The End of the Nuclear Era:
An Investigation of Nuclear Decommissioning and its Impacts on US Counties

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Abstract

Between 1957 and 1990, nearly 100 nuclear reactors were constructed throughout the United States, and nuclear power currently accounts for approximately 20% of electricity production. Nuclear plants themselves require large amounts of land and fresh water for safe operation, and, because of this, they are generally constructed in sparsely populated, rural towns, and often constitute the largest source of income and employment for nuclear host communities. To date, eighteen nuclear reactors have been closed and decommissioned, six have been partially decommissioned, and more are expected to undergo decommissioning in the future, particularly as nuclear reactors age and face increasingly strict regulations from the NRC. In this paper, I examine the impacts of nuclear decommissioning over time at the county-level on measures of employment, income, and population using both difference-in-differences regression and propensity score matching techniques. Panel data is obtained from the US Census Bureau, and covers the years 1975-2014. Surprisingly, I find that nuclear decommissioning is associated with positive and statistically significant increases in county-level employment and per capita income, which I attribute to short-term increases in local employment to facilitate the decommissioning process and a county's long term ability to adjust to the loss of a nuclear reactor, among other potential explanations. While nuclear decommissioning may be a positive force at the county level, a key limitation of this analysis is my inability to fully assess the impacts of decommissioning at town and municipality levels. To my knowledge, I am the first to investigate nuclear decommissioning from an econometric perspective, and future work should seek to build upon this analysis, particularly at smaller spatial scales.
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I. Introduction

Between 1957 and 1990, nearly 100 nuclear plants were built in the United States, and approximately 20% of all electricity in the US is produced by nuclear power (NEI, 2014). Nuclear plants themselves require large amounts of land and fresh water for safe operation, and, because of this, they are generally constructed in sparsely-populated, rural towns, and often constitute the largest source of income and employment for nuclear host communities. In some areas, nuclear power plants have accounted for as much as 50-90% of municipal tax revenue, and a comparatively high percentage of local employment (Haller, 2014). As a result, many communities come to rely on nuclear power as a major source of economic development and municipal funding. Therefore, nuclear decommissioning poses a sizeable threat to these communities.

The decision to decommission a nuclear plant depends on a variety of factors, including operating and repair costs, the stringency of Nuclear Regulatory Commission (NRC) regulations, public opinion, the operating life of the plant, and the opportunity costs involved with switching to smaller-scale, less capital intensive electricity sources like coal and natural gas (Brown and Bruttoco, 1997). To date, many of the plants that have been decommissioned have done so before their operating licenses have expired, mainly in response to mounting repair costs and continued outages and delays in electricity generation. In these cases, utility companies have determined that closing and decommissioning the plant will be more economical in the long run than continuing operation. As a result, nuclear host communities are often faced with decommissioning unexpectedly, with little time to prepare for the impacts of plant closure.

In general, plant closure has been found to impact local and regional economies in a number of ways. Plant closing literature identifies a series of ripple effects associated with the loss of a major employer: plant closing not only involves laying off workers, but also often leads to a loss of income in a community, decreasing retail and commercial spending and causing unemployment and stress on other industries in the area (Bluestone and Harrison, 1982; Wu and Korman, 1987). Specialized workforces, like those employed by nuclear plants, tend to have a more difficult time finding new employment, increasing stress on local economies and public services (Rocha and McCant, 1999). Often, workers must move away to find new jobs, or exit the labor force altogether. Therefore, previous work on plant closure reveals pervasive impacts on local employment, income expenditures, population growth, and municipal services.

This paper aims to answer one main question: in what ways does nuclear decommissioning uniquely impact nuclear host communities? To date, no empirical research has considered the impacts of plant closure from the context of the nuclear industry. Using a panel of US census data from 1975-2014, this paper empirically considers the impacts of nuclear decommissioning at the county level in the United States. Counties were chosen as the primary scale of analysis due to data availability at the town and city levels; while this poses potential concerns for this study's ability to measure the impacts of a very localized shock, the ripple effects associated with the plants would more than likely be dispersed outside of the immediate host community, causing measurable impacts at the county scale. I test the impacts of decommissioning on employment, income, and population, employing both a difference-in-differences model and a quasi-experimental design using propensity score matching techniques. Understanding how decommissioning impacts host communities is invaluable information for communities with nuclear plants today.

This paper is organized as follows: section II provides a brief history of nuclear power in the United States, detailing both the rise of nuclear power during the mid 20th century and more recent trends towards nuclear decommissioning. Section III gives an overview of previous studies on plant closings and nuclear decommissioning, and provides a general rationale for studying the impacts of nuclear decommissioning at the county level. Section IV describes the data sources used to construct my final panel dataset, discusses the challenges that arise when using census data for quantitative analysis, and details the empirical model and specification that were used for this study. Section V presents empirical results and discusses the implications of these results for future nuclear host communities. Surprisingly, I find that decommissioning is associated with statistically significant increases in employment and per capita income at the county level, indicating that decommissioning may actually improve economic conditions in nuclear host counties. Finally, I argue that while results may look promising from a regional perspective, future work should focus on studying economic impacts of decommissioning from smaller, more localized spatial scales in order to better investigate whether these results impact municipalities unevenly within counties, particularly in nuclear host municipalities.

II. The United States Nuclear Program: A Brief History

Nuclear power in the United States emerged as a response to Cold War pressures and government policy initiatives. In 1953, a Congressional Joint Committee on Atomic Energy warned that "the relations of the United States with every other country in the world would be seriously damaged if Russia were to build an atomic power station for peacetime use ahead of us." (Makhijani and Saleksa, 1999, p. 3) Despite early warnings from the Atomic Energy Commission (AEC, later called the Nuclear Regulatory Commission) that nuclear power had many technical difficulties to overcome, and a 1953 study by Bechtel, Monsanto, Dow Chemical, Pacific Gas and Electric, Detroit Edison, and Commonwealth Edison that stated that "no reactor could be constructed in the very near future which would be economic on the basis of power generation alone," utility companies rushed to build nuclear plants with the promise that nuclear power would be "too cheap to meter." Power plant manufacturers like GE and Westinghouse agreed to produce plants at a loss in order to incentivize plant construction, and the US government heavily subsidized the industry, leading to the adoption of nuclear power at a relatively low cost in the early 1950s (Makhijani and Saleksa, 1999). The vast majority of nuclear construction occurred during this time period, and construction slowed down considerably with the removal of subsidies in the 1970s and 80s. In total, approximately 100 reactors were built across the US, and nuclear power quickly became an important contribution to US energy networks. Figure 1 maps the location of these nuclear plants in the US.

As figure 2 illustrates, the nuclear power industry has lost momentum in recent years. This is likely because of three key factors: first, broad economic and social factors surrounding the nuclear power industry have undermined public opinion on nuclear power and general consensus on the role it ought to play in regional power networks. External economic events like the 1973 oil embargo and downturns in local economies led to increased capital costs, slow economic growth, and decreasing electricity demand, and tight monetary policy and soaring interest rates in the 1980s compounded these conditions, leading many utilities to invest in cheaper, less capital intensive power sources like coal, rather than nuclear power (Brown and Brutoco, 1997). Disasters at Three Mile Island and Chernobyl promoted a growing anti-nuclear power movement in the United States, and nuclear power has become the subject of many protests and campaigns, creating a climate in which it is socially and politically difficult to support the industry.

Secondly, mounting costs of sustaining nuclear power plants and increased regulatory burdens have increased operating costs for utility companies and incentivized a wave of decommissionings. Between 1974 and 1993, average operating costs per reactor per year escalated from $37 million to $126 million. Only 25% of reactors produced power more cheaply than other power sources as of 1993, and plants have continued to show signs of age in recent years. The average cost of nuclear-generated power between 1968 and 1990 was $0.088 per kilowatt hour, which was twice the cost of electricity from coal, oil, or gas during the same period (Brown and Brutoco, 1997). More recent evidence further suggests that the levelized cost of electricity[1] is generally higher for nuclear power than most other electricity sources. Figure 3 illustrates these differences. Why is nuclear power so expensive? The nuclear industry has been found to exhibit "negative learning": even as more nuclear plants are constructed, the complexity of the technology continually increases, leading to cost escalation that often outpaces gains from economies of scale (Grubler, 2010). Figure 2.2 illustrates this phenomenon in the US and French nuclear industries; in both industries, costs have visibly and consistently increased over time. Over time, as construction and operating costs climbed, some nuclear reactors were never even completed, and the financial burden faced by utilities is typically passed on to ratepayers in the form of higher electricity prices(Brown and Brutoco, 1997).

Increased regulatory standards and NRC scrutiny has also added to cost escalation. Since the Three Mile Island disaster, the NRC has continually increased safety and security regulations in the interest of preventing future disasters from occuring (NRC, 2014). Unsurprisingly, plants

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[1] Average Levelized Costs are a measure designed to allow average cost comparisons across different sources of electricity. They are defined as the average total cost to build and operate a power-generating asset over its lifetime divided by the total energy output of the asset over that lifetime, (Branker, Pathak, and Pearce, 2011):

$$\mathrm{LCOE} = \frac{\text{sum of costs over lifetime}}{\text{sum of electrical energy produced over lifetime}} = \frac{\sum_{t=1}^{n} \frac{I_t+M_t+F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}}$$

I_t	:	investment expenditures in the year t
M_t	:	operations and maintenance expenditures in the year t
F_t	:	fuel expenditures in the year t
E_t	:	electrical energy generated in the year t
r	:	discount rate
n	:	expected lifetime of system or power station

built in the early wave of nuclear construction continue to have major unresolved safety vulnerabilities as a result of the rush to build nuclear plants well before the technology had been properly investigated and developed, creating huge costs for utilities (Makhijani and Saleksa, 1999).

Lastly, state-level trends towards energy deregulation have further undermined the competitiveness of nuclear power as a source of energy: because nuclear power has often required state support and subsidies for the construction and upkeep of reactors, the costs of operating plants increases when states elect to deregulate their electricity markets. Furthermore, if electricity prices decrease in a more competitive market, profits from power generation may not be high enough to cover operating costs, causing utilities to operate at a loss. These costs are particularly high for older nuclear plants that require high maintenance expenditures. Because recent nuclear disasters have shown that the safety and longevity of nuclear plants is relatively uncertain, private investors may be less willing to take on the risk of investing in nuclear power compared to government actors (OECD, 2000). All of these factors have impacted utilities' incentives to run and repair existing nuclear reactors, and some have elected to decommission or transfer ownership of nuclear facilities in order to limit future expenditures (NRC, 2015). However, deregulation has not been universally bad: it has also allowed some nuclear facilities to be consolidated under the ownership of a few major companies, and evidence suggests that this has increased the operating efficiency of nuclear power for those plants (Davis and Wolfram, 2011).

Overall, this combination of macro and micro scale problems has ultimately facilitated a slow decline of the nuclear industry in the United States. Twenty four nuclear reactors have been decommissioned already or are in early decommissioning phases, and more are expected to be decommissioned in coming years. Table 1 lists all plants that have been decommissioned by year, indicating whether a plant has been fully or partially decommissioned. These will serve as the “treatment” group for this research. As the table illustrates, the vast majority of these plants were closed and decommissioned well before their operating licenses were expected to expire, illustrating not only that nuclear closure tends to be driven by forces beyond the natural life cycle of plants themselves, but also the fact that many of these plant closures have been unexpected for nuclear host communities.

III. Literature Review

Very little work has been devoted to studying the economic impacts of nuclear decommissioning on US communities, and most work that has been done focuses on qualitative methods or case study research. Kovtal and Mullin (1997), in their work on the closing of the Yankee Rowe Nuclear Power Plant, find that job loss, decreases in municipal budgets and services, and loss of spending in the local economy are the primary impacts of the closing of a nuclear power plant. Haller (2014), studying the Maine Yankee Nuclear Power Plant in Wiscasset, Maine, presents similar findings, concluding that the loss of the nuclear plant negatively impacted employment and the local tax base, which forced the town to make large spending cuts in education and municipal services. Nuclear workers were especially vulnerable during plant closure, as their specialized skill sets and high pay expectations made finding local employment difficult. Many local workers moved away, searching for employment in a comparable industry, or transferring to a nearby nuclear plant. Many of those who chose to stay in town retired or exited the workforce. In the case of Wiscasset, decommissioning largely impacted local income and community demographics.

Cooper (2015) studied the Pilgrim Nuclear Power Station in Plymouth, Massachusetts, and similarly finds that nuclear power plants generally constitute a large source of local employment and create business for local industry, particularly in rural communities that are distant from regional economic centers. Cooper also finds evidence that the existence of a nuclear power plant creates substantial multiplier effects in a regional economy: while the Pilgrim plant was in operation, it not only created a direct economic output of $440 million and 586 jobs with a labor income of $77 million, but it also generated a secondary economic output of $105 million, which facilitated the creation of 590 additional jobs with an additional income of $30 million. Because most workers at the plant lived in close proximity to it, most of the impacts were concentrated within the local area. Additionally, nuclear plants require regular refueling every two years, which brought nearly 1,000 contractors into the town for a month at a time, generating additional revenue for local businesses. Cooper ultimately finds that closing a nuclear plant directly impacts local people and businesses, and also leads to secondary impacts on home ownership, property taxes, and local consumer spending as communities lose a large source of income and employment.

Pasqualetti and Pijawka (1996) investigate nuclear decommissioning from a land use perspective, finding that storage of spent fuel on former sites of nuclear plants perpetuates a community’s sense of risk and continues to impact communities even after plant closure. This is an important distinction between nuclear plants and other plant closings: spent fuel storage renders former nuclear sites undevelopable, and the cultural stigma surrounding nuclear waste has the potential to prevent people and businesses from moving into the area (although waste storage is generally much less visible than an operational plant). This, combined with a highly specialized workforce and the relatively remote location of nuclear plants, poses uniquely high barriers to communities trying to overcome the loss of a nuclear plant. Overall, literature suggests that nuclear plant closure has the potential to negatively impact local economies and community wellbeing, and my research will aim to test these conclusions from an empirical standpoint.

There is a significant body of literature on the impact of general plant closing. Plant closing literature gained momentum during the 1980s, during which time a growing awareness of de-industrialization and general trends in the US economy away from large scale manufacturing prompted increasing attention paid to the ways in which plant closings disrupt regional economies and everyday life. Much work was done during that period to understand the diverse and pervasive impacts of plant closure. Wu and Korman (1987) put forward a framework for interpreting the impacts of plant closure in general. They discuss a “ripple effect,” initially theorized by Bluestone and Harrison (1982), in which communities experience primary, secondary, and tertiary shocks as a result of the loss of a major economic source. Primary shocks include losses of tax revenue and jobs: “The (closed) unit's own employees lose salaries and wages, pensions, and other fringe benefits; supplier firms lose contracts; and the various levels of government lose corporate income and commercial property tax revenue” (Wu and Korman, 1987). Secondary shocks include decreased retail spending in town and increased unemployment in other sectors, and tertiary shocks include a greater local demand for public services and tax reductions. All of these have the potential to impact the local economy in negative and quantifiable ways. Plant closings have been found to impact a wide range of actors: plant managers, unions, individuals, communities, local agencies, and government institutions are all impacted by plant closing, and impacts often vary widely from municipality to municipality (Gordus et al., 1981).

Of all of these actors, workers have been a significant focus of the literature. Rocha and McCant (1999) study the impact of plant closings on workers, and they suggest that a shift towards a service-based economy makes transitioning from plant closure even harder than it has been in the past. In their study of the closing of a national garment manufacturing plant, they found that three fourths of the workers surveyed were making lower incomes in their new employment than they previously made at the plant, and that average incomes of former employees had dropped by 27%. Workers reported having a difficult time finding jobs with comparable pay and benefits packages, and many were forced to get additional training or education in order to find a new job. Similar findings have been echoed by a number of other studies of plant closings (Flaim and Sehgal, 1985; Ginsburg, 1994; Ashton and Iadicola, 1989). Previous empirical work also suggests that outcomes for displaced workers vary by demographics, and that women, racial minorities, and individuals with lower levels of education tend to have a more difficult time finding re-employment (Ashton and Iadicola, 1989). Overall, literature generally finds that plant closure significantly impacts local economies, with displaced workers facing substantial difficulties in recent years.

Stern (1972) uses empirical analysis to study the impact of manufacturing plant closure on workers, and similarly finds that workers who find employment in the local labor force tend to face substantial decreases in annual income. However, he also finds that those who opt for inter-plant transfer options tend to fare much better overall. This is particularly relevant to the issue of nuclear plant closure because the specialized nature of nuclear jobs often means that displaced nuclear workers try to find employment at other plants, rather than remaining in the local labor force or switching to a different industry (Haller, 2014). If decommissioned nuclear plants are located in proximity to other nuclear plants, unemployment caused by plant closure may be lower than initially theorized. On the other hand, if nuclear plants are further apart, workers may face more difficulty finding re-employment locally, or may need to relocate in order to find a job.

IV. Methods and Regression Model

Data

Data was compiled from the dataset *USA_Counties_2010.dta* from the US Census Bureau. The dataset contains population and economic census data for every county in the United States, as well as data compiled from the Bureau of Labor Statistics, the Bureau of Economic Analysis, the American Community Survey, and other federal data reporting services, and covers the years 1980-2010. Because counties are the smallest spatial scale at which data is consistently collected across reporting services, they have been chosen as the unit of analysis for this project. This poses potential problems for my research design, as nuclear plants may only exhibit very localized, community-level impacts. However, I hypothesize that, given the ripple effects proposed by Bluestone and Harrison (1982), the impacts of nuclear decommissioning are likely much more geographically dispersed beyond the initial municipal level.

Census data is difficult to work with because of inconsistencies with data collection and reporting. Census data is collected in ten, five, and one year intervals, depending on the variable being collected. For example, the economic census is conducted in five year intervals, with data on business performance and the local economy obtained by sending questionnaires to approximately 4 million businesses nation-wide, while the American Community Survey is conducted yearly by the census bureau, compiling information on jobs, education, housing, and other variables of interest. In compiling this panel dataset, it became clear that some variables could not be available on a yearly basis. In order to account for these limitations, I have applied linear interpolation to demographic variables like race and gender, which were only available decennially, in order to fill in gaps and create a more balanced panel[2].

Furthermore, the USA_Counties_2010 dataset only contains data up to the year 2010. Because a number of nuclear decommissionings have begun after 2010, data for the period 2010-2014 was obtained from either the American Community Survey, the Bureau of Labor Statistics, or the Bureau of Economic Analysis, depending on whether it was a population and demographic variable (ACS) or an economic indicator (BLS and BEA). Lastly, because my income measures were reported in nominal terms, I obtained Consumer Price Index (CPI) data from the Bureau of Labor Statistics in order to compute real income values. In total, my final dataset covers all 84 counties that have ever had nuclear plants in the United States over the years 1975-2014, and contains a series of population, demographic, and economic indicators. After compiling the final dataset, I plotted histograms and scatter plots of each variable. I transformed all variables that were significantly skewed into logarithmic form, and converted total measurements (e.g. total employment, total population) into growth rates and percentage values to promote better comparison across counties. Table 2 summarizes all relevant variables and their sources.

Table 3 presents summary statistics for the dataset. The first column depicts summary statistics for the entire dataset, while the second two columns illustrate statistics for treatment and control counties, respectively. Initial statistics do not reveal apparent patterns or differences within the dataset: demographic, population, and socioeconomic variables appear to be relatively equivalent in both treatment and control counties. Controls for economic diversity (measured as

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[2] While this method is imperfect, particularly because it assumes a linear growth path where a non-linear relationship may be more appropriate, it was the best approximation that I could create, given limited time and resources, and it has been applied widely by the census bureau where similar data limitations have arisen. While this may impact the accuracy of my estimations, it will allow me to better estimate the approximate relationship between nuclear decommissioning and community characteristics using a balanced panel dataset, which is the ultimate aim of this project. Because of these limitations, these variables were only used as controls and

businesses per square mile) and racial demographics (percent black population) appear to be higher, on average, for control counties, suggesting that controls may be slightly more urban than treatment counties (although, differences could also be driven by outliers within the treatment or control groups), while the average age of the nuclear plant is slightly higher for the treatment group. I also present summary statistics for treatment counties before and after decommissioning to assess potentially significant changes: Table 4 illustrates summary statistics for an expanded range of economic and demographic indicators for treatment counties in these time periods. Initial statistics are relatively surprising: income, employment rates, poverty, and education exhibit relative improvements over time, a result that is contrary to what I might have predicted. To get a better sense of changes in income, employment, and population over time, I graph these variables for treatment and control groups from 1975-2014 in figure 5. Similarly, graphical results suggest that treatment counties experienced slightly higher employment and income than controls, particularly during the 1980-2000 period, during which time the majority of nuclear decommissionings occurred. Population growth appears to be much more variable, but both treatment and controls experience upward trends over time. Summary statistics present surprising and conflicting results, necessitating the use of empirical analysis to more precisely determine the impacts of decommissioning.

Empirical Specification: Part I

Regression analysis was employed, using a difference-in-differences approach to assess the impact of plant closure during the time periods before and after decommissioning. Panel data is particularly useful in this case because it allows me to control both for the time-invariant characteristics of each county as well as for changes over time across all counties, allowing the impact of closing nuclear plants to be considered explicitly for analysis. Furthermore, using panel data, I am able to test the impact of nuclear decommissioning while allowing for different closure or "treatment" time periods. My dataset consists of all counties that have ever had nuclear plants over the time period 1975-2014, and counties with operational nuclear plants serve as the control population for this analysis. Rather than use all counties in the United States, this subset of the population likely exhibits very similar characteristics before undergoing decommissioning, allowing for a more direct measurement of the impacts of nuclear closure.

A potential concern for this research design arises because of the small size of the treatment group: with only 18 counties having undergone total decommissioning in the 40 year period, they make up a comparatively small proportion of the 84 county sample. This could limit the amount of variation that I am able to measure using regression analysis. I deal with this in two ways (the second method is described in part II of this section): first, I increase the size of the treatment group to 24 by including all counties that have experienced partial decommissioning (see Table 1). For example, many plants have between one and three reactors on-site, and there have been a number of cases wherein one or two reactors have undergone decommissioning, while a third reactor remains operational. While the magnitude of this effect may not be as large as it would have been had the entire plant undergone decommissioning, partial decommissioning may still result in a significant decrease in the scale of the nuclear operation, leading to a downsized workforce, among other economic impacts. A larger treatment population may help my empirical design to better capture the variation associated with nuclear decommissioning. Empirical specification is as follows:

Eq. 1.1 and 1.2

$$y_{it}=\beta_0+\beta_1\text{controls}+\beta_2\text{decommissioned}_{it} + \delta_t + \gamma_i + \epsilon_{it}$$

‘Decommissioned’ will take a 0 while nuclear plants are in operation, and a 1 for each time period after decommissioning begins, allowing me to exploit differences in the timing of closure across counties. Timing of decommissioning is important: although a plant may officially close on a specified date, employees may be laid off over time, and a plant may need to hire a sizeable workforce during early years in order to complete the decommissioning process. Furthermore, because a community may be able to adjust to losing a nuclear reactor over time, it is likely that the impacts of decommissioning will be offset in the long-term by this adjustment process, thereby making initial impacts difficult to detect. To account for all of this, I run separate regressions wherein I split my “decommissioned” variable into long term and short term time intervals, using a dummy variable called “short term” that takes a one for 3-year, 5-year, and 10-year short term impacts, and a dummy that takes a 1 for the “long term” period afterwards. I am therefore able to capture impacts over time as well as across the entire period.

Additionally, nuclear closure itself tends to occur after a series of prolonged power outages or safety investigations, which may signal to employees and executives that plant closure is a likely outcome. I anticipate that this “signaling effect” produces changes in economic conditions before decommissioning even happens; for example, knowing that a plant is about to close, workers may seek alternative employment, and utility companies may decrease workers’ salaries and hours in order to offset repair and decommissioning costs. My own ethnographic work in nuclear host communities suggests that this is a likely scenario. If this is the case, then my “decommissioned” variable may not adequately capture the full effects of nuclear decommissioning in the short run. After a brief survey of plant closure announcements using Google News Archives, it became clear that rumors of potential plant closure generally began well before closure was officially announced. I run a separate regression using the date of each plant's last outage or NRC investigation before decommissioning occurred as a signaling period in order to better capture this effect, and results are presented as regression 1.2.

'δ_t' captures county fixed effects, or time invariant characteristics of each county in order to prevent observed or unobserved differences within counties from biasing my estimates. This will capture important features like the degree to which a county is urban or rural, distance from major cities and transportation routes, and other characteristics that might impact economic development over time. Similarly, 'δ_t' is a set of year fixed effects, used to control for aggregate changes over time, including the impact of national shocks like economic recessions. Other control variables include demographic measures that have been found to impact the socioeconomic characteristics of municipalities, including gender (percent of population that is female) and race (percent of population that is black), in line with the findings of Ashton and Iadicola (1989). Lastly, because a larger and more diverse local economy may absorb some of the impacts of nuclear decommissioning, I control for both population growth and economic diversity, using a measure of business density (number of establishments per square mile) as means of anticipating this outcome. My null hypothesis is as follows:

$$H_0 : \beta_2 = 0,$$
$$H_A: \beta_2 \neq 0,$$

Where rejecting the null indicates that nuclear decommissioning exhibits some relationship with my dependent variables of interest.

Primary dependent variables include employment (as a percent of the adult population), real per capita income, and population growth. These variables were chosen very carefully, based on data availability and evidence from the literature. For example, employment was chosen over unemployment because unemployment rates exclude those who have left the labor force or those who have moved away to seek employment elsewhere, which may underestimate the true impacts of nuclear decommissioning. Total employment, on the other hand, better reflects changes in the number of total employees at the county level, and was used to measure aggregate impacts on employment. Per capita income was available in nominal terms; using CPI data from the Bureau of Labor Statistics, I was able to calculate real median household income, using 1982 as a base year[3]. Per capita income was determined to be the best measure of economic wellbeing because of the limitations of other measures of income: for example, average income measures are often distorted by a few very large earners, while measures of earnings do not reflect those who are unemployed or who have exited the labor force. Table 3 illustrates the relationship I predict "decommissioned" to have with my dependent variables, after the inclusion of fixed effects and controls.

Empirical Specification: Part 2

A second method of dealing with the small size of my treatment group involves quasi-experimental matching, which allows the impacts of decommissioning to be examined more closely, using a subset of the larger sample. A quasi-experimental design is conducted by, "carefully selecting a…control group during a calibration period and examining treated subjects and their control groups for differences in performance during two periods, the pre-treatment and treatment periods," (Alesayed, Rephann, and Isserman, 1998). By matching each decommissioned county with a county in the control group, I can more precisely estimate the average treatment effects using a "quasi-experimental" design. The intuition behind this method is that the treatment county and its match exhibit similar initial conditions and characteristics before decommissioning occurs, suggesting that, in the absence of nuclear decommissioning, both counties will continue to exhibit similar growth patterns in the post-treatment period. I am,

[3] 1983 was chosen because it was used as the base year for the CPI data that I obtained

therefore, able to approximate what would have happened to the treated group if no policy or treatment was applied, in the absence of the ability to truly randomize the experiment (Ona, Hudoyo, and Freshwater, 2007).

I use propensity score matching (PSM) to perform this analysis. With PSM, counties are matched by the likelihood that the county will participate in the intervention given its observable characteristics. In this case, it will be the likelihood that a county will experience nuclear decommissioning. It does so by calculating the average distance between indicators of interest in the treatment and control groups. According to Farrigan and Glasmeier (2007), the propensity score "is defined as the conditional probability of receiving a treatment given specified observed covariates:

$$e(X) = pr(Z = 1\ X),$$

implying that Z and X are conditionally independent given e(X). The propensity score can be estimated using logistic regression or discriminant analysis." For this analysis, the sample of all nuclear counties is used, with counties undergoing any form of decommissioning representing the treatment group, and counties with fully operational plants in the control group. Again, I chose to create matches using this subset of all US counties because nuclear counties likely exhibit similar initial conditions, and would experience similar growth paths where nuclear plants constitute a relatively large economic actor. I use demographic, economic, population, and plant characteristics[4] to match treatment counties with control counties (see figure 6), and am able to calculate the average treatment effect on the treated group (ATT), which is defined as:

$$ATT = E[Y\ (1) - Y\ (0) \mid W = 1]$$

Where W is equal to 1 if the treatment (decommissioning) has been administered, Y(1) is the treatment group, and Y(0) are the corresponding matches. I examine the average treatment effect of decommissioning on employment, income, and population measures. The assumptions of

PSM matching make this method particularly useful for my analysis: first, PSM assumes conditional independence, which suggests that there exists a set X of observable covariates such that after controlling for these covariates, the potential outcomes are independent of treatment status. Secondly, PSM assumes common support, which implies that for each value of X, there is a positive probability of being both treated and untreated. This “ensures that there is sufficient overlap in the characteristics of treated and untreated units to find adequate matches,” (Baum, 2013). While traditional regression analysis may be subject to considerable selection bias, as counties that undergo decommissioning are likely not selected at random, PSM allows for the construction of a relatively unbiased counterfactual if these assumptions are satisfied. In this way, the quasi-experimental portion of this project is able to deal with potential endogeneity concerns that I am unable to address using the first method. PSM is, therefore, a good way to more nearly capture the potential causal effects of decommissioning on host counties, while also ensuring the robustness of my results from part I.

V. Results

Regression results are presented in tables 7-11, and overall findings are contrary to my initial predictions. Regression analysis reveals no statistically significant impact on employment for the three and five year time periods following decommissioning, and a positive and statistically significant impact on employment during the ten year period, as well as in the long-run. Nuclear decommissioning is, on average, associated with a 1.26% increase in employment across the entire post-decommissioning time period. Per capita income results are similarly surprising. Real per capita income is associated with positive and statistically significant impacts for all time periods, and a total increase of $1,361, on average, across the entire post-decommissioning period. Lastly, I find no statistically significant impact on population growth during any time period, suggesting that population growth has remained relatively unchanged as a result of decommissioning. Including signaling effects into the model produces relatively similar outcomes: table 11 compares impacts on employment with and without signaling effects, revealing similarly statistically insignificant impacts in the short-run even before decommissioning is officially announced. Overall, I am able to conclude that nuclear decommissioning is associated with improvements in employment and income when compared with the entire population of counties with nuclear plants.

PSM reveals similarly illustrative results. Table 12 presents PSM results for all four dependent variables. ATT (Average Treatment Effect on the Treated Group) is reported as the average difference between treatment counties and their matches during the post-decommissioning time period. Decommissioned counties were, on average, associated with a 0.77% increase in employment rate and a $1,351.24 increase in per capita income, compared with matched control counties, while there were no statistically significant differences associated with population growth. Although the magnitude of the employment estimation is smaller than the results of the regression analysis (likely due to the fact that PSM utilizes a reduced sample of the larger population), PSM similarly suggests that both income and employment have experienced increased growth during the post-decommissioning time period, when compared with matched counties, which represent expected growth in the absence of decommissioning. Using both methods of analysis, I am able to reject the null hypothesis, and reasonably conclude that nuclear decommissioning is associated with positive and statistically significant increases in employment and income, while impacts on population growth are somewhat indeterminate.

I then address potential concerns to the validity of these results. If, for example, nuclear closure has coincided with larger trends in county growth patterns over time, decommissioning may falsely appear to have an impact where none exists. For example, if nuclear counties are located within larger metropolitan areas and there is a sudden increase in urban migration and investment, then I may only be picking up the effects of these larger trends. To test this hypothesis, I include county-specific time trends in my original regression models. If the "decommissioning" variable is no longer significant, then I can conclude that this is the case. Coefficients are reported in table 13; the impact of nuclear decommissioning on employment and income remains positive and significant at the 5% level, suggesting that decommissioning itself may still be driving some of these upward trends. Another potential concern is that the inclusion of counties with partially decommissioned plants may be skewing my results upward, which could be the case if partial decommissioning has a larger positive impact on economic growth than total decommissioning. I test this theory by splitting the "decommissioned" variable into "fully decommissioned" and "partially decommissioned" groups and run a separate regression with the two categories as treatment variables. Results are also reported in table 13. Not only does the coefficient on "fully decommissioned" remain positive and statistically significant, but the coefficient on "partially decommissioned" is only weakly significant, suggesting that the inclusion of the partial counties in my sample likely impacts my results minimally. Given the results of these robustness checks, I am still able to conclude that nuclear decommissioning has a positive relationship with county level employment rates and per capita income.

The results of the linear regression analysis and PSM are not what I might have expected. Why might nuclear decommissioning be associated with upward trends in income and employment? While this research design is not able to explicitly answer this question, there are a few potential explanations for these unexpected results. The process of nuclear decommissioning itself may actually cause short-term increases in employment that offset plant layoffs. When a plant is closed, all facilities must be dismantled and safely disposed of, nuclear waste must be transferred to dry cask storage, and former nuclear sites must be returned to “Greenfield status” or the existing conditions of the site before the nuclear plant was constructed (Lochbaum, 2014). The process can take as many as ten years, and requires hundreds of contractors to be completed. This could offset plant layoffs and other job losses, potentially explaining the indeterminate short-term impacts reflected by the regression analysis. Upward trends in employment and income in the long-term may be a reflection of a county’s ability to naturally adjust to the loss of a nuclear plant and return to previous growth paths. While decommissioning takes place, former nuclear workers have time to seek additional training and employment opportunities elsewhere. While some workers may seek re-employment at operational nuclear plants, some may additionally find work in other fields over time.

Furthermore, it is possible that nuclear closure has been offset at the county level by other sources of electricity production: when a nuclear plant closes, states need to make up for the loss in electricity by switching to other power sources, particularly since nuclear power makes up such a large portion of electricity generating capacity in the United States today. For example, after the closure of the Connecticut Yankee Nuclear Plant in Middlesex County, Ct, a new gas generating plant was constructed nearby to account for losses in the local energy supply, improving regional generating capacity and creating new jobs and development in the area (Burton, 2011). As figure 6 shows, while nuclear production has stagnated over the past 20 years, other sources of electricity have experienced exponential growth. Not only do oil and natural gas require significantly lower capital costs than nuclear power, but both electricity sources have experienced significant price decreases in recent years, further incentivizing investment (USEIA, 2011). In fact, according to Prandoni (2014), jobs in oil and gas have outpaced growth in every other sector of the US economy since 2008, as shown by figure 7. Even renewables have become cheaper over time, as government subsidies and improvements in efficiency have decreased cost barriers for large-scale production. Therefore, if counties lose a nuclear plant, but invest in natural gas or renewables, plant construction and energy production could generate new employment and investment to offset or even outpace the losses accrued by nuclear closure.

Lastly, nuclear decommissioning may serve to “de-stigmatize” regions with a strong nuclear influence, particularly when plants undergo total decommissioning: as anti-nuclear sentiment in the US has intensified over recent decades, people and businesses may find counties with nuclear plants to be relatively unattractive for settlement and development, particularly due to safety and security concerns. In 2015, 51% of Americans were in favor of nuclear power, down from 62% in 2010, reflecting these downward trends in public opinion (Rifkin, 2015). Incidents like the Fukushima disaster of 2011 have clearly illustrated that nuclear power exhibits particularly high social and societal costs, and risk-averse individuals may be unwilling to take on the additional risks associated with locating their homes and businesses near a plant. When a nuclear plant is closed, the public may no longer view a county as risky or unsafe, creating new incentives for investment and job creation. However, given the nature of my research design, I am only able to speculate on the potential drivers of my results; future research should seek to better understand what happens when nuclear power plants close, and the complex causal factors that are responsible for these county-level outcomes.

While all of these developments would create the appearance of growth at the county scale, it would not reflect the ways in which growth is unevenly distributed across space: while some parts of the county would benefit from these new developments, former nuclear host communities may still experience the full consequences of nuclear closure in the form of job loss and decreased tax revenue, and former nuclear sites would be generally unavailable for re-development opportunities while waste remains stored on-site (Pasqualetti and Pajawka, 1996). This is particularly the case because nuclear host communities often make up a very small percentage of a much larger county; as table 14 illustrates, the towns and villages that host nuclear plants often constitute less than 5% of total county population, making it difficult to detect impacts at the municipal scale. As a result, my analysis is unable to capture some of these more subtle impacts: for example, if workers from former nuclear host communities move elsewhere within the county, I would not be able to capture these localized, intra-county migration patterns. Furthermore, measures of per capita income fail to account for personal tax expenditures: although property taxes may rise in former host communities, creating economic hardship for local people, I am not able to explicitly measure that impact. A key limitation of this research is its inability to consider decommissioning outcomes from town and municipal levels, and future work should seek to consider this limitation by analyzing impacts from these smaller spatial scales when possible.

VI. Conclusion

As the costs associated with nuclear power continue to rise, incentives to decommission nuclear reactors will grow in coming years. This is a particularly important issue for residents and policy makers in nuclear host communities, who are often unprepared for the costs and consequences associated with sudden decommissioning. This paper assessed the economic impacts of nuclear decommissioning at the county level, using employment, income, and population as primary variables of interest. I ultimately, and surprisingly, find that nuclear decommissioning is associated with positive and statistically significant impacts on both income and employment at the county level. I attribute these results to a number of potential regional developments (although other explanations are possible): while short term increases in employment due to the decommissioning process itself might offset initial economic impacts caused by plant closure, long run improvements could be driven by a county's ability to adjust to the shock of nuclear decommissioning, increased investment and employment in other energy sources in order to offset the loss of a nuclear plant, or decreases in the perceived risks associated with living and investing in a nuclear host county. While results suggest that the impacts of decommissioning may be much less severe than anticipated, this does not necessarily mean that all counties should decommission plants in order to reap the benefits of a post-nuclear economy. The implications of this result remain somewhat ambiguous: it is too soon to make recommendations regarding nuclear decommissioning without first investigating both the true catalysts of these positive trends, as well as whether the impacts of decommissioning are distributed unevenly across space, particularly within the individual towns and municipalities that hosted the nuclear power plants themselves. As the first study of its kind, results are still very preliminary, and will require future investigation in order to provide accurate impact and cost projections for host communities.

VII. Resources

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IX. Appendix

Figure 1: Nuclear Power in the United States

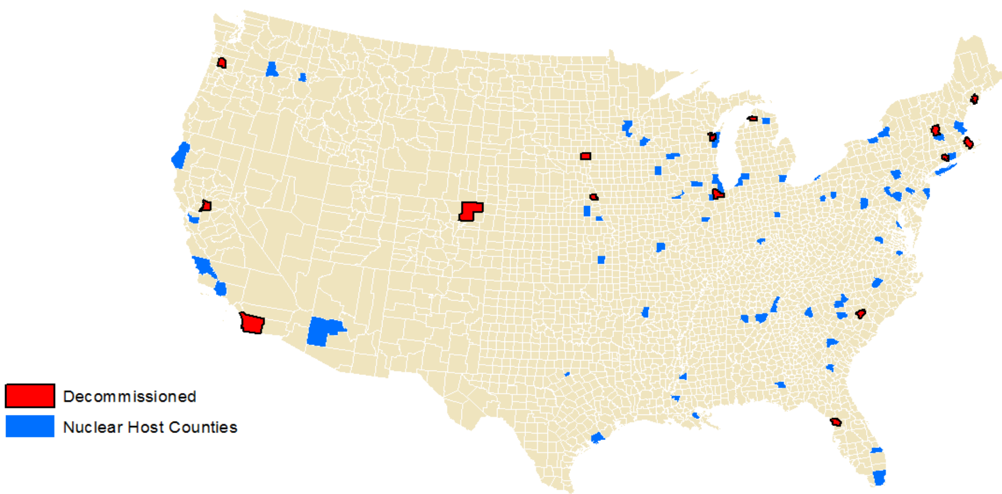

Figure 2: Trends in US Nuclear Power
Source: IER, 2015

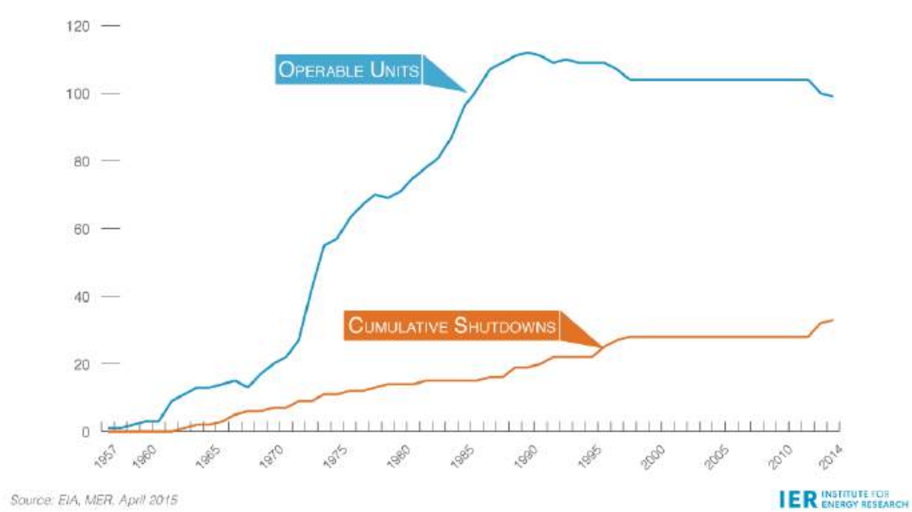

Figure 3: Levelized Cost of Electricity Generation in Various Studies
Source: Wikimedia Commons

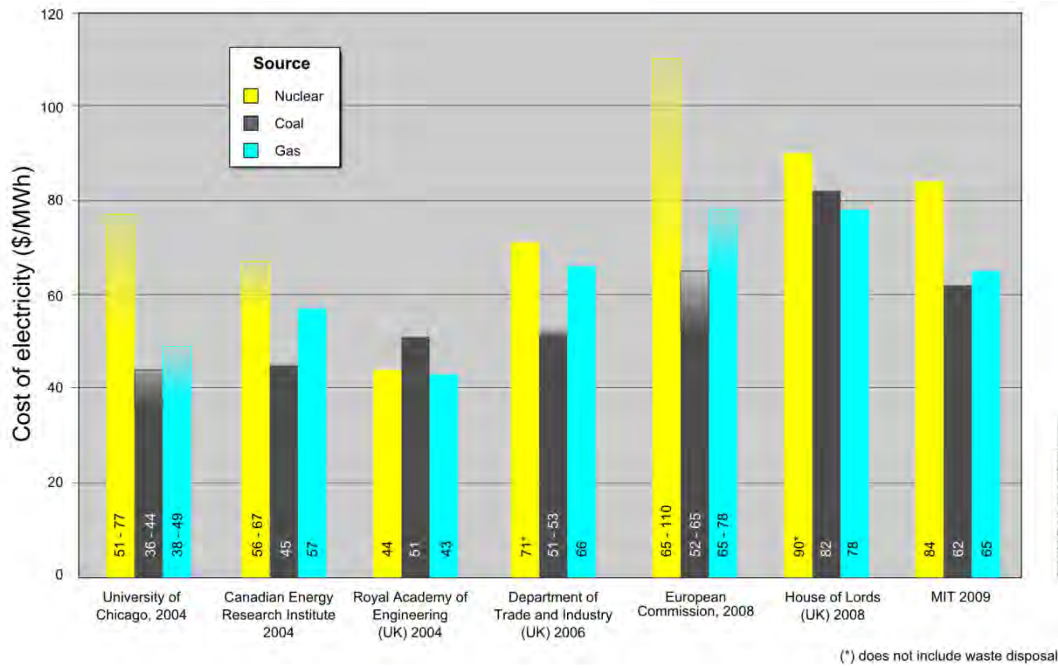

Figure 4: Cost of Nuclear Power in the US and France, 1970-2000
Source: Grubler (2010)

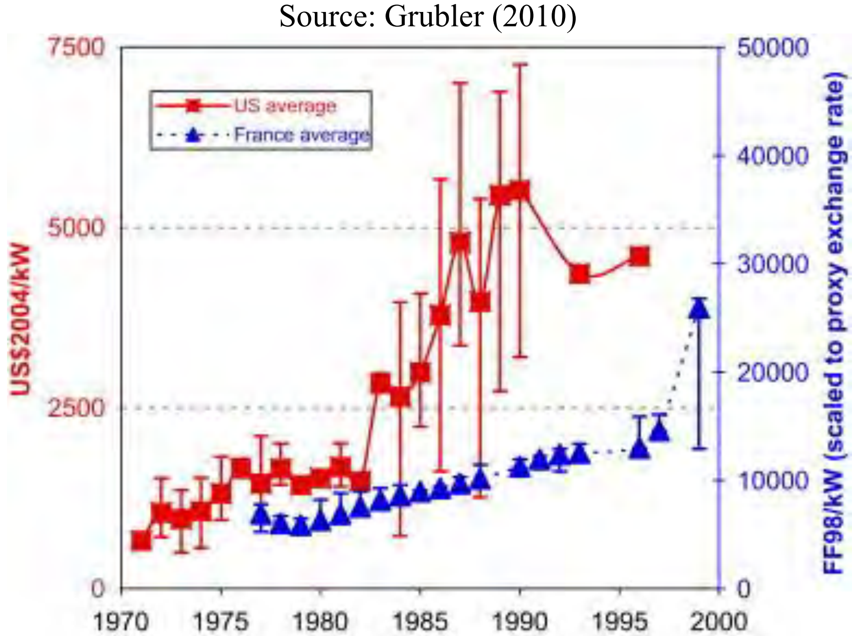

Table 1: Decommissioned Nuclear Plants in the United States

Plant Name	State	County	Year Decom. Began	Operating License Expiration Date[5]	Full or Partially Decommissioned
Hallam	Nebraska	Washington	1964	-	Full
Pathfinder	South Dakota	Minnehana	1967	-	Full
Carolinas-Viginia	South Carolina	Fairfield	1967	-	Full
Vallecitos	California	Alameda	1970	-	Full
Fermi	Michigan	Monroe	1972	-	Partial
Peach Bottom	Pennsylvania	York	1974	-	Partial
Indian Point	New York	Westchester	1974	-	Partial
Dresden	Illinois	Grundy	1978	-	Partial
Three Mile Island	Pennsylvania	Dauphin	1979	-	Partial
Lacrosse	Wisconsin	Vernon	1987	-	Full
Fort St. Vrain	Colorado	Weld	1989	-	Full
Rancho Seco	California	Sacramento	1989	2008	Full
Shoreham	New York	Westchester	1989	-	Full
Yankee Rowe	Massachusetts	Plymouth	1991	2000	Full
Trojan	Oregon	Columbia	1992	2011	Full
Millstone	Connecticut	New London	1995	-	Partial
Connecticut Yankee	Connecticut	Middlesex	1996	2007	Full
Maine Yankee	Maine	Lincoln	1996	2012	Full
Big Rock Point	Michigan	Charlevoix	1997	1997	Full
Zion	Illinois	Will	1998	2013	Full
Crystal River	Florida	Citrus	2013	2016	Full
Kewaunee	Wisconsin	Brown	2013	2033	Full
San Onofre	California	San Diego	2013	2022	Full
Vermont Yankee	Vermont	Windham	2014	2032	Full

Table 2: Main Variables and Sources

Variable Name	Source	Years	Year Structure?	Unit of Measure
Decommissioned	US Nuclear Regulatory Commission	1960-2014	Yearly	Takes a 1 when decommissioning begins and for every period afterwards, and a 0 otherwise
Employment Rate	USACounties_2010, BLS	1980-2014	Yearly	Percent of Adult Population
Real Per Capita Income	USACounties_2010, Bureau of Economic Analysis, ACS	1969-2014	Yearly	Dollars
Population Growth	USACounties_2010, American Community Survey	1972-2014	Yearly	Percent Change
Percent Female	USACounties_2010, ACS	1980-2014	Decennially	Percent of Total Population
Percent Black	USACounties_2010, ACS	1980-2014	Decennially	Percent of Total Population
Education	USDA Economic Research Service	1970-2014	Decennially	Percent of Population with Less than a HS Education
Business Density	USACounties_2010, BLS	1970-2014	Yearly	Total Establishments

[5] Data was obtained from varying sources: NRC records, electric companies' web pages, new sources, etc.; I was unable to find operating license information for a number of plants, and I have left those spaces blank.

				per Square Mile

Table 3: Expected Relationships between Treatment and Dependent Variables

Dependent Variable	Decommissioned
Employment Rate	Negative
Real Per Capita Income	Negative
Population Growth	Negative

Table 4: Propensity Score Matching

Observable Characteristics Used to Match Treatment with Control Counties:

Variable	**Category**
Plant Age[6]	Plant Characteristics
Population Growth	Population Characteristics
Education (% with less than high school education)	Demographics
Percent Female	Demographics
Percent Black	Demographics
Business Density	Economic Characteristics
Per Capita Income Growth	Economic Characteristics
Employment (% of adult population)	Economic Characteristics

Table 5: Summary Statistics

Variable	Mean (All Counties)	Mean (Treatment Counties)	Mean (Control Counties)
Employment Rate	93.13	93.25	93.10
	(3.11)	(3.51)	(2.95)
Real Median Income	13,635.39	13,672.10	13,622.36
	(1.71)	(2,888.95)	(3621.495)
Population Growth	1.04	1.14	1.01
	(1.61)	(1.39)	(1.68)
Education	22.70	20.82	23.36
	(10.38)	(8.51)	(10.90)
Percent Female	49.80	49.95	49.75
	3.13	(2.28)	(3.37)
Log(Percent Black)	0.91	0.67	0.99
	(1.86)	(1.86)	(1.85)
Business Density	6.58	5.77	6.86
	(11.67)	(6.15)	(13.07)
Plant Age	25.37	28.55	24.24
	(12.82)	(13.75)	(12.28)

Table 6: Summary Statistics in Treatment Counties, Before and After Decommissioning

[6] Because I am interested in constructing a sample of treatment and matched counties that are equally as likely to undergo nuclear decommissioning, the age of the plant is an important characteristic to consider. I would have liked to have included other plant characteristics like total plant employment and electricity output, but data was largely unavailable or insufficient for inclusion in this analysis.

Variable	Mean (Treatment, Decomm=0)	Mean (Treatment, Decomm=1)	Percent Change
Plant Age	18.16	34	87.22%
	(10.61)	(11.95)	
Unemployment Rate	7.53	6.34	-15.80
	(3.87)	(3.25)	
Employment Rate	92.47	93.66	1.29%
	(3.87)	(3.25)	
Poverty	11.34	11.21	-1.15%
	(3.36)	(4.77)	
Education	24.03	19.48	-18.93%
	(7.71)	(8.47)	
Real Median Income	13,041.93	14,003.02	7.37%
	(2,854.88)	(2,853.86)	
Median Age	35.24	36.34	3.12%
	(7.43)	(4.77)	
Population Growth	1.51	0.97	-35.76%
	(1.52)	(1.30)	

Figure 5: Employment, Per Capita Income, and Population by Group, 1975-2014

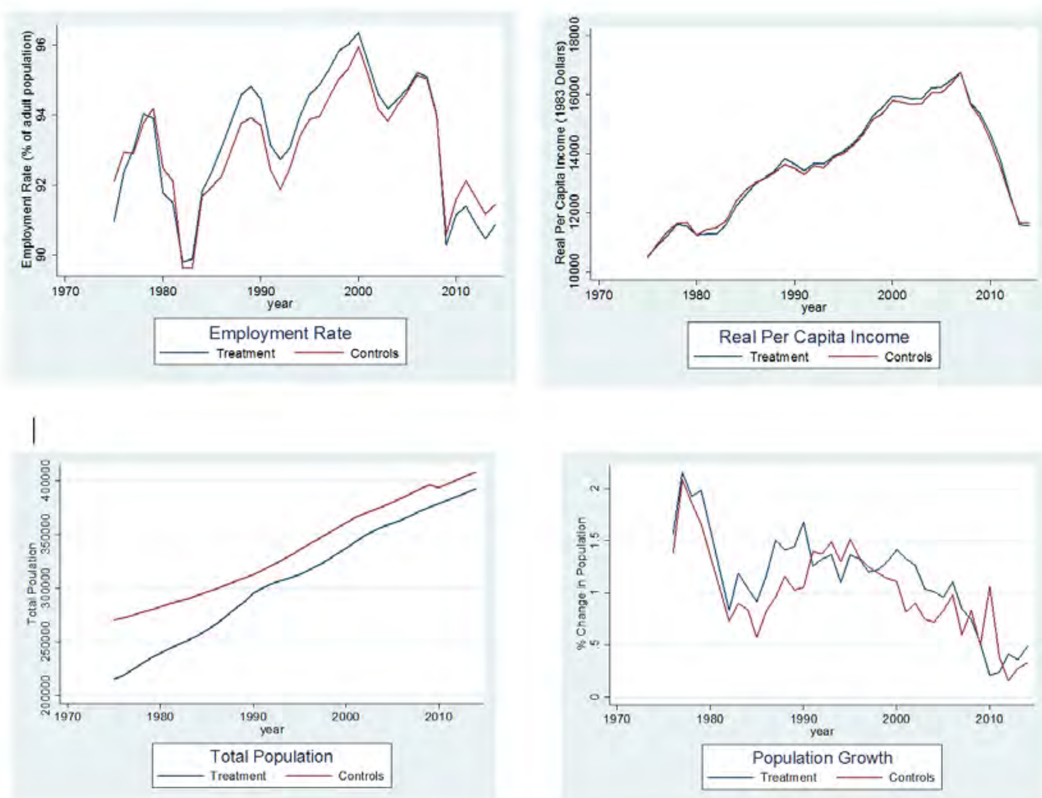

Table 7: Regression 1.1 Results – Employment

VARIABLES	(1) employment rate	(2) employment rate	(3) employment rate	(4) employment rate
Decommissioned				
Short Term: first 3 years	0.288			
	(0.717)			
After 3 years	1.438***			
	(0.454)			
Short Term: first 5 years		0.862		
		(0.553)		
After 5 years		1.408***		
		(0.492)		
Short Term: first 10 years			0.811*	
			(0.426)	
After 10 years			1.854***	
			(0.571)	
Long Term: full period				1.256***
				(0.441)
Constant	100.2***	100.0***	100.1***	100.0***
	(1.617)	(1.598)	(1.594)	(1.610)
Controls?	Yes	Yes	Yes	Yes
Year FE?	Yes	Yes	Yes	Yes
County FE?	Yes	Yes	Yes	Yes
Observations	2,345	2,345	2,345	2,345
R-squared	0.133	0.136	0.134	0.141
Number of fips	84	84	84	84

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Regression 1.1 Results – Per Capita Income

VARIABLES	(1) Real Per Capita Income	(2) Real Per Capita Income	(3) Real Per Capita Income	(4) Real Per Capita Income
Decommissioned				
Short Term: First 3 years	562.0**			
	(263.7)			
After 3 years	1,514***			
	(374.9)			
Short Term: First 5 years		761.5***		
		(277.1)		
After 5 years		1,595***		
		(392.0)		
Short Term: First 10 years			829.6**	
			(347.6)	
After 10 years			2,073***	
			(414.7)	
Long Term: full period				1,361***
				(342.0)

Constant	16,448***	16,397***	16,365***	16,591***
	(1,201)	(1,204)	(1,185)	(1,191)
Controls?	Yes	Yes	Yes	Yes
Year FE?	Yes	Yes	Yes	Yes
County FE?	Yes	Yes	Yes	Yes
Observations	2,436	2,436	2,436	2,436
R-squared	0.302	0.303	0.318	0.298
Number of fips	84	84	84	84

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Regression 1.1 Results – Population Growth

	(1)	(2)	(3)	(4)
VARIABLES	Population Growth	Population Growth	Population Growth	Population Growth
Decommissioned				
Short Term: First 3 years	-0.186			
	(0.312)			
After 3 years	0.0421			
	(0.292)			
Short Term: First 5 years		-0.145		
		(0.184)		
After 5 years		0.0641		
		(0.314)		
Short Term: First 10 years			-0.0197	
			(0.198)	
After 10 years			0.0390	
			(0.311)	
Long Term: full period				0.00539
				(0.239)
Constant	5.493***	5.477***	5.519***	5.530***
	(0.716)	(0.713)	(0.719)	(0.728)
Controls?	Yes	Yes	Yes	Yes
Year FE?	Yes	Yes	Yes	Yes
County FE?	Yes	Yes	Yes	Yes
Observations	2,436	2,436	2,436	2,436
R-squared	0.042	0.043	0.042	0.042
Number of counties	84	84	84	84

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Regression 1.2 Signaling Period Comparison – Employment

	(1)	(2)	(3)	(4)
VARIABLES	Employment Rate	Employment Rate	Employment Rate	Employment Rate
Decommissioned: With Signaling				
Short Term: 3 years	0.310			
	(0.781)			
Long Term: 3 years	1.403***			
	(0.478)	0.878		
Short Term: 5 years		(0.622)		
		1.371***		

Long Term: 5 years		(0.506)		
Short Term: 10 years			0.786	
			(0.491)	
Long Term: 10 years			1.748***	
			(0.570)	
Long Term: Full Period				1.190**
				(0.543)
Decommissioned: Without Signaling				
Short Term: 3 years	0.288			
	(0.717)			
Long Term: 3 years	1.438***			
	(0.454)			
Short Term: 5 years		0.862		
		(0.553)		
Long Term: 5 years		1.408***		
		(0.492)		
Short Term: 10 years			0.811*	
			(0.426)	
Long Term: 10 years			1.854***	
			(0.571)	
Long Term: full period				1.256***
				(0.441)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: PSM Results

Variable	Average Treatment Effect	T-Statistic
Employment	0.77*	2.33
	(0.33)	
Real Per Capita Income	1351.24*	3.63
	(372.09)	
Population Growth	0.16	1.08
	(0 .15)	
Treated Population	647	
Untreated Population	1,698	
Total	2,345	

Standard Error in Parentheses
* indicates significance at the 5% level

Table 13: Robustness Check Results

Variable	Employment (1)	Real Per Capita Income (2)	Population Growth (3)	Employment (4)	Real Per Capita Income (5)	Population Growth (6)
Decommissioned	1.40 **	504.06*	0.34			
	(0.54)	(296.65)	(0.22)			
Fully Decommissioned				1.21**	1237.06***	-.022
				(0.49)	(352.97)	(0.27)
Partially Decommissioned				1.51	2093.24**	0.17
				(1.00)	(892.74)	(0.24)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes
County Time Trends	Yes	Yes	Yes	No	No	No

R-Squared	0.3481	0.5953	0.2372	0.1335	0.2994	0.0420
Observations	2345	2436	2436	2345	2436	2436

Figure 6: Energy Growth by Source, 1776-2012
Source: US Energy Information Agency

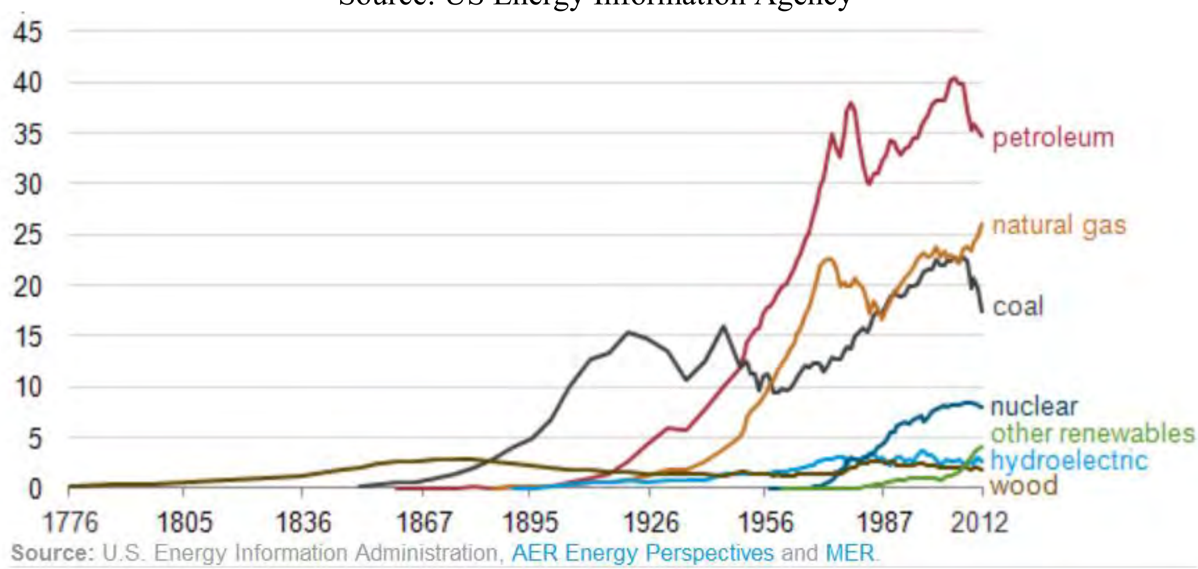

Figure 7: Trends in Oil and Gas Jobs vs All Other Sectors, 2007-2014
Source: Prandoni (2014)

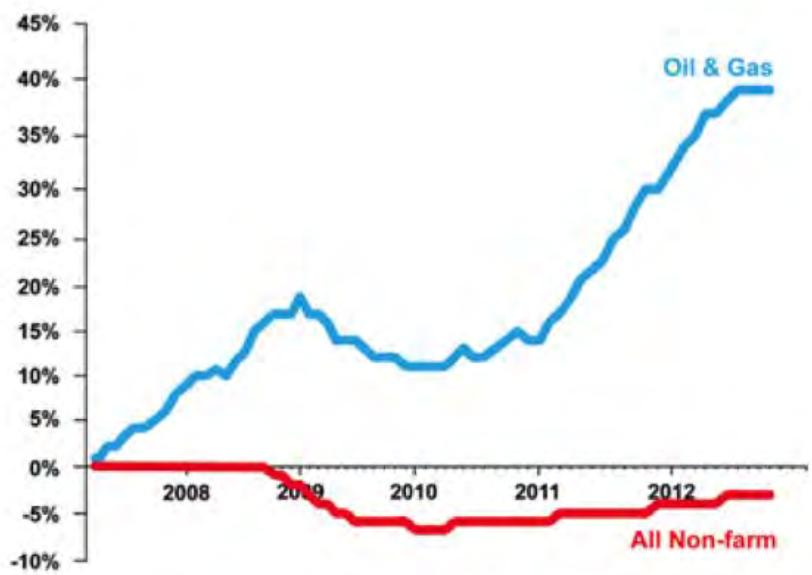

Table 14: Nuclear Host Community Population

Source: US Census Bureau

Plant Name	County Population	Town Population	Town Population (% of County)
Hallam	20,223	218	1.07%
Pathfinder	179,640	164,676	91.67%
Carolinas-Viginia	23,109	44	<1%
Fort St. Vrain	269,785	2,568	<1%
Rancho Seco	1.462 million	1,184	<1%
Shoreham	968,802	6,666	<1%
Yankee Rowe	501,915	393	<1%
Trojan	49,344	1,915	3.88%
Connecticut Yankee	165,562	7,635	4.61%
Maine Yankee	34,088	3,732	10.95%
Big Rock Point	26,129	2,534	9.70%
Zion	682,829	24,339	3.56%
Crystal River	139,271	3,062	2.20%
Kewaunee	254,586	2,921	1.15%
San Onofre	3.211 million	10,616	<1%
Vermont Yankee	43,857	2,141	4.88%