticity in the data. Additionally, I test these relationships for new versus expanded capacity to see if the relationships change. New plants account for 72% of new natural gas capacity during this time period (1996-2009). With information from previous years, I can tell if new capacity is the result of a plant expansion or a new plant. Additionally, I ran models with California removed as a sensitivity test. I used the same unit of analysis as the present paper (electricity "zones"), but a few different controls (Table B1).

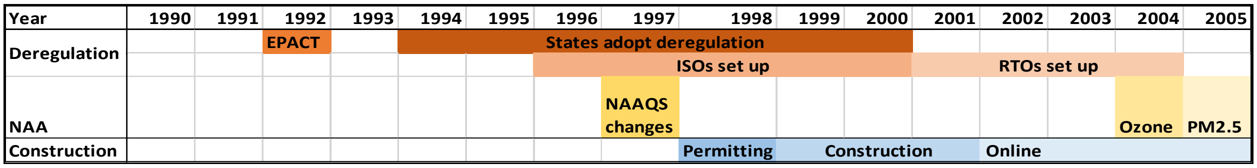
$$y_{it} = \beta_0 + \varphi_x Deregulation_{st} + \omega_y Nonattainment_{it} + cX_{it} + \theta_1 t + \theta_2 t^2 + \alpha_s + u_{it} \quad \text{(eq. B1)}$$

Table B1: Summary statistics for deregulation regressions.

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
ln_ng_cap_change	15,210	0.070	0.584	-5.897	7.795
ng_build	15,210	0.040	0.197	0	1
all capacity	16,380	754	1,547	0	19,702
ng_cap	16,380	240	836	0	12,649
ln_p	16,366	1.671	0.428	0.263	3.302
pop_chng	15,536	44	137	-156	1,477
ng_area	16,380	0.380	0.485	0	1
dereg_suspended	16,380	0.081	0.273	0	1
dereg_plan	16,380	0.090	0.287	0	1
dereg_implemented	16,380	0.219	0.413	0	1
pre_ozone1997	16,380	0.086	0.280	0	1
pre_pm1997	16,380	0.044	0.206	0	1
ozone_NAA	16,380	0.128	0.335	0	1
pm_NAA	16,380	0.076	0.265	0	1

There are two policies of interest, with several stages of development. For deregulation, the policy progressed from a pre-policy planning stage. I code this as a dummy variable with the value of one for the time when the state adopted deregulation legislation, but before electricity markets were operating, and zero otherwise. The *deregulation_implementation* variable is coded one after the state adopted deregulation adoption and electricity markets were operable. Suspension of deregulation is coded as a one when the policy was formally suspended through state legislation. For example, California adopted Assembly Bill 1890 in 1996 which signified the formal adoption deregulation for that state (Table B3). However, electricity markets and full retail access for all customers did not take place until 1998. In 2001, the provisions of AB 1890 concerning retail access were suspended, and deregulation in California remains “suspended” today.

Table B2: Timing of policies and policy anticipation.



Year	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Deregulation			EPACT		States adopt deregulation											
							ISOs set up					RTOs set up				
NAA								NAAQS changes							Ozone	PM2.5
Construction									Permitting	Construction			Online			

Table B3: Example of the coding and timeline for California’s deregulation policy variables.

California	Current Status	Adoption of Deregulation	Full Retail Access for All Customers	Suspension
Dates	Suspended	1996	1998	2001
Deregulation_plan		1	0	0
Deregulation_implemented		0	1	0
Deregulation_suspension		0	0	1

State Henry Hub natural gas prices, which are indexed spot prices per state, are provided through EIA for the entirety of the data period. The variable *ng_area* expresses if natural gas capacity existed in the area before the new natural gas capacity went in as a pipeline proxy. With the *ng_area* variable, I can control for the existence of a natural gas capacity, and hence a pipeline, in the area before the new natural gas capacity was installed. This controls as a proxy for any impacts of expanded pipeline coverage during the time period in this study. This variable is a dummy variable coded as one if natural gas capacity already existed in the zone before the new natural gas capacity was installed. All of the variables are described further in Table 3.

Table B4: Description of variables.

Code name	Description	Geographic Coverage	Source	Role
ln_ng_cap_change	$\ln(ng_{capacity_t}) - \ln(ng_{capacity_{t-1}})$	zone	calculated from eGRID	OLS dependent variable
ng_build	Dummy variable: 1 if built natural gas in that year, 0 if did not build natural gas in that year	zone	calculated from eGRID	probit dependent variable
ln_p	natural log of natural gas price	state	calculated from EIA	Control
pop_chng	$(population_{2010} - population_{2000})/1000$	CBSA	calculated from U.S. Census	Control
	$(population_{2000} - population_{1990})/1000$	CBSA	calculated from U.S. Census	Control
ng_area	Dummy variable: 1 if natural gas capacity existed in the area before that year, 0 if otherwise	zone	calculated from eGRID	Control
deregulation_suspended	Dummy variable: 1 if the area was in deregulation suspension, 0 if otherwise	state	constructed from literature	Policy
Deregulation_plan	Dummy variable: 1 if the area had passed deregulation legislation but did not have operating electricity markets, 0 if otherwise	state	constructed from literature	Policy
Deregulation_implemented	Dummy variable: 1 if the area had passed deregulation legislation and had operating electricity markets	state	constructed from literature	Policy
pre_ozone1997	Dummy variable: 1 if the area was designated nonattainment for the 1997 ozone standard but was not officially designated yet, 0 if otherwise	zone	calculated from EPA	Policy
pre_pm1997	Dummy variable: 1 if the area was designated nonattainment for the 1997 PM standard but was not officially designated yet, 0 if otherwise	zone	calculated from EPA	Policy
ozone_NAA	Dummy variable: 1 if the area was designated nonattainment for ozone, 0 if otherwise	zone	calculated from EPA	Policy
pm_NAA	Dummy variable: 1 if the area was designated nonattainment for PM, 0 if otherwise	zone	calculated from EPA	Policy

Results

The results from the OLS and probit models show slightly different things about the relationships between natural gas capacity growth and the energy and environmental policies and energy demand and supply control variables. The full results of the fixed effects model for all units of observation (column I), new plants (column II) and expanded plants (column III) for the fixed effects (columns I-III) and probit (columns IV-VI) are included in Table B5. The marginal effects from the probit are reported in Table B6.

As expected, as the price of natural gas increases, there is a decrease in natural gas capacity growth for the full dataset (all growth, whether from new or expanded plants), which remains statistically significant in the new plants fixed effects model. As prices of natural gas increase 1%, there is a 25% decrease in new natural gas capacity in the full fixed effects model. As population increases, there is a statistically significant increase in natural gas capacity growth in all models which represents the increased demand for electricity. Further, areas that already had natural gas capacity installed in the area had more natural gas capacity growth, and were 4% more likely to build any new natural gas capacity, which suggests that the new natural gas capacity was not only a result of pipeline infrastructure expansions.

Turning to the policy variables, suspension of deregulation is the only policy period for deregulation with any significant coefficients in both the fixed effects and probit models. When moving to deregulation suspension, areas had 25% more new natural gas capacity growth and were 5% more likely to build new natural gas capacity according to the marginal effects from the probit. However, the deregulation suspension variable loses significance in the fixed effects (full) and probit (new) models with sensitivity tests. Deregulation planning stages (time after deregulation was adopted but before markets were live) only had a slightly significant relationship in the new probit model, showing these areas were 2% more likely to build new natural gas plants. There were no significant relationships surviving the sensitivity tests for the deregulation implementation stages (when markets were live and before suspension). Following similar arguments to Ford’s study (2002) on policy uncertainty and boom and bust cycles, areas that eventually resulted in suspending deregulation may have had more complications in the earlier stages of deregulation which may have resulted in a longer pause in building commitments. As a result, these areas may have rushed to build more new capacity once deregulation was finally suspended, which may explain why these are the only areas with a significant coefficient as far as deregulation is concerned in all the results.

For the nonattainment variables, the pre-ozone 1997 variables experienced a statistically significant building boom in the fixed effects and probit models for all models except for the fixed effects expanded model. Areas that were eventually designated nonattainment based on the 1997 ozone standard had a 25% larger natural gas capacity growth than other areas at this time, and were 2% more likely to build based on the marginal effects of the probit model. The pre-PM variables are only significant in the full dataset probit model and are only 1% more likely to build natural gas capacity. This may be because more areas experienced ozone nonattainment than PM-nonattainment as PM is a more localized air quality concern. As hypothesized earlier, these areas that were eventually designated nonattainment may have expected nonattainment designations and stricter building regulations and rushed to build newer, cleaner natural gas capacity.

The only variables with a significant coefficient in nonattainment designation are the PM probit model for new plants. While it is unexpected, these areas were 1% more likely to build new natural gas after designation, which may be a result of implementation of other state air quality efforts to reduce PM pollution.

Based on these results, it appears the control variables for the price of natural gas, population change, and previous natural gas capacity in the area all impact natural gas capacity growth in the directions expected. However, anticipation and implementation of deregulation do not appear to play a role in the natural gas capacity boom, but rather there may have been a slight increase in capacity after deregulation was suspended. Anticipation of designations tied to new NAAQS have a more consistently, statistically significant relationship with natural gas capacity growth. Additionally, the marginal effects on the probability of building – while significant – are quite small.

I considered the role of interactions to test if combinations of policies, or different stages of different policies were more or less significant than the policy variables provided. These did not turn out to be significant and are therefore not included. I also tested different lags of the variables but the lagged results were not more robust than what is included here. The consistently significant time trend variables, low R-squares, small magnitudes, and small marginal effects suggest the policies and control variables in this study only play a minor role in explaining the natural gas capacity boom.

Table B5: Results from the fixed-effects and probit models.

	FE			Probit		
	I. All	II. New	III. Expand	IV. All	V. New	VI. Expand
ln_p	-25.13***	-19.53***	-3.33	_-0.271*_	_-0.376**_	-0.114
	(6.3506)	(5.0844)	(2.4835)	(0.1227)	(0.1406)	(0.1751)
pop_chng	0.129***	0.116***	0.0301***	0.000975***	0.00102***	0.000560**
	(0.0321)	(0.0253)	(0.0081)	(0.0001)	(0.0001)	(0.0002)
ng_area	11.92***	_4.532*_	8.119***	0.613***	0.294***	1.182***
	(2.6080)	(2.1469)	(1.1802)	(0.0540)	(0.0619)	(0.1000)
dereg_suspended	_25.31**_	24.96**	0.882	0.717***	_0.777**_	0.322
	(9.1548)	(8.1495)	(2.5605)	(0.2161)	(0.2634)	(0.2888)
dereg_plan	8.35	8.251	-1.057	0.307	0.415*	0.0456
	(4.7123)	(4.2161)	(1.3520)	(0.1694)	(0.2053)	(0.2137)
dereg_implemented	-3.336	1.957	_-3.931*_	-0.0405	0.0239	-0.216
	(4.5872)	(3.9908)	(1.8334)	(0.1774)	(0.2072)	(0.2289)
pre_ozone1997	25.06**	19.96**	2.382	0.377***	0.321**	0.372**
	(9.0154)	(7.5991)	(2.2414)	(0.0877)	(0.0993)	(0.1285)
pre_pm1997	24.31	20.13	3.382	0.214*	0.131	0.222
	(14.2327)	(11.6295)	(3.3438)	(0.1061)	(0.1215)	(0.1406)
ozone_NAA	4.891	8.032	1.142	0.0524	0.12	0.029
	(5.7298)	(4.5810)	(2.3705)	(0.0862)	(0.0888)	(0.1383)
pm_NAA	6.718	6.569	1.427	0.165	0.265**	0.0206
	(6.6145)	(6.4205)	(2.1227)	(0.0858)	(0.1000)	(0.1177)
t	17.76***	14.19***	3.348***	0.419***	0.537***	0.258***
	(2.5911)	(2.1740)	(0.8297)	(0.0459)	(0.0585)	(0.0619)
t_sq	-0.966***	-0.782***	-0.180***	-0.0257***	-0.0333***	-0.0155***
	(0.1333)	(0.1144)	(0.0425)	(0.0024)	(0.0033)	(0.0031)
Constant	0.596	-1.852	-0.981	-3.042***	-3.329***	-3.667***
	(15.2964)	(14.3032)	(5.6932)	(0.2352)	(0.3065)	(0.2918)
r2	0.0557	0.0517	0.0382			
N	14,385	14,385	14,385	14,022	13,910	13,469
State FE	X	X	X	X	X	X

Standard errors in parentheses

* p<0.05, ** p<0.01, *** p<0.001

italics indicate p > 0.05 when CA removed

Table B6: Marginal effects of the probit model.

	dy/dx		
	All	New	Expand
ng_area	0.0461***	0.0148***	0.0446***
dereg_suspended	0.0539**	0.0392**	0.0121
dereg_plan	0.0231	0.0209*	0.0017
dereg_implemented	-0.0030	0.0012	-0.0082
pre_ozone1997	0.0283***	0.0161**	0.0140**
pre_pm1997	0.0160*	0.0066	0.0084
ozone_NAA	0.0039	0.0061	0.0011
pm_NAA	0.0124	0.0134**	0.0008

* p<0.05, ** p<0.01, *** p<0.001

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CHAPTER FOUR:

Feasibility of Natural Gas Combined Cycle Utilization Targets: Evidence from Environmental Policies and Prices

1. Introduction

Setting utilization targets to increase generation from natural gas-fired combined cycle generators (NGCC) is a regulatory mechanism to decrease greenhouse gas pollutants from the US electricity sector. Average utilization of NGCC has been slowly rising (Figure 1) since a new crop of NGCC plants were installed from 2000-2005 during what has oftentimes been referred to as the natural gas capacity buildout. Traditionally, most of these new NGCC plants supplied generation during peak demand, with an overall low utilization rate. While some are slowly shifting into a new role as baseload providers, the US Environmental Protection Agency (EPA), through the Clean Power Plan (CPP), is directing that states accelerate that process in order to reduce coal generation.

NGCC units include both a gas turbine and heat recovery steam turbine that reuses the waste heat from the gas turbine for high efficiency generation. Due to lower impurities in natural gas compared to coal, and high thermal conversion efficiency of NGCC plants,[76] NGCC generators produce up to 60% less carbon dioxide (CO_2), 80-90% lower nitrogen dioxide (NO_2), and negligible amounts of particulate matter (PM) and sulfur dioxide (SO_2).[77]

Due to the environmental advantages of NGCC over coal-fired generation, the CPP includes state-level carbon emissions targets based in part on the expectation that states will increase output from existing NGCC generators. The CPP sets a target of increasing average

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[76] Some literature argues the lifecycle methane emissions of unconventional natural gas burned in a NGCC has a higher greenhouse gas footprint due to hydraulic fracturing extraction methods for shale gas (Howarth 2014), but these findings remain disputable (Allen et al. 2013). EPA and others continue to conduct research to understand the impact of upstream methane emissions on the lifecycle CO_2 emissions reductions from NGCC.

[77] Nitrogen oxides (NO and NO_2) are a precursor to ozone, and both NO_x and SO_2 are precursors to particulate matter (PM).

NGCC capacity factors (equation 1) to 75% on a net summer capacity basis, which is similar to a 70% capacity factor based on nameplate capacity in the original CPP draft rule (August, 2015).

$$CF_{year} = \frac{Actual\ Electricity\ Output}{Potential\ Output} = \frac{Annual\ Electricity\ Generation\ (MWh)}{24\ {}^{hours}/_{day} * 365\ days * Capacity\ (MW)} \qquad \text{(eq. 1)}$$

Multiple engineering and economic factors determine how much to run a power plant. Different types of system operators typically employ a dispatch process that considers reliability and variable costs of power generation to match demand. Technologies with relatively low variable costs, such as nuclear power plants, operate at high capacity factors consistently through the year (Figure 1). Units with higher variable costs – fossil fuel-fired plants – offer more flexibility in when they run to serve load. However, they are still dispatched on the basis of variable cost: a natural gas generator will be dispatched ahead of a coal generator when natural gas generation is cheaper than coal. Marginal costs of generation primarily depend on fuel prices, but can also be influenced by environmental cost of compliance due to air pollution policies. Intermittent renewable generation, such as from solar and wind, also have low variable costs and operate when meteorological conditions allow them to.

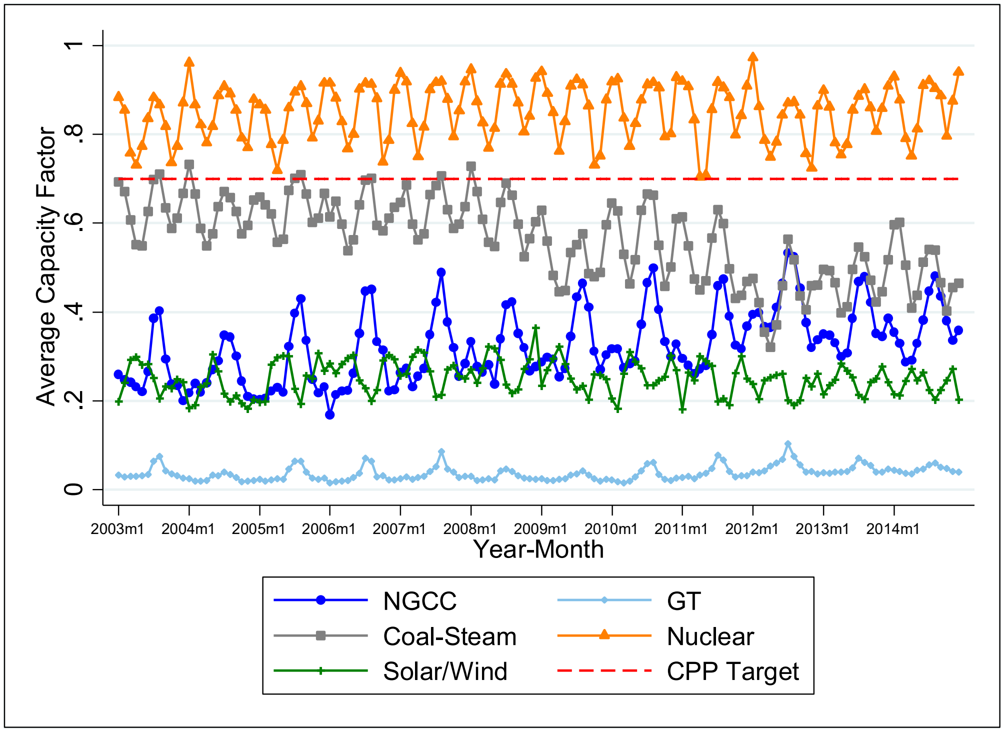

Figure 1: Average monthly capacity factor for different fuel-technology generation groups in the US.

Since 2007, tremendous changes in domestic natural gas supply have brought natural gas prices to lowest levels in recent history (Figure 2). The CPP recommendation to increase NGCC utilization is meant to influence the dispatch order in regions such that NGCC capacity is running at 70%, which would primarily displace coal generation by reducing it to one of the less frequently dispatched sources of generation, and moving more NGCC plants into the role of baseload providers.

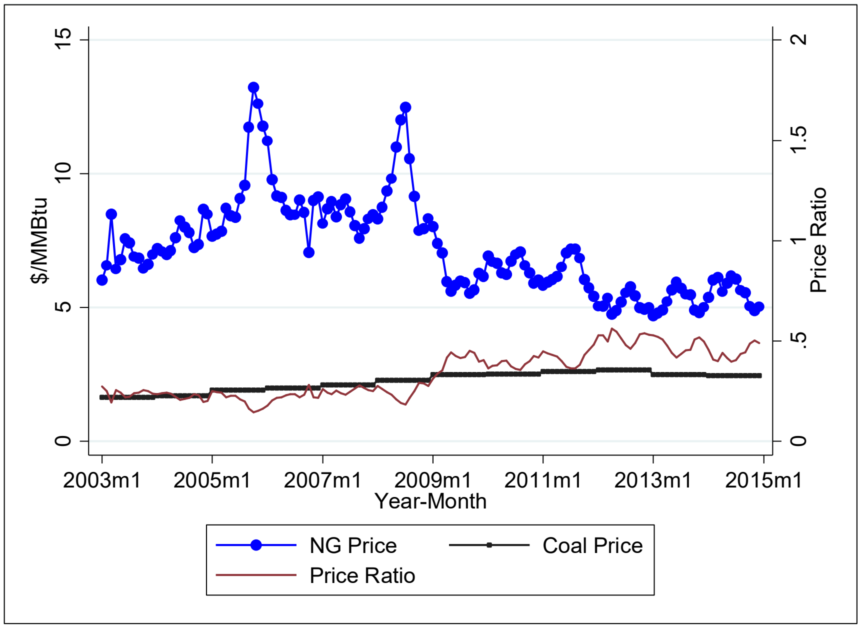

Figure 2: Nationally averaged, monthly citygate natural gas prices and nationally averaged coal prices delivered to the electric power sector per MMBtu, in 2010 dollars, with the coal to natural gas price ratio on the right axis.

The goal of this research is to identify what impediments to running NGCC at baseload level states can address through policy-making, versus the ones they cannot, such as the weather. Additionally, this research provides more information on the impact of policies versus fuel prices on the heterogeneous increase in NGCC utilization across geographic areas in the last decade. These changes in utilization have taken place during a time when dramatic changes in energy and environmental regulation, technological innovation, and fuel prices have occurred. Hydraulic fracturing and horizontal drilling have supplied the US with an abundance of natural gas beginning in 2008, decreasing prices by half to a third of what they were in the early to mid-2000s. Starting in the late 1990s, states elected to deregulate or restructure their electricity markets, changing the regulatory landscape across many parts of the US. Additionally, new environmental regulations to reduce criteria pollutants, as well as regional and state programs to reduce greenhouse gases, have affected different parts of the country over the last decade.

Recent papers on natural gas generation primarily focus on the role of low prices for natural gas. These studies from particular regions of the US are finding natural gas-fired generators are replacing coal plants as inframarginal providers of electricity as natural gas prices have started falling in recent years (Linn, Muehlenbachs, and Wang 2014; Fell and Kaffine 2014; Knittel, Metaxoglou, and Trindade 2016). In addition to changes in natural gas prices, I also consider the role of energy and environmental policies on natural gas generation which further accounts for observed heterogeneous responses in NGCC utilization. I focus specifically on utilization of NGCC, which requires distinguishing NGCC generation from other sources of natural gas generation. NGCC is the targeted technology to displace coal generation in the CPP since it can feasibly increase output to provide baseload power, which other technologies (such as single-cycle gas turbines) are not as well suited for.

I find that in addition to changes in natural gas prices, environmental policies have contributed to increases in NGCC utilization in the last decade. However, the combination of low natural gas prices and environmental policies still leave NGCC utilization short of the 70% target at this time. Other factors, such as energy demand, age of the plant, and fuel mix of the area matter as well. This paper aims to provide decision-makers with information to craft state policies for increasing natural gas utilization based on empirical evidence of what has already taken place, and identifies areas that may have difficulty meeting uniform utilization targets. I begin by evaluating the observed shifts in NGCC utilization and previous literature. Next, I describe the approach and econometric model used in this study. With the estimated results from the random effects model, I compute a counterfactual to compare the relative impact of low natural gas prices and environmental policies on CO_2 abatement from NGCC utilization thus far, finding the environmental policies had a larger impact than low natural gas prices on utilization.

2. Observed Shifts and Previous Literature

Despite the extraordinary increase in natural gas capacity in the early 2000s, much of this new capacity experienced low utilization throughout the 2000s. However, beginning around 2005 NGCC utilization and natural gas generation started increasing, and in 2016 natural gas generation surpassed coal generation for the first time in history on an annual basis.[78]

NGCC plants were initially utilized as peaking units with average capacity factors around 18%. However, there has been a slow but steady shift to higher capacity factors as seen in the kernel density plot in Figure 3. By 2014, the peak in the kernel density plot is centered around 50% capacity factor, with a much smaller peak at 18%. In the right panel of Figure 3, I compare average annual capacity factors for NGCC plants that ran in both 2004 and 2014, finding a shift in higher average capacity factors for many NGCC plants. However, it can also be seen that several plants have actually reduced capacity factors during this time (those below the 45 degree line). Lines for the 70% threshold set by CPP show more plants are at or above this threshold in 2014 than in 2004, however there are still many below the threshold with room to move to a higher capacity factor. On a monthly capacity factor basis, 7% of all NGCC capacity factors reached 70% or above in 2003, while 14% were above the target in 2014.

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[78] EIA Today from April 20, 2017: https://www.eia.gov/todayinenergy/detail.php?id=30872.

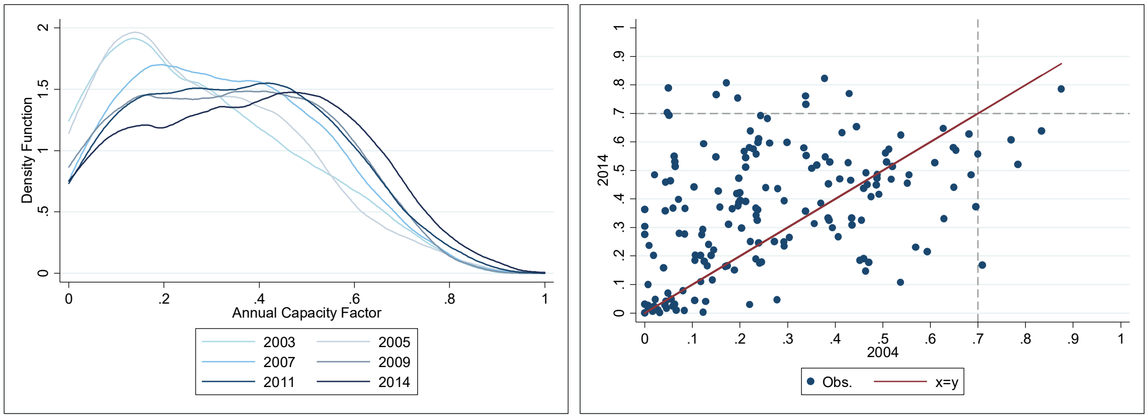

Figure 3: Kernel density plot of NGCC annual capacity factors for different years (left). Scatterplot of annual capacity factor for NGCC in 2004 and 2014 for plants running in both 2004 and 2014 only (right). Gray lines at 0.7 represent the CPP's NGCC average capacity factor target.

Although average utilization has been increasing, plants in different regions are responding in distinctive ways. For example, Figure 4 shows differences in not only initial utilization of NGCC plants by region, but also in the timing and amplitude of this shift to higher capacity factors for six states. While these states have different amounts of NGCC capacity, they share a similar increase in NGCC capacity from 2003-2014. Some states experienced steady gains throughout the timeseries (e.g Pennsylvania) while others only began increasing utilization after 2008 (e.g. Alabama, Florida). Of the latter group, Alabama had a large increase in utilization while Florida's was more modest. New York experienced a more discontinuous increase in NGCC utilization followed by a significant decrease after 2012. Meanwhile, on the West Coast there were little to no changes in NGCC utilization.

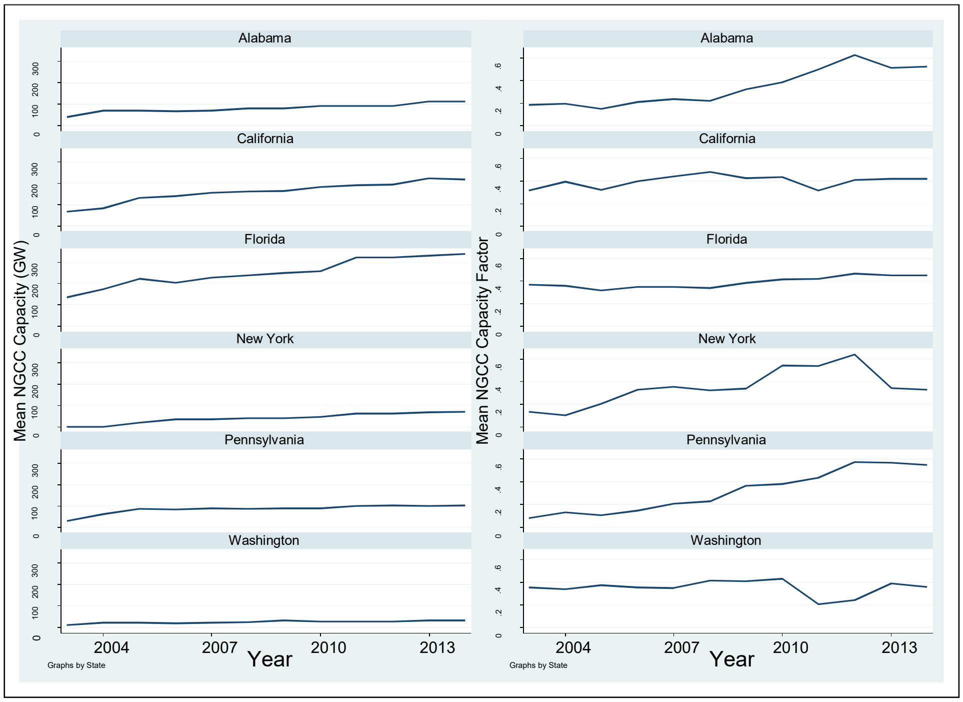

Figure 4: Average annual NGCC capacity factors for six states.

Recent studies on this shift to increased generation by natural gas power plants focus on decreases in natural gas prices relative to coal as reponsible for increases in natural gas generation. This would suggest utilization should be increasing across the country, which is not the case in Figure 4. Most of these studies focus on particular regions of the US (Kaffine, McBee, and Lieskovsky 2013; Novan 2015), or limit themselves to ISO/RTO regions (Fell and Kaffine 2014). Or, studies analyze aggregated emissions reductions in particular regions based on generation switching (Cullen and Mansur 2014). Recent studies on natural gas generation may be limited to evaluating dual-fired plants with the option of internally switching from coal to natural gas (Knittel et al. 2015), or focus on decreases of coal generation in response to changes in natural gas prices (Fell and Kaffine 2014). Some studies analyze the impact of decreased natural gas prices on electricity prices (Linn et al. 2014). These studies confirm the intuitive relationship between natural gas generation and natural gas prices; areas with ample available natural gas capacity increase generation as a replacement for coal generation as natural gas prices decrease, resulting in decreased CO_2 emissions. They also find increases in renewable generation may have displaced natural gas generation at first, but is now displacing coal generation as natural gas prices have recently fallen during the shale gas revolution (Fell and Kaffine 2014).

This study focuses specifically on capacity factors for NGCC plants as the dependent variable, and explicitly considers the role of environmental policies in addition to low natural gas prices. It does not include an analysis on the coupled interaction of utilization and capacity expansion (Peters and Hertel 2017), another importance source of increases in natural gas generation, but focuses on capacity factors alone. This limits the analysis to changes in natural gas generation from NGCC plants – the specific technology and mechanism the CPP targets for increases in natural gas generation. This study includes all NGCC plants that are not combined heat and power plants in the US.[79] The present analysis also includes an evaluation of the impact of regulatory, plant, and area characteristics on NGCC generation, and implicity assumes increases in NGCC generation is replacing coal, established in previous studies (Linn et al. 2014; Fell and Kaffine 2014).

3. Policy Impact on Natural Gas Generation

There are several important environmental policy changes that took place during the time period that NGCC utilization was increasing. None of the policies explicitly aimed to increase NGCC generation; rather all of them are rooted in curbing either conventional or greenhouse gas emissions, with a byproduct that resulted in increasing NGCC generation to displace coal generation. In this section I describe the three environmental policies of interest, and how they contribute to increases in NGCC utilization.

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[79] Combined heat and power plants do not typically dispatch to the grid, therefore utilization is driven by extremely localized energy demand. I do not include them for these reasons since they are not reflective of utilization responses for power plants that dispatch to the grid.

3.1 Ozone Nonattainment

The National Ambient Air Quality Standards (NAAQS) serve as one of the primary means for controlling air quality through the use of standards for criteria pollutants to protect public health and welfare. Areas with air quality levels that are not meeting the NAAQS are designated as nonattainment until they come into compliance with the standards. Firms in nonattainment areas are subjected to stricter construction and operation standards in efforts to improve air quality to acceptable levels. States or local areas may set policies or programs to improve air quality to compliance levels and return to attainment (Frey 2012).

NAAQS were tightened for ozone, particulate matter (PM), lead, and sulfur dioxide (SO_2) during the time period of this study. However, the changes in ozone nonattainment had the largest spatial impact (Figure 5), and nearly all of the areas designated as nonattainment for PM were also nonattainment for ozone as they share important precursor pollutants. As a result, I focus on areas that experienced nonattainment for ozone. During the time period covered in this study, ozone standards were set in 1997 at effectively 85 ppb, with official nonattainment designations promulgated in 2004. These standards were tightened again in 2008 to 75 ppb, with designations taking place in 2012. I expect that firms in areas designated as nonattainment will need to shift their generation from coal to natural gas in order to comply with the tightened regulations needed to bring the areas back into attainment (since NGCC plants emit significantly lower amounts of precursor and criteria pollutants). Operationally, I use ozone nonattainment status information from EPA's Green Book,[80] and assign nonattainment values based on different NAAQS for ozone. The unit's nonattainment value is based on the county's ozone nonattainment status for that year.

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[80] Available at: https://www3.epa.gov/airquality/greenbook/.

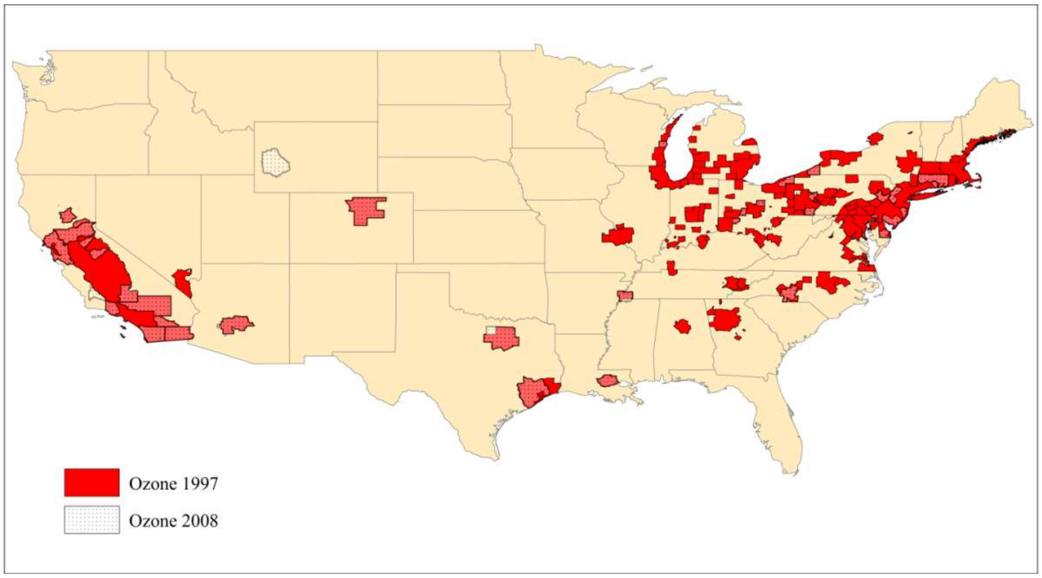

Figure 5: Map of all initial nonattainment areas for the 1997 and 2008 ozone NAAQS.

3.2 Cross-State Air Pollution Transport

In light of new scientific information about the adverse impacts of fine particulates associated with SO_2, the Bush administration promulgated the Clean Air Interstate Rule (CAIR) in May of 2005. The main purpose of this rule was to lower the cap on SO_2 emissions already established in the SO_2 allowance market stemming from the 1990 Clean Air Act Amendments. CAIR would apply specifically to the eastern United States where upwind emissions were contributing to downwind nonattainment problems for fine particulate matter. However, shortly after promulgation of the rule, EPA announced it would reevaluate the rule, which was challenged and eventually vacated in 2008. Despite the vacature, the court allowed CAIR to remain in effect until the EPA established a rule that abided with the Clean Air Act (Schmalensee and Stavins 2013). In effect, the 2008 vacature confirmed the continuation of the SO_2 market until EPA was able to replace the rule. CAIR requirements officially began in 2009, however the SO_2 allowance market experienced a small uptick in allowance prices upon the court decision in 2008 that CAIR would be allowed to continue in the interim before EPA designed a new interstate transport rule, which is set to begin in 2017.[81]

Since NGCC generation has significantly lower SO_2 and NO_x emissions than coal generation, I code the 28 eastern states where CAIR was in effect beginning in 2008, once CAIR was temporarily reinstated by the courts, as my cross-state air pollution transport variable.[82] I anticipate the cost of compliance with the cross-state rules for coal generators will shift them down the economic dispatch order, allowing NGCC generators to run more.

3.3 Regional/State Greenhouse Gas Programs

The Regional Greenhouse Gas Initiative (RGGI) was the first operational, multi-state greenhouse gas cap-and-trade system to be implemented in the US. It was initiated in 2003, but implemented in full with the first auctions for carbon allocations starting in 2009.[83] RGGI currently includes the states of Connecticut, Delaware, Massachusetts, Maryland, Maine, New Hampshire, New York, Rhode Island, and Vermont.[84] RGGI developed a mandatory greenhouse gas cap-and-trade program for the electricity sector among states that adopted a core model rule crafted by RGGI. Under this program, states auction off a decreasing number of emission permits for CO_2. The success of RGGI has been mixed, with critics stating that the recession and a lenient cap rendered the program ineffective (Legrand 2013). However, a recent study by Murray and Maniloff (2015) attributes about half of CO_2 emissions reductions during RGGI to

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[81] In July 2011, EPA issued the Cross-State Air Pollution Rule (CSAPR), which allowed only intrastate trading of SO_2 and NO_x emissions allowances in eastern states of the US. Implementation of this rule faced substantial court challenges leading to a delay in CSAPR's start date until May 2017. During that time, CAIR continued to regulate SO_2 and NO_x emissions in these 28 eastern states.

[82] I also tried using a SO_2 intensity variable, coded by multiplying the SO_2 allowance price in that year by the SO_2 emissions in the area where the NGCC plant resides. However, this did not prove significant. Additionally, I tested starting the cross-state transfer variable in 2009 when CAIR was officially operational, rather than in 2008 when the court announced CAIR would be reinstated. A Hausman test reveals the coefficients are not systematically different with the 2009 start date versus 2008, therefore I use 2008.

[83] From the RGGI website, available at http://www.rggi.org/

[84] New Jersey, an original state in RGGI development, left in 2011.

the program. Since NGCC CO_2 emissions are about 50% lower than the emissions from a traditional coal plant, I expect NGCC plant utilization to increase upon implementation of RGGI in RGGI states as cost of compliance for coal generators will be higher in these areas.

California started its own GHG cap-and-trade program, the Air Resources Board (ARB) Emissions Trading Program, with the first auction of allowances in 2012 and first compliance obligation in January 2013. The ARB Emissions Trading Program covers approximately 450 entities in California including electricity generators and large industrial facilities, and features a declining emissions cap each year.[85] I include California's program in the "regional program" variable which turns on in 2013 for units in California.

The time line for these three policy variables is indicated by the percent of NGCC units affected by each policy in Table 1.

Table 1: Percent of NGCC units affected by policies.

		2003	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
Ozone	1997		21	24	25	29	26	24	25	25	25	31	32
	2008										26	27	27
Cross-State	CAIR						65	64	65	66	66	64	64
Regional Program	RGGI							13	12	11	11	11	11
	CA											13	13

3.4 Age of the Plants Affected by Policies

Most of the new NGCC capacity was built during the natural gas capacity buildout from 2000-2005 (59%), with another significant portion constructed after the buildout (23%). Plants built during or after the buildout represent a new generation of the technology and are significantly cleaner, more efficient, and more reliable than earlier plants (Curtis 2003). Therefore, environmental policies aiming to reduce air emissions may decrease use of older

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[85] Information on the ARB Emissions Trading program is from the California Air Resources Board website: http://www.arb.ca.gov/cc/capandtrade/guidance/cap_trade_overview.pdf.

NGCC units (i.e. built before 2000) that are not as clean or efficient as the newer NGCC plants. I will account for this separately in the model, discussed in section 4.2.2.

4. Analysis

4.1 Data

The dataset was built from multiple EIA forms on the electric power sector, seen in Table 2. To determine which plants are in the electric power sector, I use a compilation of EPA's Emissions and Generation Resource Integrated Database (eGRID)[86] from 2003-2012. For 2013 and 2014, I keep plants that are in the electric sector based on EIA form-860 value "SectorName." I remove plants that are combined heat and power plants since they typically do not dispatch to the grid, and remove observations that are missing capacity or generation data, or have unrealistic capacity factors, which are less than 1% of the data.

Table 2: EIA forms used to construct this dataset.

Years	Generation	Plant Characteristics
2003-2006	906, 920	860
2007	906, 920, 923	860
2008-2014	923	860

Using the dataset, I create units based on plant-fuel-technology group. This combines multiple emissions units of the same fuel and technology type from the same plant into one unit to match the way EIA generation data is provided. The technology groups are described in Table 3. The only individual generation unit information this compromises is the year the generator came online and its size. For the age of the unit, I calculate a capacity-weighted average age for each observation. The size is the mean nameplate capacity of the generating units at each NGCC

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[86] More information and data available at: https://www.epa.gov/energy/egrid.

plant.[87] The extraction process and combining of datasets yields significantly comparable capacity totals to EIA and eGRID summary tables.

Table 3: Fuel and technology codes for creating plant-fuel-technology groups in this study.

Group	**Abbreviation**	**Fuel**	**Technology**	**EIA fuel codes**	**EIA technology codes**
Combined Cycle	NGCC	natural gas	combined cycle	NG	CC, CA, CT, CS
Gas Turbine	GT	natural gas	gas turbines	NG	GT
Coal-Steam	coal_steam	coal	steam turbine	BIT, LIG, ANT, SUB, WC	ST
Nuclear	nuke	uranium	steam turbine	NUC	ST
Oil	oil	oil	any	JF, KER, DFO, RFO	Any
Dispatchable Renewable	d_renew	water, geothermal, municipal waste, landfill gas, waste	any	WAT, GST, WDL, GEO, LFG, MSW, OBG, WDS	Any
Intermittent Renewable	i_renew	sun, wind	any	SUN, WND	Any
Natural gas other	ng_other	natural gas	any besides combined cycle or gas turbine	NG	any besides CC or GT
Other	other	any not already categorized	any not already categorized	any not already categorized	any not already categorized

The EIA forms provide locational information on each plant. Figure 6 displays all the units in my time series, based on their nameplate capacity in 2014, and color coded by fuel-technology type.

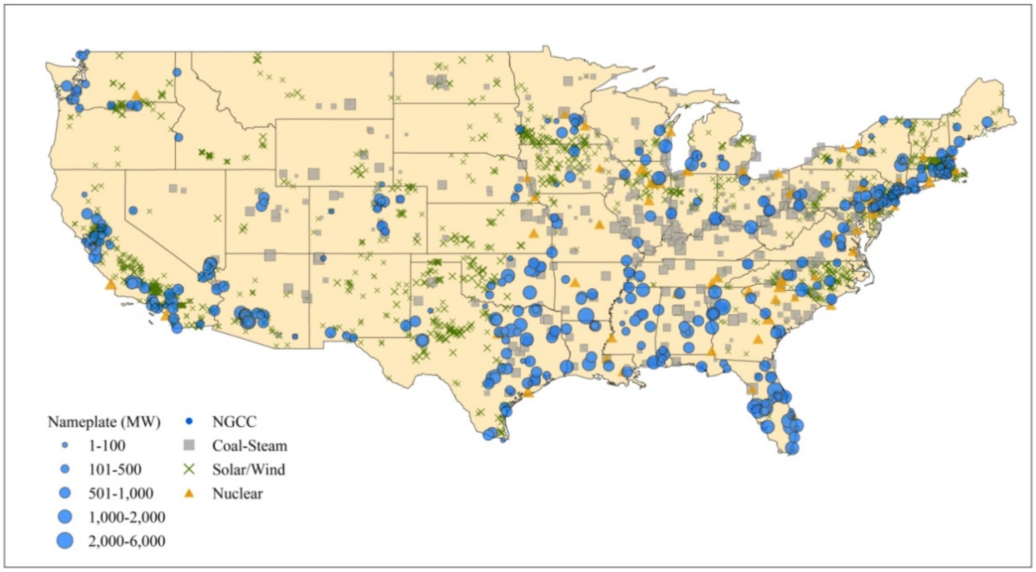

Figure 6: All units in the dataset, sized by nameplate capacity in 2014 (MW), and color-coded by fuel-technology type.

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[87] $mean\ capacity = (plant\ NGCC\ capacity/number\ of\ NGCC\ units)$

4.2 Control Variables

4.2.1 Natural Gas Prices

As discussed earlier, I include the ratio of coal to natural gas prices at the month-state level. I divide the state citygate price of natural gas by the state average coal price delivered to the electric power sector provided through EIA (in MMBtu, in 2010 dollars).

4.2.2 Plant Characteristics

Using the EIA form-860 data, I use the mean size of the NGCC generators in each unit to calculate the mean capacity. To determine mean capacity, I divide the plant's NGCC capacity by the number of NGCC generating units at the plant. I anticipate age to be an important factor in determining which plants are more likely to experience changes in capacity factors based on previous literature (Fell and Kaffine 2014). I calculate age as the capacity weighted age of the generators in the NGCC unit in 2014. For each of the policies, I also include an $age * policy$ interaction variable to account for the different impacts the policy may have had on old versus newer generators for each of the three policies described above.

Both the operational and ownership control of power plants can vary, and may impact dispatching. At the ownership level, there are utilities, primarily made up of investor-owned utilities (IOU), and independent power producers (IPP). A utility transmits and distributes electricity and is classified as "regulated" in EIA form-860. An IPP is a non-utility power plant that sells power into the grid without transmitting or distributing it, and is classified as "non-regulated." In 2014, regulated utilities produced 63% of generation while owning 61% of all nameplate capacity in the electricity sector. The EPA estimates that all ownership and operational structures will be able to respond to NGCC capacity factor targets in the CPP.

Additionally, these power plants either operate in a traditional market in areas that did not elect to restructure following deregulation in the 1990s, or in a deregulated wholesale market. In a traditional market, dispatch is typically operated by vertically-integrated utilities that also operate transmission and distribution systems. The wholesale markets, where they exist, are coordinated by Independent System Operators (ISOs) and Regional Transmission Organizations (RTOs), referred to as ISO/RTOs in this study, which operate a market to determine which owners will dispatch to meet load on the local grid. About 60% of plants in the electric sector participate in an ISO/RTO. According to the CPP, any of the different types of ownership and dispatch control combinations will be able to meet the NGCC utilization target by different mechanisms. However, I still control for these unit characteristics in case the relationships differ at all.

4.2.3 Weather

Natural gas supply constraints may also cause changes in natural gas generation. Natural gas generation experiences two seasonal peaks. The first peak is during wintertime heating to meet increased energy demand, and the second is during summertime to meet cooling energy demand. The summertime peak is the larger of the two (Figure 1). Additionally, natural gas is used for residential and commercial heating which reduces the availability of natural gas for power generation in the wintertime. For these reasons, I include heating degree days (*HDD*) and cooling degree days (*CDD*) from the National Ocean and Atmospheric Administration's Climate Prediction Center.[88]

4.2.4 Area characteristics

I also include several variables that control for the characteristics and load of the transmission grid the NGCC plants are a part of. I determine the plants included in this "area"

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[88] These datasets do not include variables for Alaska and Hawaii, and since they are very small amounts of the total electric power sector, I drop all power plants from Alaska and Hawaii from my database. Plants in these states also face different natural resource constraints and are likely to behave differently than power plants in the contiguous US. There are no NGCC generators in Hawaii, and the 4 in Alaska represent less than 0.3% of all NGCC capacity in the US.

based on a shared transmission or distribution system owner, provided by the EIA-860 data. Based on the full set of generators in the electricity sector (i.e. not exclusively NGCC plants), I have 854 areas of approximately 1.5 GW of capacity. Of these, 143 areas contain at least one NGCC unit. To control for the demand in the area, I divide the monthly demand by the maximum demand of the area in the time series.

I also include variables that control for the percentage of nameplate capacity in each area provided by coal power plants, and nuclear power plants, separately. Further, I include the percentage of generation provided by intermittent renewable generation in each area as well. Capacity provides a sufficient control for coal because it is the primary competition for NGCC generation, and inclusion of coal generation would account for a large portion of the variation in NGCC generation without determining the effects of what contributed to the decision to switch from coal to NGCC. Nuclear power plants and intermittent renewable units (defined as solar and wind in this study) have relatively low variable costs, and therefore run at maximum output while they can. Nuclear plants operate near maximum output most of the time resulting in high capacity factors; therefore I use percentage of nuclear capacity as a control. Intermittent renewables, however, run at a high output while their resources are available but at much lower rates during other times, resulting in lower average capacity factors. For this reason, I use intermittent renewable generation rather than capacity as the control for intermittent renewable power.

4.2.5 Policy Controls

The model includes several state difference-in-difference dummies for the cross-state and regional program policies. These difference-in-difference dummies are an extra check that the measured policy effect is truly due to the policy, and not attributable to omitted factors related to the areas where the policy was applied or the time period the policy took place in. The variables *Treat Cross-State* and *Treat Regional Program* are time invariant dummies for the states where the policies took place. The dummy *Post Cross-State/RGGI* captures the time period for the cross-state air pollution rules and the RGGI portion of the regional program variable since they are roughly during the same time period (e.g. 2008-2014). Since RGGI actually begins in 2009, I do not use a *Post*Treatment* interaction variable for my policy variables as would be the case in a classical difference-in-difference model. Instead, the *Cross-State* policy variable turns on when the policy is in effect (e.g. 2008-2014) in the states that it is in effect, and the same is true for the *Regional Program* variables (e.g. California from 2013-2014, and RGGI states from 2009-2014). Since ozone nonattainment occurs in smaller areas at different time spans, I do not use difference-in-difference controls for this policy.

4.3 Descriptive Statistics

The descriptive statistics of the 368 NGCC plants in my dataset are provided in Table 4. The dataset consists of monthly capacity factors from 2003-2014 for these plants. Of these NGCC plants, 16 plants retire, while 218 plants began operation during this time period. Of these new plants, 79 were built at the end of the natural gas capacity buildout included in this time series (2003-2005). The average time spent in the series is 7.3 years, and approximately 70% of the plants are in the dataset for 5 years or more.

Table 4: Descriptive statistics.

	Unit	Obs.	Mean	St. Dev.	Min	Max
Dependent Variable:						
CF		35,397	0.337	0.258	0	0.999
Price:						
Price ratio (coal/ng)		35,397	0.410	0.251	0	2
Policy:						
Ozone NAA		35,397	0.286	0.452	0	1
Regional Program		35,397	0.101	0.302	0	1
Cross-State		35,397	0.432	0.495	0	1
Policy controls:						
Post Cross-State/RGGI		35,397	0.663	0.473	0	1
Treat Cross-State		35,397	0.654	0.476	0	1
Treat Regional Program		35,397	0.242	0.428	0	1
Age*Policy Interaction:						
Age*Ozone NAA	years	35,397	4.142	7.965	0	47
Age*Regional Program	years	35,397	1.394	4.706	0	39
Age*Cross-State	years	35,397	6.564	9.818	0	55
Unit characteristics:						
Nameplate	MW	35,397	676	482	11	4,263
Generator Count		35,397	4	2	1	12
Mean Capacity	MW	35,397	168	74	4	410
Mean Capacity^2	MW^2	35,397	33,782	23,173	13	167,690
Age	years	35,397	15	9	0	72
ISO/RTO		35,397	1	0	0	1
Regulated		35,397	0.482	0.500	0	1
Weather:						
HDD	degree days/1,000	35,397	305	361	0	1,886
CDD	degree days/1,000	35,397	141	182	0	782
Area characteristics:						
Load	percent	35,397	0.633	0.213	0	1
Coal capacity	percent	35,397	0.199	0.206	0	0.88
Nuclear capacity	percent	35,397	0.072	0.115	0	0.72
Renewable generation	percent	35,397	0.035	0.091	0	1

4.4 Random-Effects Model

I begin by using a random effects (RE) model to evaluate the impact of price (τ), policies (δ), plant characteristics (φ), weather (γ), and area load (ε) on NGCC plant capacity factors from 2003-2014, seen in equation 2. The RE model includes a composite error term $(c_i + \epsilon)$ to address unobserved effects particular to each plant, assuming the unobservables are not correlated with the explanatory variables. Under this assumption, an RE model can include variables that are constant over time, such as the mean generator size or age of the plant, unlike a fixed-effect (FE) model which includes a time invariant variable to capture the unobserved effects at each plant through the time series. Additionally, an RE model uses the generalized least squares transformation to eliminate serial correlation in the adjusted error term (Wooldridge 2000). Since the model in this study has ample controls, it is unlikely that the unobservable are correlated with the explanatory variables. The model passes a Hausman test finding no systematic difference in the coefficients between the FE and RE model, which indicates the RE assumption holds. The RE is preferred and used in this study in order to include the time invariant variables in the model and for more efficient estimation. The results of the RE and FE model (II vs. IV in Table 5) shows little difference in the coefficients of interest.

$$\begin{aligned} cf_{it} = {} & \beta_0 + \tau_1 price\ ratio_{st} + \delta_1 ozone_{it} + \delta_2 cross\ state_{st} + \delta_3\ treat\ cross\ state_s \\ & + \delta_4 post\ cross\ state/RGGI\ _t + \delta_5 regional\ program_{st} + \delta_6\ treat\ regional\ program_s \\ & + \boldsymbol{\partial}_k (age_i \cdot Policy_{st})_{it} + \boldsymbol{\varphi}_1 X_i + \boldsymbol{\gamma}_1 W_{st} + \boldsymbol{\varepsilon}_1 A_{at} + \theta_1 month_t + \theta_2 region_r \\ & + (c_i + \epsilon) \end{aligned} \qquad \text{(eq. 2)}$$

$i = unit\ of\ observation$
$t = time\ (month)$
$s = state$
$a = area$
$X = unit\ characteristics$
$W = weather\ variables$
$A = area\ characteristics$
$(c_i + \in) = random\ effect\ composite\ error$

The RE model also includes seasonality and region fixed-effects ($\theta_1 month, \theta_2 region$), as well as robust, clustered standard errors at the area level to address potential heteroskedasticity and errors that may be correlated within an area. In addition to the original RE model (I), I include several additional models to control for time trends that may be due to advances in technology or learning by doing. Model (II) includes a year FE, while model (III) includes a $year * month$ fixed-effect.

5. Estimation Results

The four models have similar coefficients on the policy variables of interest, but inclusion of the year and $year * month$ fixed-effects impacts the statistical significance and size of the coefficient for the resource price ratio. The variation in the resource prices over time is absorbed by the time fixed-effect, which has led other researchers focusing on resource prices to avoid using it as well (Knittel et al. 2016). However, I include these versions of the model to show the consistency of other variables of interest, including the cross-state policy, $Age * CrossState$ interaction, mean capacity, weather variables, area load, area coal capacity, and area intermittent renewable generation. I focus my analysis on interpretation on model (I), but discuss the deviations from this model in the other versions of the model as appropriate.

5.1 Policy Effects

The only policy variable with strong statistical significance in all of the models is the cross-state rule representing the CAIR regulations. Both the cross-state policy variable and $age * policy$ variables are significant at the 99.9% confidence level. The coefficient on the cross-state policy variable is positive, while the cross-state $age * policy$ interaction variable is negative. This indicates that a brand new plant under the cross-state rule has higher capacity factor of 0.156, on average. However, for each additional year in a plant's age, the overall impact to the capacity factor decreases by 0.0044, the coefficient for $Age * CrossState$. To calculate the overall policy impact for each policy (x) for every observation (i) where the policy takes place, I use the coefficients for both the policy variable (δ_x) and the $age * policy$ interaction variable (∂_x) as seen in equation 3. Given the average age of the plants affected by the cross-state rule (Table 6), the average impact of the cross-state policy was an increase in capacity factor by 0.09. With an average capacity factor of 0.33, this leads to a 27% increase in the capacity factor for units impacted by the cross-state rule.

$$Policy\ effect_{xi} = (\delta_x + \partial_x * age_i) * policy_{xi} \quad \text{(eq. 3)}$$

Since coal has much higher SO_2 and NO_x emissions, NGCC utilization increased to make up for decreases in coal generation encouraged by the cross-state air pollution transport policy. Since I control for the natural gas to coal price ratio, this uptick in utilization is beyond the increases caused by decreases in natural gas prices at this time. However, NGCC units older than 35 years of age decreased utilization under the cross-state air pollution transport rules using equation 3. While the coefficient with the year (II) and $year * month$ fixed-effect (III) decreases in magnitude slightly, the two policy coefficients associated with the cross-state policy remain at 99.9% statistical significance.

The coefficient on ozone nonattainment is positive, and $age * policy$ interaction is also negative, but neither of these coefficients is statistically significant. NGCC plants that are in a regional and state greenhouse gas program and brand new have a higher capacity factor by 0.0547, significant at the 96.2% significance level. The interaction with age is negative but not statistically significant, which is likely because these areas have fewer, older NGCC units. This complements the findings from Murray and Maniloff (2015) that RGGI had an impact on decreasing CO_2 emissions beyond changes in natural gas prices and the economic recession. Part of the emissions decreases may be due to increased generation by NGCC, supporting the CPP's recommendation that states could embark on regional greenhouse gas cap-and-trade programs, like RGGI, to reach their carbon emission targets by increasing NGCC utilization. However, causality is not determined since the policy variable is only weakly significant. It is possible that as these programs continue, a more significant policy effect can be measured with additional observations, as only 10% of the observations in this data are included in a regional program.

Table 5: Results of models with standard errors clustered by the transmission area.

	(I) RE		(II) RE		(III) RE		(IV) FE	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Price:								
Price ratio (coal/ng)	0.110**	0.0349	0.0656+	0.0343	0.0447	0.0363	0.0628+	0.0344
Policy:								
Ozone NAA	0.0289	0.0261	0.00987	0.0266	0.00977	0.0268	-0.00251	0.0284
Regional Program	0.0547*	0.0263	0.0461+	0.0259	0.0446+	0.0259	0.0441	0.0278
CrossState	0.156***	0.0283	0.149***	0.027	0.147***	0.0271	0.150***	0.0277
Policy controls:								
Post Cross-State/RGGI	-0.0413**	0.0145	-0.0228	0.0224	-0.00824	0.0208	-0.0421*	0.0189
Treat CrossState	-0.0619	0.0503	-0.0568	0.0519	-0.0579	0.0517		
Treat Regional Program	-0.0592	0.0451	-0.0319	0.0438	-0.0215	0.0441		
Age*Policy Interaction:								
Age*Ozone NAA	-0.00185	0.0013	-0.00158	0.0014	-0.00164	0.0014	-0.000809	0.0014
Age*Regional Program	-0.00173	0.0014	-0.00168	0.0014	-0.00168	0.0014	-0.00152	0.0014
Age*CrossState	-0.00441***	0.001	-0.00434***	0.001	-0.00434***	0.0009	-0.00450***	0.001
Unit characteristics:								
Mean Capacity	0.00134*	0.0006	0.00131*	0.0006	0.00132*	0.0006		
Mean Capacity^2	-2.0E-6	1.5E-6	-1.9E-6	1.4E-6	-1.92E-6	1.5E-6		
Age	3.51E-5	0.0014	3.21E-6	0.0014	-6.08E-6	0.0014		
ISO/RTO	0.0245	0.0356	0.0216	0.0354	0.0189	0.0355		
Regulated	0.00903	0.0207	0.00436	0.0214	0.00353	0.0215		
Weather:								
HDD	-0.0961***	0.0183	-0.0906***	0.018	-0.0967***	0.0202	-0.0925***	0.0185
CDD	0.282***	0.0419	0.289***	0.0428	0.304***	0.0462	0.292***	0.0436
Area characteristics:								
Load	0.438***	0.0445	0.430***	0.0454	0.422***	0.046	0.432***	0.0462
Coal capacity	-0.277**	0.0996	-0.276**	0.1014	-0.271**	0.1028	-0.265+	0.1519
Nuclear capacity	-0.238*	0.1169	-0.231+	0.1201	-0.228+	0.1206	-0.0954	0.2345
Renewable generation	-0.311***	0.0614	-0.334***	0.0648	-0.333***	0.0652	-0.334***	0.068
Constant	-0.119	0.1022	-0.101	0.1022	-0.0814	0.1085	0.043	0.0731
N	35,397		35,397		35,397		35,397	
R-sq (Overall)	0.337		0.332		0.334		0.279	
Month FE	X		X		X		X	
Year FE			X				X	
Month*Year FE					X			
Region FE	X		X		X		X	

Standard errors in parentheses

+ p<0.10, * p<0.05, ** p<0.01, ***p<0.001

Table 6: Average policy effect using coefficients from the policy and $age * policy$ variables.

	Coefficient			
	Policy	Policy*Age	Avg. Age	Avg. Effect
Ozone NAA	0.0289	-0.00185	14.5	0.002
Regional Program	0.0547*	-0.00173	13.7	0.031
Cross State	0.156***	-0.00441***	15.2	0.089

+ $p<0.10$, * $p<0.05$, ** $p<0.01$, ***$p<0.001$

Figure 7 provides a visual interpretation of the coefficients from the policy variables with 95% confidence intervals to convey uncertainty in the estimates. The 95% confidence intervals are calculated as a function of the policy coefficients (eq. 3). The figure shows the impact of the cross-state rule declines in older plants, as older technology may not be as economically advantageous to run under new environmental regulations. However for ozone, the impact for a brand new plant is very close to zero with a larger confidence interval, indicating low statistical significance. The regional program policy coefficient's confidence intervals remain above zero out to 10 years, the median aged plant.

In most cases, the policy control variables (i.e. post and treatment variables) are not significant. However, in model (I), the *Post Cross-State/RGGI* variable is significant at the 99.6% level, and negative with a relatively small coefficient. This indicates that plants outside of the cross-state and regional programs experienced a small decrease in capacity factors while these policies took place.

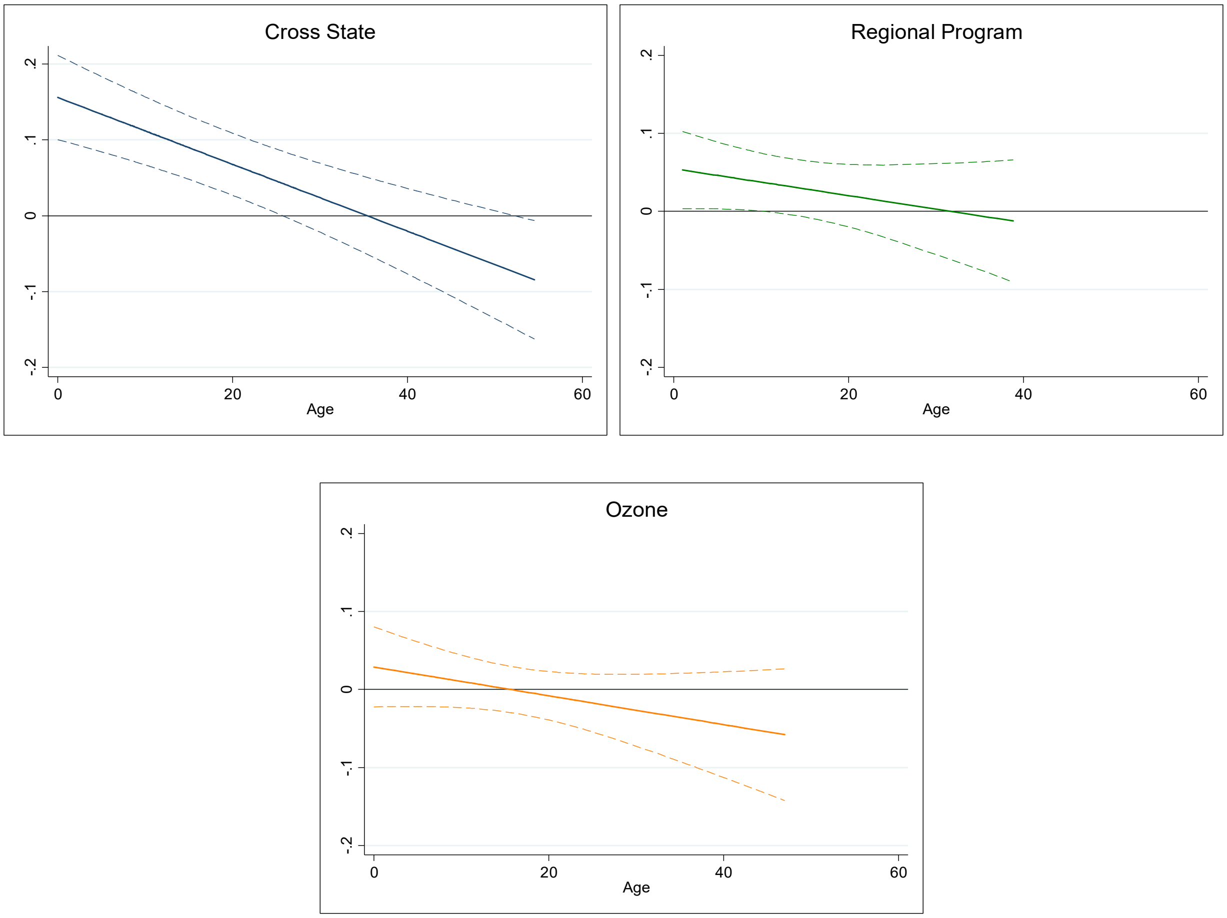

Figure 7: The average impact of each policy on NGCC capacity factors (ranges from 0 to 1), based on the age of the plant. The dotted lines indicate the 95% confidence intervals, and the solid line is the average effect.

5.2 Other Explanatory Factors

As expected, NGCC utilization increases as natural gas prices decrease in model (I), a well-supported hypothesis in previous literature (Linn et al. 2014; Fell and Kaffine 2014; Cullen and Mansur 2014). However, the statistical significance decreases from 99.8% significance in model (I), to 94.4% significance with a year FE, and out of statistical significance with the $year * month$ FE in model (III), which is to be expected since resource prices vary with time.

In addition to the policies and resource prices, the physical characteristics of the plants may have contributed to differences in utilization of NGCC. The mean capacity is weakly statistically significant, but the quadratic term falls out of statistical significance. The capacity weighted age variable is not significant because much of the age variation has been absorbed by multiple $policy * age$ interactions. As conjectured in the CPP, the regulatory ownership and membership in an ISO/RTO do not have a statistically significant impact on NGCC utilization, suggesting that neither ownership nor market type is significantly underperforming in NGCC utilization.

The heating and cooling degree day coefficients are both strongly significant at the 99.9% level in all of the models. Increases in heating degree days decrease NGCC capacity factors, confirming that residential and commercial heating competes with natural gas available for NGCC generation. The coefficient on cooling degree days is positive, showing that increased demand required for air conditioning increases NGCC capacity factors, even after removing the seasonality fixed-effect. This would mean particularly hot summers experience the highest NGCC capacity factors.

The EPA Clean Power Plan lays out the framework for when the NGCC utilization target should be met based on historical changes in NGCC utilization. From 2011 to 2012, the largest increase in natural gas generation (22%) took place. Based on the magnitude of this one-year jump, the EPA estimates that the electric power sector can reach an average 22% increase in natural gas generation by 2022, with a 5% increase thereafter until 2030. This would result in natural gas generation achieving 70% capacity utilization in 2030. The EPA argues that this is a reasonable target because the sector has already demonstrated its ability to (temporarily) increase utilization, and necessary infrastructure changes can be made in the interim to make additional increases possible. As it turns out, 2012 was an exceptionally warm winter followed by an anomalously hot summer (Figure 8). The warmer winter led to a decreased demand of natural gas for heating, resulting in an increase in supply and storage of natural gas before a hot summer with high energy demand. These two factors, combined with the anomalously cold winter in 2011, contributed to this 2011-2012 increase in natural gas generation. Since the EPA used the 2011-2012 increase as the basis for determining future utilization targets in each area, this suggests this target may be more difficult to reach when winter and summertime temperatures are not anomalously warm. This occurred in 2013, and NGCC generation levels were lower than in 2012.

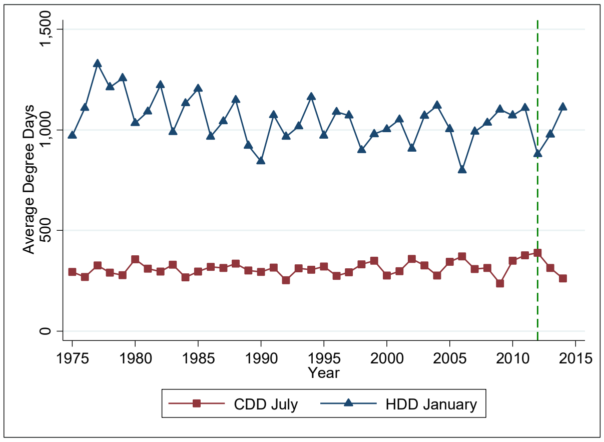

Figure 8: Average heating (HDD) and cooling (CDD) degree days for contiguous US for July (CDD) and January (HDD), with dashed line indicating CPP reference year 2012.

The characteristics of the load in each area are mostly significant in each version of the model. As energy demand in each area increases (*Load*), the NGCC capacity factors increase, which is strongly significant in each model. As coal and nuclear capacity in an area decreases, NGCC utilization increases in most models, but varies from weak to medium significance. The coefficient on renewables generation is consistently 99.9% significant, and indicates that as renewable generation increases, NGCC utilization decreases. Studies focusing on complementary and substitution effects of intermittent renewable generation on natural gas generation have found intermittent renewables displaced natural gas generation in studies with a dataset from 2000-2010 (Kaffine et al. 2013; Cullen and Mansur 2014). More recent papers evaluating changes from 2008-2013 as renewables became more prominent and natural gas prices decreased find a complementary effect (Fell and Kaffine 2014). Therefore, it is possible this coefficient is negative because it is more heavily influenced by the earlier portion of the time series. This could also show that as intermittent renewable generation increases, which ultimately drives CO_2 emissions down even further, NGCC will phase out. This requires further investigation outside of the scope of this paper to determine what is causing this negative coefficient.

5.3 Counterfactual Calculation

I use the RE model (I) coefficients to run a counterfactual calculation to estimate the effect of the policies, natural gas prices, and carbon taxes on natural gas generation and CO_2 emissions. The baseline scenario uses the model's predicted capacity factors with no changes to the policies or natural gas prices. The alternative scenarios presume the policies never occurred or that natural gas prices remained at 2007 levels. Additional alternative scenarios presume a social cost of carbon priced at \$36/ton is applied to the natural gas and coal prices, or a policy equivalent tax is applied (found to be at \$55/ton) in place of the policies. I use the predicted capacity factors and capacity data to calculate differences in natural gas generation from baseline.

Table 7: Counterfactual calculation scenarios.

Scenario	Price and Policy Settings
1. Baseline	Actual data
2. Without policies	Policies and age*policy set to zero
3. Historical NG prices	2007 NG prices fixed
4. Social cost of carbon tax	Policies and interactions set to zero and SCC added to fuel costs
5. Policy equivalent tax	Policies and interactions set to zero and tax added to fuel costs

In order to apply a carbon price in the SCC and tax scenarios, I use the most recent EIA carbon intensity numbers[89] and multiply these respective values by the tax to get the appropriate values to add to the natural gas and coal prices in MMBtu. Figure 9 displays the total difference over the time period for each scenario in terms of percent of total NGCC generation with 95% confidence intervals.

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[89] August 17, 2016 EIA's Today in Energy carbon intensity values of 95 $\frac{MM\ tons\ CO_2}{quad\ BTU}$ for coal, and 52 $\frac{MM\ tons\ CO_2}{quad\ BTU}$ for natural gas, converted to $\frac{tons\ CO2}{MM\ Btu}$ provided at: https://www.eia.gov/todayinenergy/detail.php?id=27552.

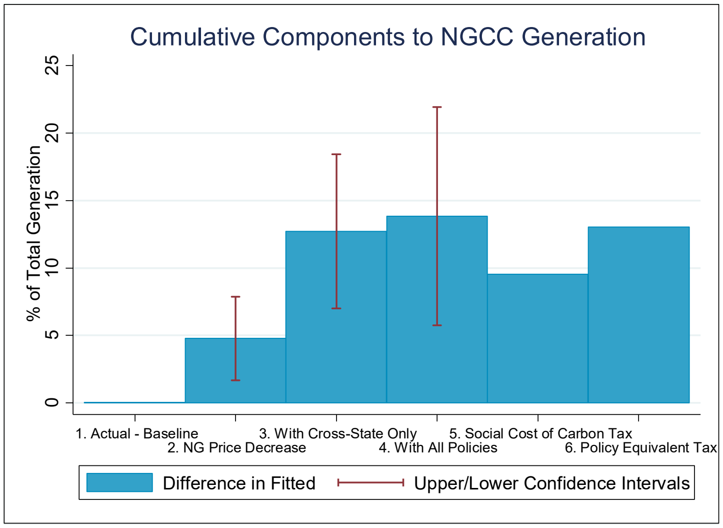

Figure 9: The percent of NGCC generation that occurred due to increased utilization over the time period 2003-2014 by the different components.

The total impact of the cross-state rule (13%) is approximately 2.6 times larger than the impact of the natural gas price decrease (5%) on combined cycle utilization. The total impact of the policies (14%) is only slightly higher than the cross-state rule, but the confidence interval is rather large due to the uncertainty associated with the coefficients on ozone and regional program. The cross-state rule had the same impact on increasing NGCC generation as a $55/ton carbon tax issued from the beginning of the time series. Since the bulk of the policies and natural gas price decreases did not occur until midway through the time period, the percent contributions to aggregate generation seems small. However, in a single year with both the policies and the low natural gas prices, the relative contributions are much larger, and may even be closer between the policies and price decreases. The difference between actual generation and model predicted values (baseline) is less than 1%.

Using this information about the difference in NGCC generation from each scenario, I calculated the amount of CO_2 emissions averted assuming the increased NGCC generation replaced coal. I use the carbon intensity coefficients provided by EIA to calculate the million tons CO_2 averted per month by the decrease in natural gas prices beginning in 2007, versus the policies (Figure 10). Over the total time series, this is 371 million tons of CO_2 due to the policies, 341 million tons due to cross-state alone, and 142 million tons due to the decrease in natural gas prices since 2007. In 2014, the decrease in CO_2 emissions due to the cross-state rule and low natural gas prices was approximately 4% of all electric sector CO_2 emissions, with 3% of that due to the cross-state rule and 1% due to the lower natural gas prices. Cullen and Mansur (2014) estimate a $60 ton CO_2 price would decrease CO_2 emissions by approximately 9%. Since the cross-state policy equals the impact of a $55 tax, my value is smaller primarily because it represents the emissions decrease due to increased utilization of *existing* NGCC plants, and not due to additional generation from *new* NGCC capacity related to a tax, or other natural gas-fired plants.

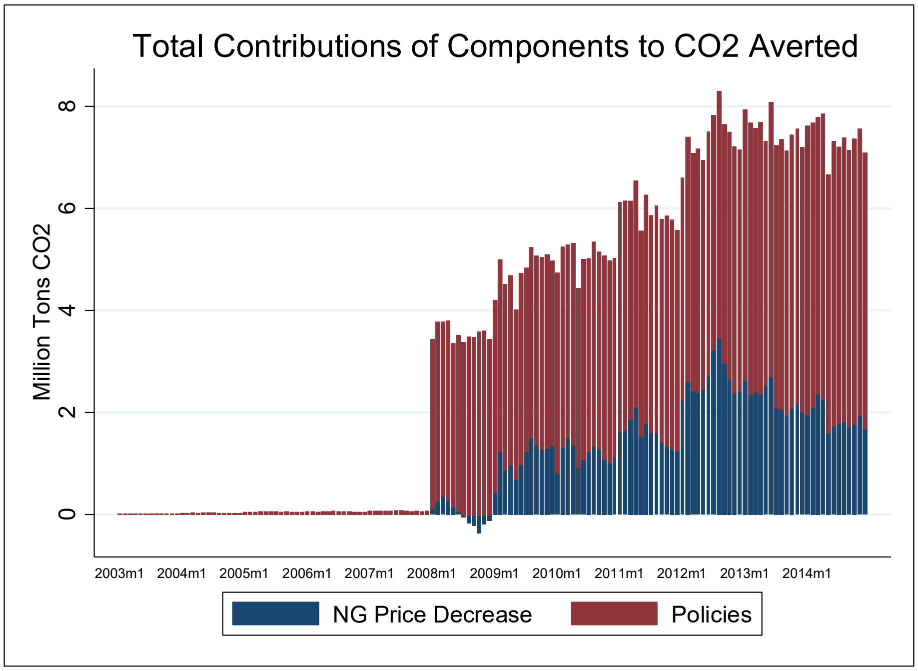

Figure 10: CO_2 emissions averted by increased NGCC generation from the policies and natural gas price decrease (since 2007) components per month.

6. Conclusion

This study focuses on the changes in NGCC capacity factors that have already taken place from 2003-2014 in order to shed light on the new utilization targets to decrease US carbon emissions from the electricity sector in EPA's Clean Power Plan. While most recent studies on natural gas generation focus on the role of natural gas prices and renewable generation, this study also considers the role of energy and environmental policies to produce a counterfactual analysis determining the relative contribution of decreases in natural gas prices versus several environmental policies on increases in NGCC utilization.

The findings show the cross-state air pollution transport policy, or CAIR reinstated, significantly contributed to increases in NGCC utilization. It effectively lowered the cap on SO_2 and NO_x emissions in upwind states contributing to nonattainment in the mid-west and northeast, rendering coal generation more costly. However, the impact of the policy declines with the age of the plant. This indicates a substantial co-benefit from a criteria pollutant policy in incentivizing increased NGCC utilization, which in turn reduces carbon dioxide emissions.

Variables representing NAAQS nonattainment status or regional programs are not strongly significant, in terms of impact and statistics. However there were also fewer observations in this study affected by these policies compared to the cross-state rule. Therefore, this finding does not prove that these policies did not contribute to increases in NGCC utilization, and more research should be done in this area. Since the Clean Air Act requires that the NAAQS be reviewed every 5 years, they will remain an important piece of the regulatory framework during implementation of the Clean Power Plan (or any greenhouse gas reduction program). Decreased natural gas prices since 2008 due to increased extraction of unconventional domestic natural gas has also led to increased NGCC generation. However, the combined effect of the policies on natural gas generation is typically 2.6 times as high as the decreases on natural gas prices, thus averting nearly three times as much CO_2 emissions as low natural gas prices over the cumulative 2003-2014 time period. However, there are individual years and months when natural gas prices were particularly low, resulting in a more equivalent impact by the policies and prices.

Despite the increases in NGCC utilization, few plants have run at high capacity factors even with low natural gas prices and environmental policies that favor gas over coal. The fuel mix of each area, and the age and size of the generators are also important. This suggests that while policy can certainly nudge NGCC utilization, these other factors must also be considered when evaluating the efforts of areas to reach their NGCC utilization targets. This study shows NGCC capacity factors will decrease for older generators faced with more costly compliance requirements. Since the CPP emissions targets are calculated on the basis that existing NGCC capacity will be run at 70%, this means it would be quite costly for older NGCC plants to meet the same 70% target since they have higher emissions than the newer technology. Or, areas may need to install new NGCC units or make substantial modifications to their old units to reach their emissions targets. Figure 11 identifies the areas of the country with older NGCC generators that may particularly struggle to increase utilization. Some of the states with older NGCC generators, such as Oklahoma, Iowa, and Texas may need to lean more heavily on the other building blocks of the CPP to reduce carbon emissions.

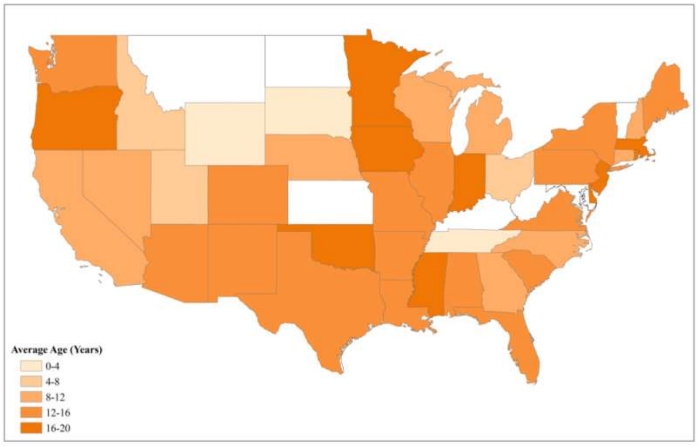

Figure 11: Average capacity weighted age of NGCC plants, per state.

Finally, the results raise another important cautionary note for the CPP: capacity factors increase most in years with anomalously warm winters and hot summers. This situation leads to more natural gas storage in the winter, followed by increased energy demand in the summer. The base year used by the EPA in setting state targets, 2012, was unusual in exactly that respect: it had an exceptionally warm winter followed by an anomalously hot summer. The CPP may thus overstate the rate at which capacity factors are likely to increase with lower storage or less energy demand in the summer.

While the EPA's Clean Power Plan is currently stayed by a Supreme Court decision in February 2016, NGCC generation will remain an important aspect of the energy sector for the foreseeable future. As the domestic natural gas glut continues, and environmental standards perhaps tighten, areas are likely to continue the trend towards replacing coal-fired and aging nuclear plants with available NGCC generation. This study illustrates how demonstrated policies can be applied or enhanced to increase natural gas utilization from existing NGCC plants, but cautions against uniform utilization targets that may be costly for particular plants to achieve.

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CHAPTER FIVE:

Conclusion

The essays comprising this dissertation evaluate aspects of three important developments for natural gas-fired combined cycle generators in the US over the last thirty years: (1) efficiency increases from technological change in the 1990s, (2) rapid capacity growth in the early 2000s, and (3) increased utilization from 2003-2014. After a review of the findings, policy implications, and areas for future research, I consider how the lessons learned from this research will affect NGCC in the future.

1. Findings

Chapter 2 uses patent data to evaluate the impact of a US public-private partnership between DOE and NGCC turbine manufacturers to stimulate NGCC innovation in the 1990s. Through econometric analysis, I find that the DOE-ATS program affected the two participants, GE and SWPC, differently. Towards the end of the program, GE increased patent volume and sustained the higher level for several years following the program. SWPC, on the other hand, did not increase patenting volume but rather had higher impact patents (i.e. higher citations) during the early years of the program. This suggests that public-private partnership design and evaluation should consider the intended impact of a program on participants separately. Additionally, I use both a global sample of patents authorized anywhere in the world, and patents that were only authorized in the US, and the results vary between the two samples. Researchers may be tempted to only consider the local impact of a domestic program measured by domestic patents. However, this study finds that the domestic sample does not fully capture global innovation, and international patents should be evaluated (when available) for a truer sense of a program's impact on innovation. The patent analysis conducted in this study provides quantitative information on the impact of the program on NGCC patenting. Future research should conduct more qualitative research, through interviews with program participants and patent content analysis, to further investigate why the program affected each participant differently, and how the program patents translated into commercialized technologies. This information will provide more details to future program participants on how to design and evaluate public-private partnerships designed to stimulate innovation for complex technologies.

Chapter 3 evaluates the impact of environmental policy anticipation on rapid deployment of improved NGCC technology in the early 2000s. Using an econometric analysis of natural gas capacity data, I find that firms in areas anticipating ozone and particulate matter nonattainment built more natural gas capacity before nonattainment regulations took place. Since natural gas capacity is cleaner than coal generation, firms acted in advance of regulation to either reduce the chance of nonattainment designation, or to avoid stricter building regulations that result from nonattainment regulations. In this case, this was not an adverse anticipatory reaction to new policy, but rather anticipatory action with environmental benefits. For those crafting and evaluating policy, this study shows it is also important to consider the impact of a policy even before implementation. Despite significant variables measuring policy anticipation, the overall variance of natural gas capacity growth explained by the model is low. Future research should consider the impact of anticipation of additional policies that took place in the late 1990s, such as the Kyoto Protocol, which may have also contributed to an expectation of future environmental regulations.

In Chapter 4, I evaluate the impact of environmental policies and natural gas prices on NGCC utilization. Despite capacity expansion discussed in Chapter 3, new NGCC units had low utilization rates and were generally not used for baseload power. Over time, NGCC utilization gradually increased and continues to grow. In this study, I evaluate the relative contributions of low natural gas prices and environmental policy on NGCC utilization, finding that the environmental policies had three times the effect of low natural gas prices on growing NGCC utilization. This shows that policy and market forces matter, and exclusion of either when designing and evaluating policy could lead to inaccurate conclusions. This study also cautions against the use of uniform utilization targets for NGCC generators since the age of the plant and weather conditions also affect utilization. Despite recent gains in NGCC utilization, overall utilization of these generators remains low. Future research should consider why NGCC in most places continues to provide power for marginal demand, and how to incentivize higher utilization in areas with coal generation and higher pollution.

2. The Future of NGCC and Renewables

While this dissertation focuses on developments over the last thirty years for NGCC, the future of NGCC—including innovation, capacity growth, and utilization—will largely be shaped by its relationship to renewable generation. Intermittent renewable generation and capacity continues to increase in the US, with more than half of the capacity additions in 2016 coming from wind and solar.[90] Because of NGCC's flexibility and quick start-up and shut-down time, NGCC is expected to play an important role complementing intermittent renewables as their contributions to the electricity sector grow. The improvements in NGCC efficiency, cost competitiveness, and emissions reductions that occurred in the 1990s allowed new NGCC units to move into the role of baseload power providers. Today, there is growing interest in improving NGCC ramp speeds to better complement the growing use of intermittent renewable generators. The patent analysis of the DOE-ATS public-private partnership in Chapter 2 provides insights on

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[90] EIA Today in Energy, January 10, 2017: https://www.eia.gov/todayinenergy/detail.php?id=29492.

advanced NGCC patenting, and factors to consider while assessing the need for future programs and policies targeting the next round of NGCC innovation.

Similarly, NGCC capacity growth in the future will likely be more heavily influenced by the location of intermittent renewable capacity. Chapter 3 found anticipation of traditional environmental policy impacted NGCC investment in the past. Today, politics has become even more partisan leading to more frequent and longer regulatory delays. It will be interesting to consider how renewable and climate policy anticipation, which are more political and uncertain, may impact NGCC capacity growth and investment going forward.

Last, there are many potential consequences of the relationship between NGCC and intermittent renewables for NGCC utilization. In my study of NGCC utilization (Chapter 4), I control for renewable capacity without further evaluating the specifics of the relationships, which is currently an evolving area of research with inconclusive findings thus far. Since I find policy in addition to market forces influence NGCC utilization, future research should consider the role of renewable policies on NGCC utilization.

My dissertation discusses the impact of three decades of energy and environmental policies on NGCC. This research is focused on NGCC in the US, but includes implications for other sources of generation, countries, and policies. I have used various data and methods to evaluate multiple types of energy and environmental policies, including government sponsored research programs, command-and-control environmental regulations, market-based policies, and regional greenhouse gas policies. New types of policies, not yet conceived, will influence the future of energy generation. New methods and analyses will be integral to prediction and assessment. Through it all, evidence-based policy research will remain necessary for measuring and shaping future policy decisions.

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Oneonta State Scholar Athlete of the Year, 2003
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