THE UNIVERSITY OF CHICAGO

# INDUSTRIAL INVESTMENTS IN ENERGY EFFICIENCY: A GOOD IDEA?

A DISSERTATION SUBMITTED TO

THE FACULTY OF THE DIVISION OF THE SOCIAL SCIENCES

IN CANDIDACY FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

DEPARTMENT OF ECONOMICS

BY

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JUNE 2017

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# ACKNOWLEDGMENTS

I am thankful for the advice and support from my dissertation committee: Steven Davis (Chair), Michael Greenstone, and Ali Hortascu. I learned a great deal from each of them. I am particularly grateful to Steve for both increasing the quality of my work through patient mentoring, and helping me make better decisions on career decisions by providing thoughtful insights. I am grateful to Michael for nudging me into the direction this work has taken, which significantly improves the importance and relevance of this work, and to Ali for providing multiple opportunities to work with him on various projects, including coauthoring on one of them. I thank them for always believing in me and guiding me along the way.

I am also thankful to Robert Burns, Cheryl Grim, John Hughes, Dean Karafa, Nathan Petek, Nolan Pope, Devin Pope, and seminar participants at the University of Chicago for comments that substantially improved the paper. Help from staff members at the US Census Bureau and US Energy Information Administration is greatly appreciated. Support for this research at the US Census Research Data Center from the University of Chicago is gratefully acknowledged. I thank Frank Limehouse at the Data Center for suffering several disclosure processes and annual reports. I am also grateful for the generous funding support from the Energy Policy Institute at University of Chicago.

I am grateful for my boyfriend Nathaniel Verhaaren. His passion in his field of computer science, his inquiring mind, and his sincere search for truth has inspired me to desire further knowledge and deeper understanding in my own studies. Finally, I thank my mother Liping, for her unconditional love and support, for her timeless wisdom, and for her encouragement and good humor. Her optimism and unwavering trust in me have saved me and motivated me to try harder and do better.

Disclaimer: Any opinions and conclusions expressed herein are those of the author and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed.

# ABSTRACT

Industrial investment in energy efficiency could harm adopting plant's long term performance. Although total energy spending decreases, energy cost per output increases 20% after investment, along with 8% productivity decline. These are the main conclusions we reach by conducting the first large-scale study on cogeneration technology adoption – a prominent form of energy-saving investments – in the U.S. manufacturing sector, using a sample that runs from 1982 to 2010 and drawing on multiple data sources from the U.S. Census Bureau and the U.S. Energy Information Administration. Our baseline results using difference-in-difference and a series of event studies are robust across specifications, with nonparametric matching, and IV strategies.

# CHAPTER 1

# INTRODUCTION

Given the enormous scale of energy and environmental regulations and energy related subsidies in the United States and around the world, it is important to assess claims that firms and households systematically under invest in energy efficient technologies (a.k.a. energy efficiency gap). While market failures or behavioral theories are popular explanations (Allcott et. al (2012) [1], Gerarden et. al. (2015) [12], Gillingham et. al. (2014) [13]), recent investigations have gone into the direction of understanding the relationship between projected and realized returns. Through conducting an experimental study, (Fowlie, 2015, [11]) shows that projected savings to the investments made in the nation's largest residential energy efficiency program are 2.5 times greater than the realized savings. Accounting for the social benefits of reduced pollutant emissions, the return was approximately -9.5% annually. Recent work by Burlig et. al. (2016 [3]), on the other hand, shows that projected savings to energy efficiency investments made by public K-12 schools in California are roughly the same as the realized savings. These works do not necessarily contradict each other since different sectors are studied – residential sector and public sector. Our study lies in the industrial sector. This adds another layer of complexity – the impact on the commercial activity the other two sectors do not have to consider.

Our work is the first to study the effect of energy efficiency investment on both energy savings and on total output and productivity in the U.S. manufacturing sector. While household consumers may be utility maximizing or cost minimizing, the stake at hand is not life or death as firms face in a competitive environment, particularly when these investments cost a few hundred thousands or millions. The technology we investigate is one of these expensive investments–cogeneration, also known as combined heat and power, or CHP. Based on projections, both government agencies and private consulting firms suggest cogeneration technology yield large positive returns and is under invested in the US industrial/commercial sector[1], indicating many firms leaving potential profits on the table. In this work, we investigate such claims through analyzing the realized returns through energy savings, and the effects of adoption on business production.

The calculation of energy savings is dependent on technology. Cogeneration achieves energy savings by simultaneously producing electricity and steam (or other useful thermal output). Without it, plants purchase electricity from a central power plant and produce steam through a traditional boiler. Adopting a cogeneration system thus provides three private monetary benefits: savings from reduced electricity purchase, revenue from electricity sales, and potential profits from efficiency gains. These benefits unsurprisingly come with a cost. Aside from the upfront investment cost, two main costs are considered: incremental natural gas purchase (primary fuel input for cogeneration) and incremental operating and maintenance (O&M) cost. Net flow private benefit is therefore the sum of the reduction in electricity bill and the revenue from electricity sales, minus the incremental fuel cost and O&M cost. Alternatively, we can compute it as the total cogenerated electricity multiply by the electricity grid prices, assuming cogenerated electricity can be sold at grid price[2]. From the social perspective, to generate the same quantity of electricity and steam, using cogeneration emits less pollutants than the combination of central power plant and on-site boiler. A second environmental benefit is that by generating electricity on site, cogeneration avoids power loss in transmission and voltage transformation. The social savings is

1. See, for example, McKinsey (2009) [18], DOE (2012) [7]. In particular, DOE (2012) [7] claims that 150 million metric tons of $CO_2$ can be reduced by doubling our current cogen capacity. Davis et. al. (2012) [5] find that deregulation of U.S. nuclear power industry only reduces almost 40 million metric tons of $CO_2$.

2. Clearly, plants cannot sell to the grid at their purchase price. Due to data limitation, we make this assumption for all our computation.

sum of these two environmental benefits, translated into monetary values, plus the private savings. We compute both the private and social savings in our analysis.

Our empirical strategy is based on the observation that adoption event casus an immediate, persistent change in energy consumption and producction activities. Using a difference-in-differences estimator, also controlling for industry-by-year and state-by-year fixed effects, we estimate both the incremental fuel cost and the reduction in electricity purchase associated with cogeneration adoption. We compare the change in natural gas and electricity purchase quantity after the adoption of the cogeneration technology to before, relative to that of the plants which have not yet adopted the technology or never did by the end of our sample period, clean of industry and location effects. The change in fuel purchase quantity can be translated into incremental fuel cost to calculate the reduction in pollutant emission. Then, combined with the change in electricity purchase quantity, we can compute both private and social savings.

The main identification threat for the difference-in-differences estimator is that the adoption decision for a profit maximizing firm is endogenous and time-varying factors that affect energy demand may also affect the adoption decision. For example, plants in anticipation of an increase in on-site electricity usage may find cogeneration more attractive and push forward the adoption process more aggressively. Our event study analysis shows limited pre-trend in either the purchase or usage of electricity, or that of natural gas, mitigating the concerns some what. The figures also show that the drop in purchase electricity and increase in cost of fuel is persistent over time, with majority of the change occurring within the first two years of technology adoption.

We use roughly thirteen thousand plants that span across 1982-2010 from the Manufacturing Energy Consumption Survey, Annual Survey of Manufacturers/Census of Manufacturers at the Census Bureau, and Annual Electric Generator Survey from the Energy Information Administration. Our main results show that electricity purchase quantity reduce by about 60% and fuel consumption increase by 30%, the realized net benefits are roughly consistent with projections. Returns can be computed as internal rate of return given these annualized net benefits and initial investment cost. The distribution of returns projected and realized largely overlap, for both private returns and social returns, and across 15, 25, 35 year horizon. We find that the median realized per annum internal rate of private return for 25 year horizon is about 7%, and 13% for social return.

However, this needs not suggest firms are under investing since these returns are based on energy savings alone and not considering the impact on the manufacturing production side. While plenty of evidence show technology adoption enhances productivity, it may not be the case for energy efficiency technologies. In our main parametric specification, we find a 20% decline in TFP and similar size decline in output for adopters relative to none-adopters that persist over 7-10 years. Due to the reduction in output, we further our investigation in energy cost per output. We find that despite the decline in electricity purchase cost, energy spending per output increases 30% after the adoption of cogeneration. Our non parametric approach suggests a milder decline in TFP, still about 8%, and a strong increase in energy cost per output 20%. We measure output by real output (shipment plus new inventories divided by industry price, deflated). TFP is computed as a Solow residual using industry level cost shares. Other patterns of manufacturing activities also show significant change after the technology adoption. We see a sizable decline in cost of materials, cost of energy, and total employment. The capital expenditure event study figure confirms the timing of adoption coincides with an increase in capital expenditure and in later years decline to the pre adoption level. Moreover, conditional on surviving through our entire sample period, we discover that the average life span of a plant without cogeneration is about 2 standard deviations higher than those adopted cogeneration. Conditional on same birth year and same industry, adoption is negatively, statistically significantly, correlated with life span.

Admittedly puzzling, we are not the first to document a decline in TFP with the adoption of new technology. Nakamura et. al. (2004) [20], in particular, studies the adoption of new steel refining furnace (Basic Oxygen Furnace, BOF) in Japan. They show a clear reduction in TFP post adoption of the technology and never caught up to the pre-adoption level for 10 years. Another empirical study conducted by the World Bank, Fernandes (2006) [9] shows that manufacturing firm productivity in Bangladesh are lower with a larger fraction of new machinery (less than 5 years old) than those firms using older machinery, and firms operating with a larger share of computerized machinery have significantly lower TFP. A very recent study Hotternrott et. al. (2016) [16], shows that in Germany, the adoption of carbon-dioxide abatement technology or greenhouse gas abatement technology reduces plant TFP by 5.9%.

To confirm our surprising finding, we redefine our adoption definition, work with different control groups (match plants on birth cohort-industry-size), split the sample by different rules, and focus on the top 3 most concentrated cogen industries. The decline in TFP are present across these robustness checks, although some more evident than others. We also employ two different types of instrumental variable strategies. One uses the variation in state level policies across time, with the identifying assumption that state level policies are made exogenous to plant level unobservables. The second type of instrument uses within-firm out-of-state adoptions. The identifying assumption is that within-firm out-of-state adoptions drives adoption decisions exogenously to a plant's own unobservables. For example, even if I want to adopt, my parent firm used all the resources to my sister plant and I could not adopt. Or I adopt only because my sister plant in a different state adopted. It turns out that state level policies have very little predictive power in the adoption decision. Instrumenting adoption decision using same-firm adoptions has shown a decline with TFP post adoption. We conclude with our evidence that while cogeneration largely fulfills its electricity saving duty, it has long term negative effects on plant's output and TFP.

The paper proceeds as follows. Chapter 2 covers some key elements on cogeneration technology that are relevant for the economic analysis. Chapter 3 explains our conceptual framework. Chapter 4 discusses our data and provides summary statistics. Chapter 5 explains our empirical strategy for estimating energy savings and environmental effects, as well as explaining different instrumental variable strategies. Chapter 6 discusses the results from our empirical estimates and provide some interpretations. Chapter 7 concludes.

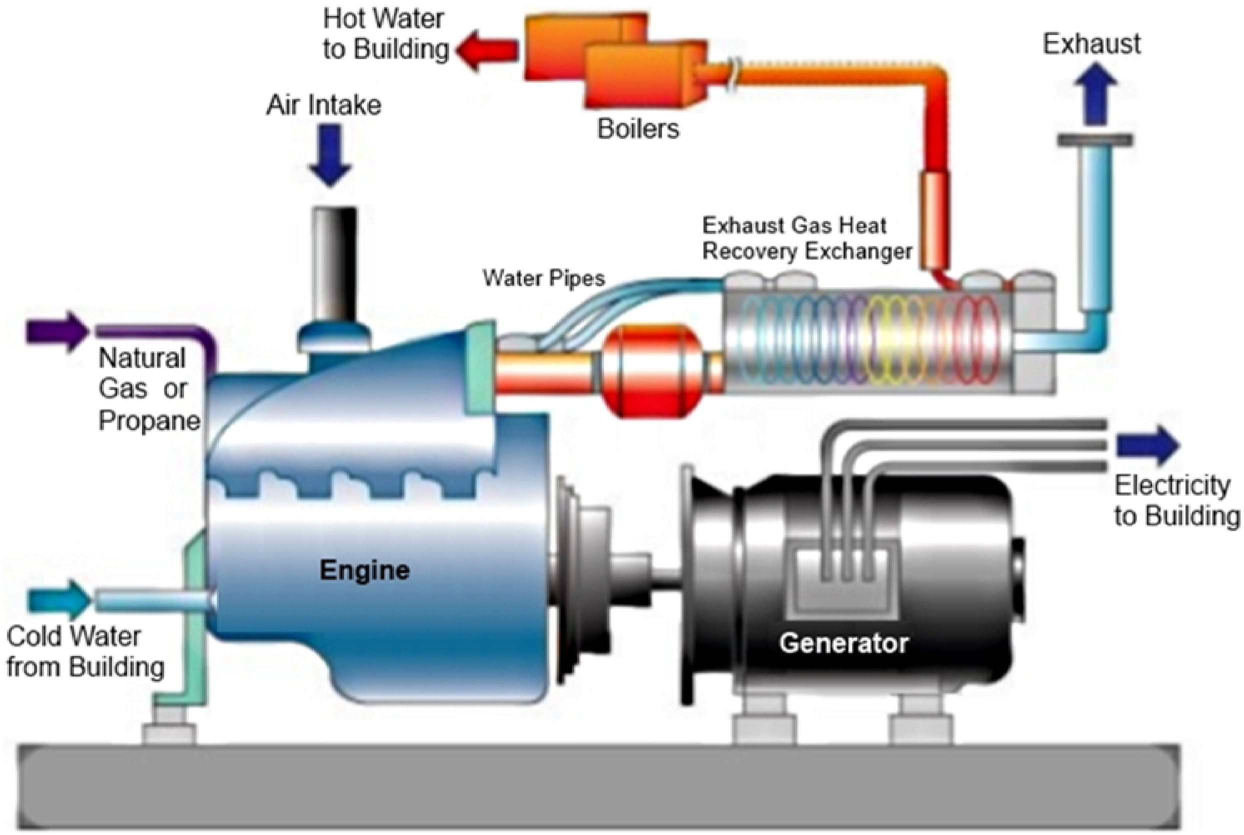
# CHAPTER 2

# BACKGROUND ON COGENERATION

Cogeneration, also known as Combined Heat and Power (CHP), allows plants to reduce electricity purchased from the grid by simultaneously generating electricity and steam (or other form of useful thermal energy), from one primary fuel, such as natural gas. In a common configuration (see Figure 2.1), the combustion of fuel is used in a gas turbine which is directly connected to a generator to produce electricity, the exhaust hot air is then passed through a heat recovery steam generator to produce steam for industrial process. Although electricity is first generated in the process, cogeneration is typically designed to meet the plant's steam load demand. This is because while we can potentially sell excess electricity to (or buy shortage electricity from) the grid, it is more difficult to sell excess (or buy shortage) steam since steam cannot travel far without losing the heat content. In fact, only plants with steam demand would deem cogeneration beneficial.

In general, Department of Energy (2008) [8] reports the average installation time for a cogeneration system is somewhere between 6-18 month. Author's own calculations from the EIA data shows that it takes power plants roughly 15 months to install a cogeneration system. Considering that the power plants often install larger systems than an average manufacturing plant, we expect the installation time to be less than a year. More discussion on this can be found in Appendix.

**Figure 2.1**. Cogeneration System




Notes: A common cogeneration system configuration. Widely used in commercial buildings and manufacturing facilities.

The joint production of steam and electricity increases overall efficiency from around 45% to 75% according to Department of Energy estimates[1] (DOE 2012 [7]). However, the efficiency improvement for producing one without utilizing the other output is limited. For example, if we waste the steam and only use the electricity produced through cogeneration, central power plants are more efficient in electricity generation. Similarly, if we do not need the electricity, a boiler can do a good enough job in providing the steam. Besides, the thermal dynamics of cogeneration system also does not allow for very flexible decou-

1. In some cases, the overall efficiency could reach over 90% in newer cogeneration facilities. See also Quinn et. al. (2013) [22]

pling of the joint production. Therefore, the cogen plants do not have incentives to produce electricity and steam in isolation with cogeneration. The most engineeringly efficient way to operate a cogeneration system is to produce electricity and steam at fixed proportion. Deviating from the fixed ratio by ramping up or down the production of one or the other loses overall efficiency, requires more capital investment, and is costly to manage. Therefore, the ideal candidate for cogeneration adoption is a plant with simultaneous balanced (or fixed proportional) demand for electricity and steam at all time, where both output can be utilized without the need to adjust the production quantity on the intensive margin for one but not the other.

This nature of cogeneration has three important implications for economic studies. One, the marginal cost of producing electricity is highly nonlinear. It is extremely low (lower than that of the grid) when steam is being utilized, as in this case, electricity can be viewed as a by-product from steam generation. But the marginal cost is very high when electricity is being produced without using the steam. Analogous holds true for the marginal cost of steam. Two, altering the quantity of electricity output would be infrequent. The priority for cogeneration production is to meet the steam demand. Steam demand is fairly constant each 6- to 8-hour shift basis. Adjusting the electricity output independent of the steam demand is costly. So timing the production of electricity according to the real-time electricity pricing–ramp up production in peak demand and ramp down in low demand–is made difficult[2]. This relaxes the requirement on data frequency needed to compute for savings and justifies our usage of annual level data. Third, cost benefit analysis for cogeneration adoption is between incremental cost in fuel input and the reduction in electricity bill. It only makes sense for a plant to adopt the technology if the cost of the additional fuel input is less than the avoided cost of purchasing the electricity from the grid.

2. Although not impossible, some large cogenerators have the ability to adjust electricity output every five minutes.

We test this third implication by providing evidence that cogeneration penetration is higher for plants in locations with a higher price of purchased electricity relative to the price of natural gas. The baseline specification for cross section linear probability model we used is

$$A_{ijt} = \alpha + \beta P_{ijt} + \mathbf{1}_j \times \mathbf{1}_t + X_{it} \quad (2.1)$$

where $A_{ijt}$ is an indicator for cogeneration technology presence at plant $i$ in industry $j$ at time $t$. $P_{ijt}$ is the log price ratio of purchased electricity price to purchased natural gas price plant $i$ faces at time $t$. $X_{it}$ consists a rich set of plant level controls at time $t$, including plant hours, age, size (value of shipments), and electricity usage on site (electricity generated plus purchased minus sold). $\mathbf{1}_t \times \mathbf{1}_j$ is 3-digit NAICS by year fixed effect. Parameter of interest $\beta$ is again identified through spacial variation. The likelihood of having the technology presence is expected to be increasing the price ratio of purchased electricity price to purchased natural gas price. This is indeed what we observe in the regressions. Table 2.1 shows the regression results. In the cross section, plants face higher relative price and use more electricity are more likely to have cogeneration on site as we would predict[3]. This is also important later in our discussion on instrument variable strategy as electricity price is indeed an important factor that drives adoption decision.

3. In our cross sectional data, large variation in electricity prices exist. This coincides with the findings in Davis et. al. (2013) [6]

Table 2.1: Cross Section Linear Probability Regression

| **Dep: Cogen Technology Presence** | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Log(price of elec/price of natural gas) | 0.011*** | 0.011*** | 0.010*** |
| | (0.002) | (0.002) | (0.002) |
| Log(on site elec usage) | 0.044*** | 0.049*** | 0.037*** |
| | (0.004) | (0.005) | (0.006) |
| Indicator on fuel type | | | X |
| Quintile indicator for $X_{it}$ | | X | X |
| N (approx.) | 22 K | 22 K | 22 K |
| $R^2$ | 0.23 | 0.24 | 0.28 |

Notes: Standard errors clustered at the state level are in parentheses. Data is from U.S. Census Bureau, the Manufacturing Energy Consumption Survey (MECS). All figures are unweighted. Table reports regressions of the pooled cross section (from years 1985-2010) indicator of cogeneration technology on corresponding plant level controls. $X_{it}$ consists a rich set of plant level controls at time $t$, including plant hours, age, size (value of shipments), and electricity usage. All regressions include a constant and year by 3-digit NAICS fixed effect. Technology presence equals 1 if a plant cogenerates nonzero electricity on site. Due to confidentiality protection, number of observations are rounded to the nearest thousand. Each observation is a manufacturing plant in the survey. * p <0.1, ** p<0.05, *** p<0.01

Although only plants that require simultaneous usage of electricity and steam would benefit from cogeneration technology, many plants indeed do satisfy the criterion. Chemical manufacturing, steel manufacturing, paper and forest products (e.g., paper mills), glass manufacturing, petroleum refining, food processing, fertilizer, and mining are notable industries suitable for cogeneration. In 2010, out of all the cogenerated electricity in our sample, 44 percent is from chemical manufacturing (3-digit NAICS code 325), 32 percent is from paper manufacturing (3-digit NAICS code 322), 13 percent is from petroleum and coal products manufacturing (3-digit NAICS code 324). The rest 11 percent is from the other industries combined (also, see table 2.2).

Table 2.2: Cogeneration Activities by Industry

| | Percentage of the total |
|---|---|
| Chemical Manufacturing | 44.47% |
| Paper Manufacturing | 32.34% |
| Petroleum and Coal Products Manufacturing | 13.33% |
| Others | 9.86% |
| Total | 100% |

Notes: Data is from the U.S. Census Bureau, the Manufacturing Energy Consumption Survey (MECS), 2010. Percentage of the total represents the percentage of the overall cogenerated electricity that is cogenerated from each industry (3-digit NAICS). 2010 is the latest available year for the MECS.

Aside from the defrayed electricity purchase, a cogenerator can potentially sell excess electricity to the grid and generate revenue. But many manufacturing plants hesitate to enter into the electricity market since it could be resource intensive to acquire expertise in a different industry other than its primary business. The resistance from the utility sector adds another layer of complication. The median cogeneration plant in our sample does not sell anything to the grid. The median cogeneration plant from an different source – the Energy Information Agency – also only sells small amount of electricity.

Additional benefits of cogeneration include increasing reliability of electricity supply, reduced greenhouse gas emissions or pollutants, and potential equilibrium effects on electricity price level. For the scope of this paper, we include environmental effects in the calculation of returns for cogeneration investment, but not the other two. Utility power plants are increasingly better at providing electricity reliability, and efficiently. The potential effect of cogeneration on long run electricity prices is small at best, with the possibility of going to the wrong direction – making it more expensive, when operating at high marginal cost region. Putting a dollar amount on reliability is difficult and most manufacturers do not factor it in themselves when making adoption decisions. For increasing reliability purposes, having backup power storage, or keeping a small electricity generator for emergency, among others, are less expensive alternatives for manufacturers. Losing steam/heat often has more dire consequences than losing electricity. For petroleum refinery, explosion could occur when the temperature of the pipes drop below a critical level.

For both industry and government agencies, the average cost of initial investment in a cogeneration system – purchasing and installing, or construction – is accepted to be about \$1000/KW for large industrial systems with generating capacity greater than 50 MW, and \$2000/KW for smaller systems.We use \$1500 per KW in computing fixed cost of cogeneration investment. Aside from fuel costs, the average cogeneration system has incremental operating and management (O&M) costs of \$0.0125/kWh [4]. Initial investment, O&M, and fuel are all the costs we consider in our analysis.

4. These figures, also the \$1500 per KW installation cost, are provided by the Department of Energy, and are the result of their collaboration with consulting firms

# CHAPTER 3

# CONCEPTUAL FRAMEWORK

The private gains of cogeneration technology adoption came in through two main channels: reduced energy expenditure, and efficiency-induced production re-optimization. The first channel is direct savings to the plant due to more efficient use of energy. The second channel occurs with re-optimization: when cost of production inputs – electricity, steam – decrease due to an increase in energy efficiency, profit maximized output quantity may change, which may lead to an increase in profit.

To facilitate our discussion in this chapter, we introduce some notations. Suppose prior adoption, a plant's profit is $\pi_0$ and it uses $e_0$ electricity and $n_0$ natural gas, with $p_e$ and $p_n$ being the per unit purchase price for electricity ($/kwh) and natural gas ($/mmbtu). After adoption, it uses $e_1$ electricity and $n_1$ natural gas, with profit $\pi_1$. From the total $e_1$ electricity used, it purchases $e_p$ from the grid. From the $n_1$ natural gas used, $n_c$ is incremental consumption due to cogeneration. Let us further suppose that this plant cogenerates $e_c$ electricity and sell $e_s$ quantity back to the grid, with $p_s$ being the per unit sales price . $e_c$ necessarily have to be used either on site or for sale. Therefore, $e_c + e_p - e_s \equiv e_1$, generated electricity plus incoming (or purchased) electricity minus outgoing (sold) electricity is the electricity used on site.

The direct savings from reduced energy expenditure can be split into four components: reduced electricity spending, electricity sales, incremental natural gas consumption, and incremental operating and management cost. Since our data do not allow us to measure the incremental operating and management cost directly, we will proxy it by $\$0.0125 \times e_c$ ($e_c$ is the amount of electricity cogenerated on site), following common practice by government agencies and consulting firms. Incremental natural gas consumption is $n_c \times p_n$ (incremental increase in natural gas times natural gas price). Electricity sales is $p_s \times e_s$ (electricity sold times electricity price). Reduced electricity spending can be computed two ways: directly from cogenerated electricity – $p_e(e_c - e_s)$, or indirectly from reduced electricity purchase and increased electricity usage – $p_e(e_0 - e_p + e_1 - e_0)$. These two ways in theory give identical results due to the identity $e_c \equiv e_1 - e_p + e_s$, and are founded on that an one-to-one mapping exists between per unit cogenerated electricity used on site and per unit grid purchased electricity, because the only outside option for a plant without generating capacity to acquire electricity for usage is to purchase from the grid. These two approaches differ in terms of the control group we can use. The savings and returns computed in the first approach is without control group, via direct accounting. The second approach is more flexible in terms of control group since each element is observed for both none adopters and adopters, whereas in the first approach none adopters, by definition, all cogenerate zero electricity. Thus, the second approach is our more preferred approach. The private savings from reduced energy expenditure can be summarized as $p_e(e_0 - e_p + e_1 - e_0) + p_s e_s - p_n n_c - 0.0125 e_c$, savings from reduced electricity purchase plus sales of cogenerated electricity minus the incremental fuel cost and incremental operating and management cost.

The profit gain through re-optimization is $\pi_1 - \pi_0$. This is not observable in the data. We focus our study in the TFP and output to understand the magnitude of this second channel. Much to our surprise, the TFP and output does not increase after the adoption of the cogeneration, instead, both decrease significantly. In fact, long term losses likely occurred since we find cogen plants die sooner than comparable none adopters (more discussion see Chapter 6.2). We therefore continue our discussion on conceptual framework around the energy savings and omit the second channel for now.

## 3.1 Emission effects

The social gain of cogeneration adoption is realized through reduction of pollutant emissions. In computing the monetary value of emission reduction, we use national average emission factors with the understanding that we could do better with more disaggregated local level emission factors. Avoided emissions of CO2 are valued at $38 per ton (Greenstone et. al., 2013 [15]).[1] We use basic accounting to compute the emission effects.

Monetary value of avoided grid emission is the dollar value of total avoided carbon dioxide emissions from reduced electricity purchase:

$$\underbrace{38}_{CO_2\,\$\,per\,ton} \times \underbrace{0.000792}_{ton\,per\,kwh} \times \underbrace{(e_0 - e_p + e_1 - e_0 + e_s) \times 1.065}_{kwh\,saved} = 0.032 \times (e_1 - e_p + e_s)$$

We first translate the $CO_2$ per ton value into per kwh since the electricity quantity units are often measured in kwh. Kwh saved from the transmission grid is described as $e_0 - e_p + e_1 - e_0 + e_s$, the difference in pre and post adoption purchase quantity, plus the difference in pre and post usage quantity, plus quantity sold. We multiply this quantity by 1.065 to account for the avoided power loss in transmission and voltage transformation. From most engineering sources, the loss appear to be in 3-10% range (Benedict et. al., 1992 [2]). A

1. We can compute the nitrogen oxide and sulfur dioxide emissions as well. But comparing to CO2 emissions, these are secondary and we will omit the effects from nitrogen and sulfur dioxide. Nitrogen oxide and sulfur dioxide emissions from residential gas consumption are valued at $250 per ton and $970 per ton, respectively (Muller, 2009 [19]). Per mmbtu emission translate into $0.010 for nitrogen oxide, and $0.0003 for sulfur dioxide. This figure is $2.014 for CO2.

well cited paper estimated the transmission and distribution losses at 6.6% in 1997 and 6.5% in 2007 (Nourai et. al., 2008 [21]). We use the average number of 6.5% in my paper for the main results.

The avoided grid emission comes at the cost of increased natural gas consumption. The monetary value of increased natural gas emission is calculated as the incremental natural gas purchase quantity due to cogeneration (measured in mmbtu) multiply by the $CO_2$ monetary value evaluated at mmbtu unit:

$$\{ \underbrace{38}_{CO_2\,\$\,per\,ton} \times \underbrace{0.053}_{ton\,per\,mmbtu} \} \times \underbrace{n_c}_{mmbtu\,added} = 2.014 \times n_c$$

The monetary value of emission effects of cogeneration is the difference between the two, the avoided emissions from grid purchase minus the increased emissions from natural gas consumption: $0.032(e_1 - e_p + e_s) - 2.014 n_c$.

## 3.2 Per period savings

To summarize, we can compute two types of per period savings: per period private savings and per period social savings.

The per period private savings is the sum of reduced electricity expenditure plus sales revenue minus the increased cost in natural gas and O&M cost.

$$PPS = p_e(e_0 - e_p + e_1 - e_0) + p_s e_s - p_n n_c - 0.0125 e_c \tag{3.1}$$

The per period social savings is per period private savings plus the monetary value of reduced emissions (value of avoided emissions from the grid minus the increase in natural gas emissions).

$$
\begin{aligned}
PSS &= p_e(e_0 - e_p + e_1 - e_0) + p_s e_s - p_n n_c - 0.0125 e_c \\
&\quad +0.032(e_1 - e_p + e_s) - 2.03 n_c
\end{aligned}
\tag{3.2}
$$

## 3.3 Internal Rate of Return computation

The internal rate of return (IRR) is the interest rate (or the discount rate) required so that the discounted value of annual benefits exactly equals the initial investment. This is the definition of our returns.

$$
\sum_{t=1} \frac{Per\,Period\,Saving_{it}}{(1+IRR)^t} = I(\kappa_i)
$$

where $I(\kappa_i)$ is the upfront investment cost and it depends on the size of the cogeneration system $\kappa_i$.

An important assumption we make in computing the IRR is that the per period saving is constant across the years. This clearly is not ideal since price fluctuations in electricity and natural gas move savings significantly and learning-by-doing could generate more reduction in electricity and natural gas purchase. To address these concerns, we use the average prices across the years to smooth out the price fluctuation, and use the event-study graphs to show that most learning-by-doing are done within the first two or three years of adoption.

# CHAPTER 4

# DATA AND SUMMARY STATISTICS

## 4.1 Data Sources

This primary data source for this project is from the US Census Bureau[1] and the US Energy Information Administration. The US Census Bureau has detailed information on manufacturing activities, which has been exploited greatly by researchers. However, the energy usage dimension of the data has not been studied nearly as much. In combination with labor, capital, and productivity data at the plant level, we can paint a more complete picture of plant performance when experiencing a change in energy efficiency.

The Manufacturing Energy Consumption Survey (MECS) from the Census Bureau covers from 1985 to 2010. We use it to identify plants in the control group since it surveys both none adopters and adopters. We use the Annual Electric Generator Survey from the Energy Information Administration to identify the adopters since only plants with more than 1 MW generating capacity are surveyed. Using an independent data source from the ICF International Combined Heat and Power Installation Database[2], table 4.1 shows that over 70 percent of the total cogeneration capacity in operation in year 2013 were added during 1985-2010. Among which, about 80 percent are added in the manufacturing sector. Within the manufacturing cogeneration, 77 percent uses natural gas as fuel input. Thus, our analysis is mainly in the manufacturing sector with natural gas as primary fuel input.

1. Author is under Special Sworn Status to use the confidential data from the US Census Bureau.

2. The Department of Energy and the Environmental Protection Agency use this database to produce public brochures on cogeneration. However, this dataset only contains information on capacity level, without any information on fuel consumption, nor manufacturing outputs.

Table 4.1: Cogeneration Capacity Added

| Time Period | GW added | % Manuf. | % NG |
|---|---|---|---|
| 1900-1985 | 22.63 | 85.15% | 54.32% |
| 1985-2010 | 58.38 | 79.85% | 76.85% |
| 2010-2013 | 1.10 | 34.90% | 41.34% |
| Total | 82.11 | 80.71% | 70.10% |

Notes: Column 1 lists the cogeneration capacity (GW) added. Column 2 lists the cogeneration capacity added in the manufacturing sector as a percentage of overall cogeneration capacity added. Column 3 lists the share of manufacturing cogeneration capacity added that use natural gas as primary fuel input. Data is from the ICF International Combined Heat and Power Installation Database; last updated in July, 2013. Maintenance of this database is supported by the U.S. Department of Energy and Oak Ridge National Laboratory.

The frequency of the MECS is every three to four years. Although annual data on manufacturing activities (payroll, employment, capital, etc) is available for these plants from the Annual Survey of Manufacturers (ASM), the Census of Manufacturers (CM), and the Longitudinal Business Database (LBD), data on cogeneration usage is only available from the MECS. It started in 1985 and the latest available data is from 2010. In total, we have 8 MECS surveys from 1985, 1988, 1991, 1994, 1998, 2002, 2006, and 2010. Unlike the CM, the MECS does not cover the universe of all manufacturers. Instead, the MECS focuses on energy intensive plants and often misses smaller plants. For example, the 2006 MECS sample size of approximately 15,500 establishments was drawn from a nationally representative sample frame representing 97-98% of the manufacturing payroll. The MECS asks specifically the amount of electricity generated through cogeneration. We use this information to identify our control group, which are all the plants in the 2010 survey that one, do not have any cogenerated electricity throughout the survey years (1985-2010), and two, can be matched with LBD/ASM/CMF. Roughly 13,000 plants qualify the requirements to be in the control group. Other alternative survey questions can be used to identify control groups, we use those as robustness checks and report the results in Appendix. One of such questions is whether or not a plant has these five types of cogeneration technology present: 1. steam turbines supplied by either conventional or fluidized bed boilers, 2. conventional combustion turbines with heat recovery, 3. combined-cycle combustion turbines, 4. internal combustion engines with heat recovery, and 5. steam turbines supplied by heat recovered from high-temperature processes. We prefer to use none-zero cogenerated electricity to identify cogen presence because there could be a cogen on site that does not fall into any of these five types of cogeneration, but regardless the type, electricity is a by-product with any cogeneration. We nonetheless find our results consistent across using any of these control group definitions.

We use the Annual Electric Generator Survey from the Energy Information Administration (EIA) to identify our treatment group. It collects detailed information on all electricity generators with above 1 MW or greater nameplate capacity, which includes both non-utilities and utilities[3]. Although the survey only started to collect information for non utilities in late 1990s, it asks for the year of cogeneration adoption and planned retirement, as well as its generating capacity. In other words, if a plant adopted cogeneration in 1960s but survived till 1990s, the survey will capture it. We merge the EIA data unto the Census data using plant name, industry, street address, zip code, and state. Out of around 800 manufacturing plants captured in the EIA data, we matched more than 500 with the Census data. Of which, we have a bit less than 300 plants with first adoption year between 1982-

3. Some cogenerators have smaller capacity than 1 MW. But in total, missing these plants do not make up a large difference. The ICF International Combined Heat and Power Installation Database have very basic capacity and location information for each cogenerator regardless of size. US Department of Energy uses this data to produce the 82 GW current capacity figure in 2013. Data from EIA disagrees with the 82 GW figure, and only have roughly 70 GW. From author's calculation using ICF database, total cogenerator capacity from plants with less than 1 MW generating capacity amounts to less than 0.6 GW. It remains unclear where the differences might be coming from. But since EIA is the main agency in charge of collecting electricity generator level data, and plants with less than 1 MW capacity seems to make up a small portion of the total capacity, I will use the EIA data for empirical analysis.

2010 (available CM/ASM years). Roughly one-third plants adopted more than one unit of cogeneration. We use the first adoption year as the event year in our analysis.

The CM/ASM has information on electricity purchase quantity and expenditure, generated electricity, and quantity sold. However, the CM/ASM does not have breakdown on different fuel (natural gas, coal, etc.) consumption and expenditure like the MECS. Instead, the total fuel expenditure is available from the CM/ASM. Total fuel expenditure is defined as the total amount actually paid or payable during the year for all fuels consumed for heat, power, or the generation of electricity. It excludes cost of fuels when consumed as raw materials. To construct an annual panel, we use the CM/ASM as the backbone. The CM/ASM also provides information on plant industry, number of employees, payroll, capital expenditure, and total value of shipment. The LBD provides unique identify to link plants longitudinally and provides information on plant birth and death (or latest available) year. In summary, we use the CM/ASM/LBD to track annual manufacturing activities and energy consumption activities from 1982 - 2010 of plants we identify as cogeneration adopters or never-adopters from the MECS and EIA surveys. From the 13,000 plants we identified as either in the control or treatment group, we have in total a bit less than 200,000 plant-year observations.

### 4.2 Energy Consumption, Purchase, and Sales Data

Electricity quantity purchased and sold are available in both the ASM/CM and the MECS. The ASM/CM have data on total electricity generated on site, which may or may not be from cogeneration. From the MECS, it segments the generated electricity quantity by source of generation: cogeneration, solar, wind, hydro, and others. Over 97 percent of the on-site electricity generation is through cogeneration. When we use the generation quantity from the ASM/CM, we multiply by 97 percent to impute the cogenerated quantity. The total electricity usage on site is computed by adding all the incoming electricity and generated electricity, then subtracting off the outgoing quantity.

Electricity expenditure and total fuel expenditure are available in the ASM/CM and the MECS. The MECS breaks down the total fuel expenditure by fuel type. It has fuel quantity purchased by each type. The ASM/CM on the other hand has only a combined measure of total cost of fuel. The average price of fuel by fuel type is computed from the MECS using annual expenditure divided by purchase quantity. Natural gas is the primary fuel used in cogeneration. Technically, the MECS asks for the percentage of natural gas used for cogeneration. However, there are too many missing values to make use of that variable.

## 4.3 Manufacturing Data

Manufacturing data is from the ASM, CM, and LBD. Data are merged using unique longitudinal plant identifier from the LBD. Since the MECS is sent to a subset of plants from the ASM, the match rate is in the upper 90 percent range.

Plant total value of shipment, first and last year in operation, number of employees, total wage and salaries, and material cost (energy cost excluded) are all directly observed in the ASM/CM. Real output, and log TFP are taken from Foster et. al. (2014) [10] data which uses the raw data from ASM/CM. Real output is computed by dividing the plant level total value of shipment and new inventories by industry level price, deflated to 1997 price level. Log TFP is obtained by computing the log of output-input ratio, assuming a Cobb-Douglas production function and using industry level cost shares[4]. Take industry

4. This is a measure of revenue TFP, not physical TFP, as mentioned in Syverson (2011) [23].

level labor, capital, energy, and material share from the Bureau of Labor Statistics, then subtracts log real output by the sum of log real inputs weighting by their perspective shares. Age is computed by using the survey year minus the first year in operation.

Consider the manufacturing process in two steps. First, convert fuel input into steam and electricity. Second, use steam, electricity, and other intermediate inputs to produce the final output. Cogeneration affects the first step of the production by increasing the energy efficiency in converting natural gas to steam and electricity. Per unit of final good still demands the same amount of materials, electricity, and steam. In other words, the production function in the second step remains unchanged. However, the cost of the intermediate input, the electricity and steam, changed. This could lead to a change in the optimal final good production quantity after re-solving the cost minimization or profit maximization problem. Quite surprisingly, we observe all the input and output go down for an adoption plant and a sharp decline in TFP (more see chapter 6 and table 6.4).]

## 4.4 Adoption Cost and Sales Revenue Measures

Although the electricity quantity sold is available in the MECS and the ASM/CM, the price or revenue is not recorded. Revenue is measured by using the quantity of electricity sold multiply by the average purchase price, with the assumption that unit sales price is equal to the unit purchase price, to make up for the lack of sales price. This unambiguously biases our savings calculations upwards by overestimating the sales revenue. No utilities would be willing to offer a buy-back rate higher than its gird price. The marginal cost for a cogenerator to generate electricity is also lower than most fossil fuel power plants. Combining these factors, along with conversations with the industry experts, we have no reason to believe the electricity sales prices would be higher than purchase price for a cogenerator.

Investment cost is computed to be $I(\kappa_i) = 1500 \times \kappa_i$, where $\kappa_i$ is the kw capacity of the cogenerator installed.

## 4.5 Summary Statistics

Table 4.2 summarizes the mean value and difference of three energy measures and three manufacturing production measures between EIA identified cogeneration plants and MECS identified none adopters plants by the end of the same sample period 2010. The top panel summarizes electricity usage, purchase quantity, and cost of fuel. The bottom panel summarizes the real output, TFP, total employment hours, cost of materials, and lifespan (death year minus birth year).

Table 4.2: Differences in Sample Means

| | Adopters (1) | None Adopters (2) | (1)-(2) (3) |
|---|---|---|---|
| **Panel A: Energy Measures** | | | |
| Cost of Fuel (log 1997$) | 8.54 | 5.67 | 2.87*** |
| | | | (0.02) |
| Electricity purchased (log kwh) | 9.43 | 7.38 | 2.06*** |
| | | | (0.04) |
| Electricity consumed on site (log kwh) | 11.36 | 9.08 | 2.29*** |
| | | | (0.02) |
| **Panel B: Manufacturing Activities** | | | |
| Real output (log 1997$) | 12.22 | 10.52 | 1.70*** |
| | | | (0.02) |
| TFP | 1.48 | 1.66 | -0.19*** |
| | | | (0.01) |
| Lifespan (years) | 32.85 | 29.83 | 3.02*** |
| | | | (0.09) |
| Total worker hours (log) | 6.85 | 5.76 | 1.09*** |
| | | | (0.015) |
| Cost of materials (log 1997$) | 11.44 | 9.65 | 1.78*** |
| | | | (0.02) |
| Approx. number of plants | 500 | 13,000 | |
| Approx. plant-year obs | 13,000 | 160,000 | |

Notes: Data is from U.S. Census Bureau: Manufacturing Energy Consumption Survey, Annual Survey of Manufacturers, and Longitudinal Business Database. Sample period is from 1982-2010. We split the total sample by two sub samples: plants that adopted cogeneration and plants never adopted cogeneration by 2010, adoption is identified by data from the Energy Information Administration. Column (1) and (2) reports average values of each sample. Column (3) reports differences in means (with standard errors in parenthesis). * p <0.1, ** p<0.05, *** p<0.01

The first two columns show the sample means, while the third column is the difference between the first two columns, with standard error in the parenthesis. Across energy measures, adopters use significantly more electricity and fuel. This is within expectation as cogeneration benefit large energy consumers the most. However, larger energy consumers may not be more productive as Panel B shows.

Although the level may be very different between these two groups, the pre-adoption trends prove to be similar. Our preferred specification includes plant fixed effects which control for all time invariant differences between plants. The endogenous selection into adoption could be correlated with time-varying factors that are unobserved. We find none differential pre-trend in energy purchase and various manufacturing output measures signals that the adopting plant did not change their behavior prior the adoption, mitigating the concern slightly, though not completely. More discussion on this can be found in Chapter 6.

Appendix table A.1 shows that the top ten industries by cogenerated electricity quantity stay relatively stable from 1985 to 2010. The penetration ratio by total value of shipment, employment, and number of establishment is still low for many of these top industries in 2010, especially those out of the top three. Even among the top three, penetration ratios for chemical manufacturing (#1), and petroleum and coal products manufacturing (#3) are still below 30 percent by total value of shipment. Table 4.1 shows that after 2010, the cogeneration growth slowed significantly. However, despite the low growth in recent years and the low penetration ratio, cogeneration as of 2013 is already an important part of electricity generation. Through author's own calculation, EIA survey shows that 6.303% of the total name plate generating capacity in the US for all generators with 1 MW or larger capacity is cogeneration. 7.623% of the total net electricity generated (megawatt hours) in 2013 is from cogeneration. 130 GW of potential CHP capacity still exist for commercial and industrial facilities by estimates from the Department of Energy (DOE, 2012 [7]). There is much room still available for cogeneration growth.

# CHAPTER 5

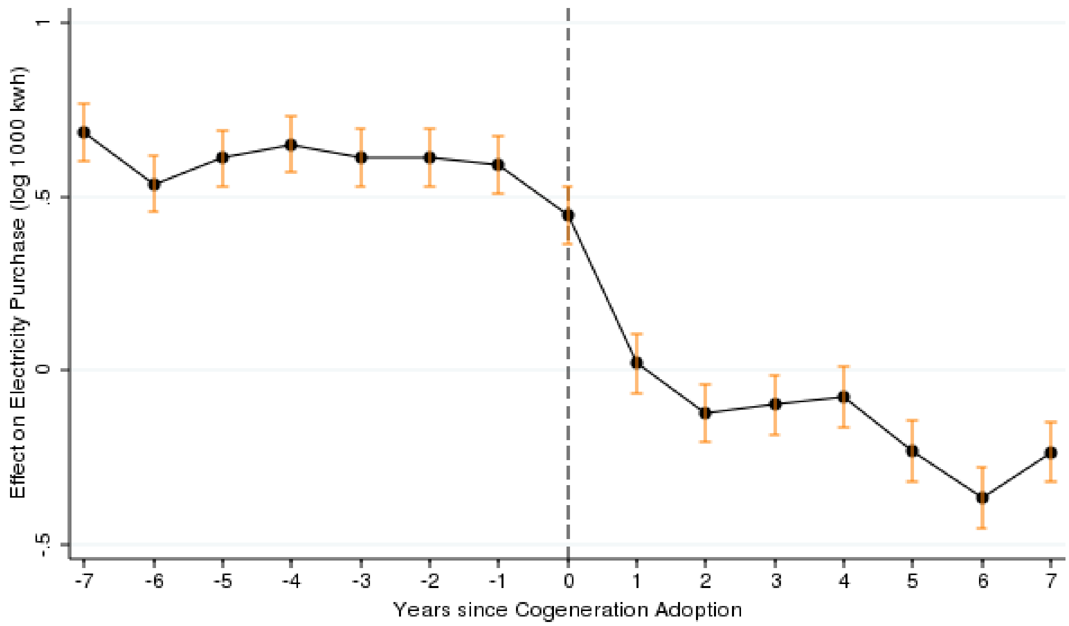
# EMPIRICAL STRATEGY

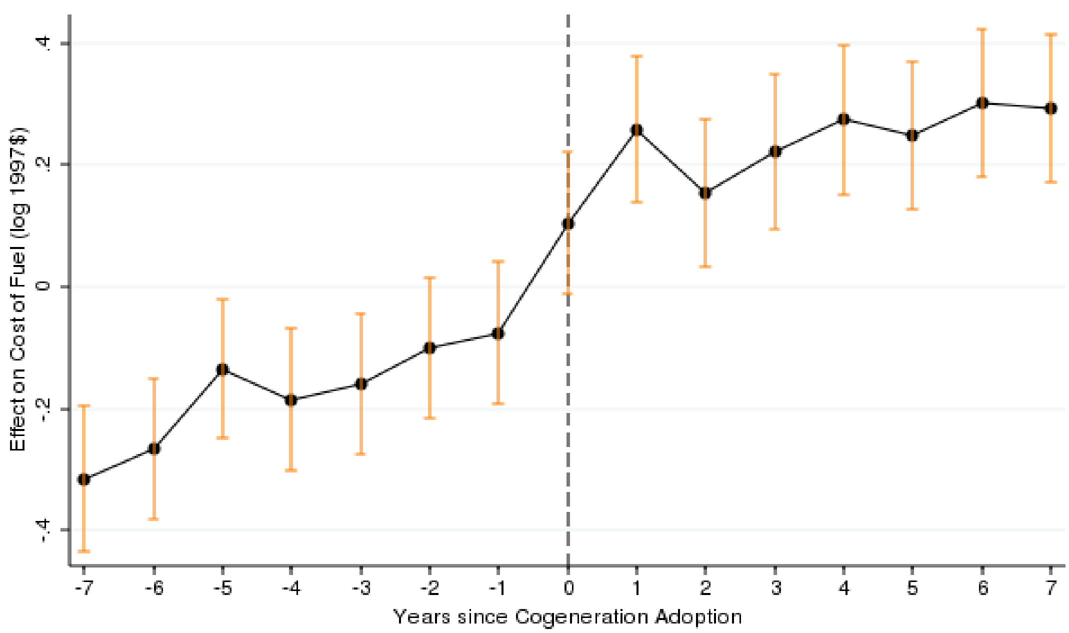
We first employ a series of event study figures to determine if any pre adoption differential trend exists between the control and treatment group:

$$\ln(y_{it}) = \alpha + \sum_{\tau} \sigma_{\tau} D_{\tau,it} + \alpha_i + \alpha_{jt} + \alpha_{st} + \varepsilon_{it} \tag{5.1}$$

where $\ln(y_{it})$ is the natural log of fuel purchase quantity (natural gas, or electricity) at plant $i$ in year $t$. $D_{\tau,it}$ is an event indicator which turns on 1 at event time $\tau$ for plant $i$ in year $t$. Event time 0 is defined as the year EIA survey reports the plant's first cogenerator is installed. $\alpha_i$ is plant fixed effects. $\alpha_{st}$ is state-by-year fixed effects where $s$ is the state plant $i$ is located. $\alpha_{jt}$ is industry-by-year fixed effects where $j$ is plant $i$'s 3-digit NAICS industry. All of our event study figures use balanced panel. Figure 5.1 shows the effect on electricity purchase quantity and cost of fuel before and after cogeneration adoption using window size of 7. This balanced panel has over 100 adopting plants and over 1 K control group plants. Ideally, we want to graph one where the y-axis is natural gas purchase quantity. Unfortunately, fuel specific quantity are only collected in the MECS every three- or four-years. In Appendix, we show that the general pattern holds for various window size. It appears that there is no differential trend exist between the control and treatment group prior adoption for electricity purchase. Most of the changes happen around the year of or first two years post adoption. Post adoption level persists throughout the following 6 years.

**Figure 5.1**. Effect of Adoption on Manufacturing Plants




Notes: Data is from the EIA and the US Census Bureau. Event time is zero when a plant reports to have a cogenerator on site for the first time. Data covers from 1982 to 2010. $N$ is roughly 60K with 2K unique establishments.

Although the trend break seems evident from the event study figures, to test it formally, we follow Greenstone et. al. (2014) [14]:

$$\hat{\sigma}_\tau = \pi_0 + \pi_1 \mathbf{1}\{cogen\}_\tau + \pi_2 \tau + \pi_3 (\mathbf{1}\{cogen\}_\tau \times \tau) + \varepsilon_\tau \tag{5.2}$$

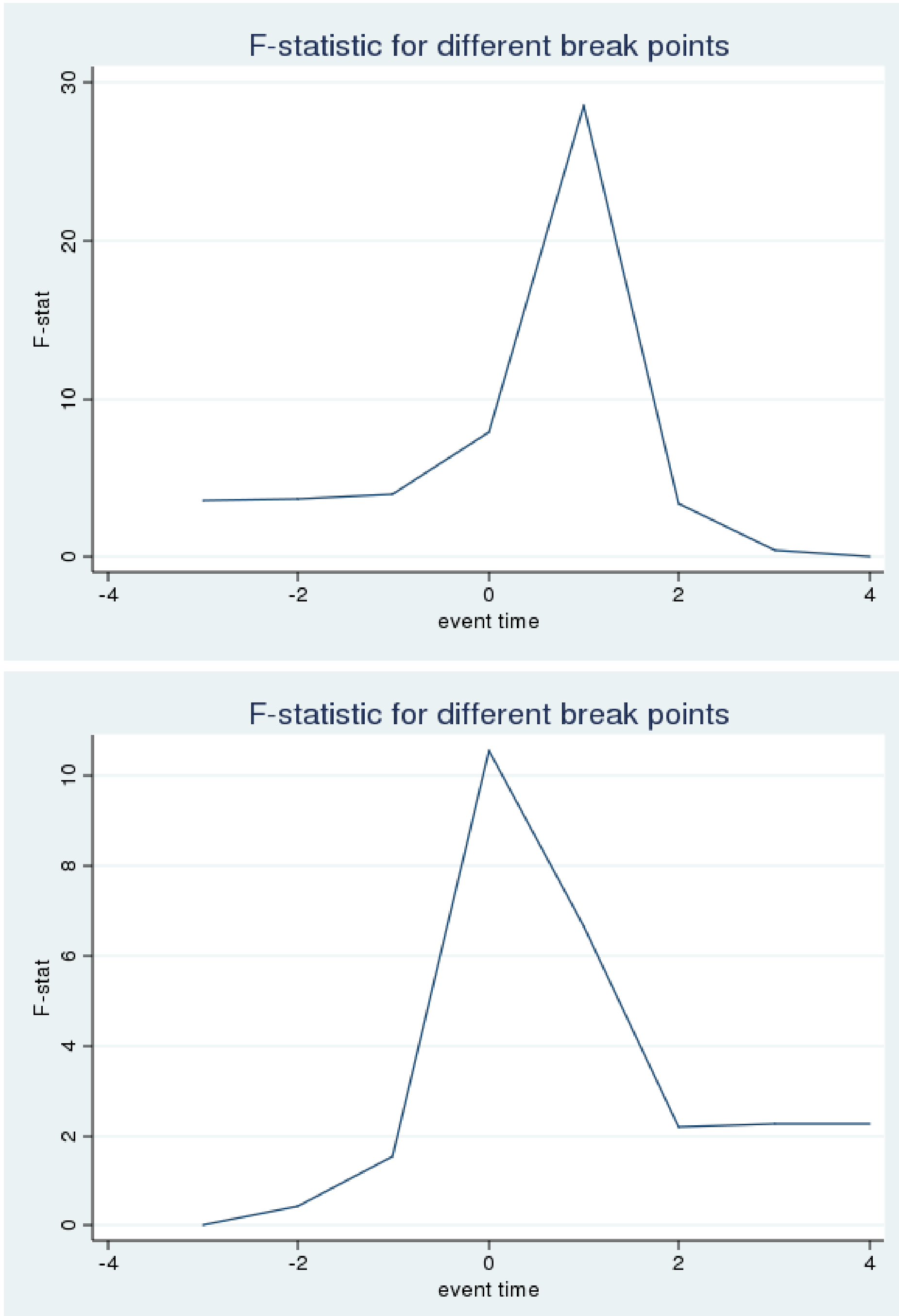
where $\mathbf{1}\{cogen\}_\tau$: is an indicator variable for whether cogeneration is on site (i.e., $\tau \geq 1$). We control for a linear time trend in event time and allow adoption impact to evolve over time. There is an analogous one step procedure:

$$\ln(y_{it}) = \alpha + \theta_1 \mathbf{1}\{cogen\}_\tau + \theta_2 \tau + \theta_3 \mathbf{1}\{cogen\}_\tau \times \tau + \alpha_i + \alpha_{jt} + \alpha_{st} + \varepsilon_{it} \tag{5.3}$$

We report both two step and on step results in Chapter 6.

We further test for the event year when the trend break most likely occurred with a Quandt likelihood ratio (QLR) statistics. This is done by first re-estimating equation 5.2 using a new adoption date at each event time and then calculating the joint F-statistics with the null hypothesis that $\pi_1 = 0$ and $\pi_3 = 0$. Second, the QLR test selects the maximum of the F-statistics to test for a break at an unknown date. For the event study graphs in figure 5.1, figure 5.2 and table 5.1 report the results of the QLR test. Event time $\tau = 1$ is associated with the most substantial trend break for the reduction in electricity purchase quantity and event time $\tau = 0$ for the increase in cost of fuel.

**Figure 5.2**. Trend Break Analysis




Notes: The first panel shows the QLR statistics for corresponding first panel in figure 5.1, the event study figure for electricity purchase quantity. The second panel shows the QLR statistics for corresponding second panel in figure 5.1, the event study figure for cost of fuel.

These results are suggestive that one, most of the learning-by-doing is done within the first few years of adoption event; two, the effects of adoption are persistent over a long horizon; and three, the adoption impact does not evolve over time. We center our computation for savings and returns around these findings.

Table 5.1: Trend Break Analysis

| | Event year<br>(1) | QLR test statistic<br>(2) |
|---|---|---|
| Panel A. Electricity Purchase Quantity | | |
| | 1 | 28.52 |
| | 0 | 7.90 |
| | -1 | 4.01 |
| Panel B. Cost of Fuel | | |
| | 0 | 10.57 |
| | 1 | 6.65 |
| | 4 | 2.27 |

Notes: This table provides the QLR test statistic, as well as the corresponding event year of the break for equation 5.2.

Combine equations 3.1 and 3.2 from the conceptual framework chapter and the accounting identity $e_1 \equiv e_c + e_p - e_s$, electricity usage equals generated plus purchased minus sold, we could use two different approaches to estimate the per period private savings and the per period social savings: from the reduced electricity purchase, or from the cogenerated quantity. Although we prefer the reduced electricity approach due to more flexible control group, we nonetheless show results using the both approaches.

## 5.1 Using reduced purchase to compute for energy savings

Recall that the per period private savings can be expressed as

$$\begin{aligned} PPS &= p_e(e_0 - e_p + e_1 - e_0) + p_s e_s - p_n n_c - 0.0125 e_c \\ &\approx p_e(e_0 - e_p + e_1 - e_0) + p_e e_s - p_n(n_1 - n_0) - 0.0125 e_c \end{aligned}$$

As explained in Chapter 4, we do not observe the electricity sale price, we use the purchase price to approximate. We also know very little on $n_c$, the increase in natural gas consumption due to cogeneration. Instead, we make the assumption that all the increase in natural gas consumption is due to cogeneration adoption. This assumption is based on the fact that the output declined after the adoption. Natural gas consumption cannot be going up for the production of more output.

We further introduce how each element is computed. $e_0 - e_p$, $e_1 - e_0$, and $n_1 - n_0$ can be calculated directly for each plant from the raw data, or imputed from our difference-in-difference estimator. Direct calculation is straightforward. For example, $e_0 - e_p$ can be computed as the difference between the average electricity purchase quantity across all pre-adoption years and the average across all post-adoption years. Since our event study figures suggest that most of the drop occurs in the first year post adoption, for robustness check, we compute $e_o - e_p$ as the difference between the electricity purchase quantity just one year prior adoption and one year post adoption. Another robustness check uses the difference between the average electricity purchase quantity across 7 pre-adoption years and 7 post-adoption years. $e_1 - e_0$, and $n_1 - n_0$ are similarly computed. The difference-in-difference approach relies on running the following regression:

$$\ln(y_{it}) = \alpha + \theta_1 \mathbf{1}\{cogen\}_t + \alpha_i + \alpha_{jt} + \alpha_{st} + \varepsilon_{it} \tag{5.4}$$

where $\ln(y_{it})$ is the log quantity of interest (electricity purchase, natural gas, electricity usage). $\mathbf{1}\{cogen\}_t$ is an indicator that turns one in and after the adoption year. $\alpha_i$, $\alpha_{jt}$, and $\alpha_{st}$ are plant , industry-by-year, state-by-year fixed effects. $e_0 - e_p$, for example, will be computed as $[\exp(\hat{\theta}_1 - \frac{1}{2}var(\hat{\theta}_1)) - 1]e_0$, where $var(\hat{\theta}_1)$ is the estimated variance of $\hat{\theta}_1$. Since $\mathbf{1}\{cogen\}_t$ is a binary variable, the formula gives an almost-unbiased estimator of the % impact of the dummy on the dependent variable (Kennedy, 1981 [17]), assuming normal errors $\varepsilon_{it}$. Again, $e_0$ here can be the average electricity purchase across all pre-adoption years, one year prior adoption, or across seven pre-adoption years. Our baseline figures use the average across all pre-adoption years. For $p_e$, $p_n$, electricity and natural gas unit prices, we can use the average prices across all pre-adoption years, one year prior adoption, or across seven pre-adoptions. In another specification as robustness check, we used $\mathbf{1}\{cogen\}_t \times \kappa_i$, where $\kappa_i$ is the generating capacity of the system installed. This does not change our main results.

We compute the per period private savings for each plant that experienced an adoption event. The internal rate of return (IRR) can then be calculated from:

$$\sum_{t=1} \frac{PPS}{(1+IRR)^t} = I(\kappa_i)$$

We use \$1500/kw as the investment cost, which means $I(\kappa_i) = 1500 \times \kappa_i$. When using the regression based method, $\hat{\theta}_1$ does not vary by plant. It is a mean effect of treatment on the treated. Becuase the pre-adoption prices and quantities vary by plant, we can obtain an distribution of private IRRs.

An distribution of social IRRs can be obtained likewise. We use per period social savings $PSS = p_e(e_0 - e_p + e_1 - e_0) + p_s e_s - p_n(n_1 - n_0) - 0.0125e_c + 0.032e_c - 2.014(n_1 - n_0)$ instead of per period private savings. The environment effects $0.032e_c - 2.014(n_1 - n_0)$ can also calculated directly or via regression.

## 5.2 Using cogenerated electricity to compute for savings

As described earlier, by identity $e_c \equiv e_1 - e_p + e_s$, per period private saving can also be

$$
\begin{aligned}
PPS &= p_e(e_0 - e_p + e_1 - e_0) + p_s e_s - p_n n_c - 0.0125 e_c \\
&\approx p_e(e_1 - e_p) + p_e e_s - p_n(n_1 - n_0) - 0.0125 e_c \\
&= p_e(e_1 - e_p + e_s) - p_n(n_1 - n_0) - 0.0125 e_c \\
&= p_e e_c - p_n(n_1 - n_0) - 0.0125 e_c
\end{aligned}
$$

By definition, there is no $e_c$ for any pre-adoption periods. Our difference-in-difference approach would not work here in computing savings occurred to electricity expenditure, but still works in natural gas consumption. Again, the $e_c$ can be the average post-adoption cogenerated electricity across all years, one year post adoption, or across seven years.

Per period social savings $PSS = p_e e_c - p_n(n_1 - n_0) - 0.0125 e_c + 0.032 e_c - 2.014(n_1 - n_0)$ can be likewise computed. An IRR distribution can be obtained once armed with these per period savings.

## 5.3 Projected savings

Projected savings are computed by the same method used at the Department of Energy in their 2012 report (DOE, 2012 [7]). Per period private savings is

$$
\begin{aligned}
PPS &= p_e e_c - p_n(n_1 - n_0) - 0.0125 e_c \\
&= (p_e - 0.0125 - p_n \times 5/1000)(\kappa_i \times 8760 \times 75\%)
\end{aligned}
$$

which is entirely based on the generating capacity of the cogeneration system, and does not depend on any pre-adoption information. Industry/Government projection assumptions are that a cogeneration system has 75% load factor and 5 mmbtu/mwh incremental heat rate (see Appendix for an example). Per period private saving is the cogenerated electricity times the grid price minus the incremental O&M cost and fuel cost.

The per period social savings is $PSS = (p_e - 0.0125 + 0.032)(\kappa_i \times 8760 \times 75\%) - (p_n \times 5/1000 - 2.014)(\kappa_i \times 8760 \times 75\%)$. Since plants with the same cogenerating capacity generates the same quantity of electricity and uses the same quantity of incremental natural gas, the only variation in the distribution of IRR in this subsection is from the differential prices faced by each plant.

## 5.4 Instrumental Variable Strategy

Clearly, the adoption decision is not exogenous to the plant. We attempt two categories of IVs. It is worth noting that since our baseline controls for state-by-year fixed effects, any instrument exploiting the difference across states would require taking out the state-by-year fixed effects.

### *5.4.1 Policy Incentives*

We coded up state level policies across the years, using both binary coding and percentage tax benefit coding. The identifying assumption is that state level policies are exogenously given to the plants and that plants in different states face different adoption prices moved by state regulatory changes.

In first stage, we proxy cogen adoption with predicted value

$$\mathbf{1}\{cogen\}_{it} \quad = \quad \beta \mathbf{1}\{policy\}_{it} + \gamma_i + \gamma_t$$

where $\mathbf{1}\{cogen\}_{it} = 1$ during and after the adoption year for plant $i$. $\mathbf{1}\{policy\}_{it} = 1$ during and after the policy incentive set in place at $i$'s location (state). $\gamma_i$ is plant fixed effect and $\gamma_t$ is year fixed effect.

In second stage, we run

$$\ln(y_{it}) \quad = \quad \alpha \mathbf{1}\{\hat{cogen}\}_{it} + \gamma_i + \gamma_t \tag{5.5}$$

where $\ln(y_{it})$ is the log variable of interest. $\mathbf{1}\{\hat{cogen}\}_{it}$ is the predicted value from first stage.

### *5.4.2 Same-Firm Instruments*

The second category of instruments use within firm variation. The potential source of exogeneity arises from within firm adoptions that exogenously impact a plant's adoption decision. For example, a plant does not necessarily benefit from cogeneration but adopts just because some other plants within the same firm adopted elsewhere. Or a plant that would benefit from adopting does not adopt because another adopting plant in the same firm exhausted capital, either tangible or intangible, that would be used for the adoption of this plant.

We tired four different within firm instruments: first, the cumulative number of same firm adoptions in different state; two, the number of adoptions within the same firm same

2–digit NAICS in different state; three, the number of adoptions within the same firm in different 2–digit NAICS; and four, the number of adoptions within the same firm same state but in different 2–digit NAICS. These four all have similar results, thus we report the results using the cumulative number of same firm adoptions in different state in Chapter 6 without loss of generality.

In the first stage,

$$\mathbf{1}\{cogen\}_{ijt} \quad = \quad \beta num_{-i,j,t-1} + \gamma_{jt}$$

where $\mathbf{1}\{cogen\}_{ijt} = 1$ during and after the adoption year for plant $i$ from firm $j$. $num_{-i,j,t-1}$ is the instrument. $\gamma_{jt}$ is the firm-by-year fixed effect. For example, for instrument one, $num_{-i,j,t-1}$ is the total number of cogen adopted (cumulative adoption) within same firm $j$ in different state than $i$, prior the year $t$.

Another example, for instrument two, $num_{-i,j,t-1}$ is the total number of cogen adopted within same firm $j$ and same industry as $i$, but in different state than $i$, prior the year $t$. The rest follows.

The second stage is

$$\ln(y_{it}) \quad = \quad \alpha \mathbf{1}\{co\hat{g}en\}_{it} + \gamma_i + \gamma_t \tag{5.6}$$

where $\ln(y_{it})$ is the log variable of interest. $\mathbf{1}\{co\hat{g}en\}_{it}$ is the predicted value from the first stage.

# CHAPTER 6

# RESULTS AND INTERPRETATION

## 6.1 IRR using quantity of cogenerated electricity approach and reduced purchase approach

First of all, table 6.1 and 6.2 report the difference-in-difference results for both electricity purchase quantity and cost of fuel. Table 6.1 shows robust evidence on the decline of electricity purchase post adoption of cogeneration. MECS collect electricity purchase quantity through a different survey than the ASM, yet column (3) and column (5) using the MECS measures are almost identical as those use the ASM measures. Column (1) uses the two step estimation method described in the previous chapter. Column (2) - (3) use the analogous one step estimation method. The five year effects of adoption from column (1) - (3) is about the same as the average post adoption effects, not allowing for time trend nor effect to vary by event time (column (4) and (5)). In computing for annual savings, we use results from column (4), highlighted in bold. Table 6.2, on the other hand, shows that the effect of adoption on cost of fuel varies by the regression design. MECS collect fuel specific purchases. Dependent variable for column (3) and (5) is the natural gas purchase quantity instead of cost of fuel–an expenditure measure. In computing for annual savings, we use results from column (4), highlighted in bold.

Table 6.1: Effect of adoption on Electricity Purchase

**Dependent Variable: Annual Electricity Purchase Quantity in Logs**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| $\pi_2$: time trend | -0.004 | -0.005 | -0.011 | | |
| | (0.021) | (0.013) | (0.037) | | |
| $\pi_1$: $\mathbf{1}\{cogen\}$ | -0.309** | -0.632*** | -0.688*** | **-0.654*** ** | -0.713*** |
| | (0.115) | (0.129) | (0.294) | (0.108) | (0.197) |
| $\pi_3$: $\mathbf{1}\{cogen\}\times$ | -0.079** | 0.005 | 0.005 | | |
| time trend | (0.094) | (0.016) | (0.069) | | |
| 5-year effect | -0.706*** | -0.606*** | -0.662*** | | |
| Plants (approx.) | 13,000 | 13,000 | 8,000 | 13,000 | 8,000 |
| Observations (approx.) | 170,000 | 170,000 | 24,000 | 170,000 | 24,000 |

Notes: Column (1) use two step procedure described in Chapter 5 (see equation 5.1 and 5.2), while column (2) - (3) use the analogous one step (5.3). Column (4) and (5) do not control for time trend or allow adoption effects to vary over time. Column (3) and (5) use the purchase quantity data from the MECS, while the rest columns use the ASM. All columns include plant fixed effects and survey year fixed effects. Standard errors are clustered at plant level. * p <0.1, ** p<0.05, *** p<0.01

Table 6.2: Effect of adoption on Cost of Fuel

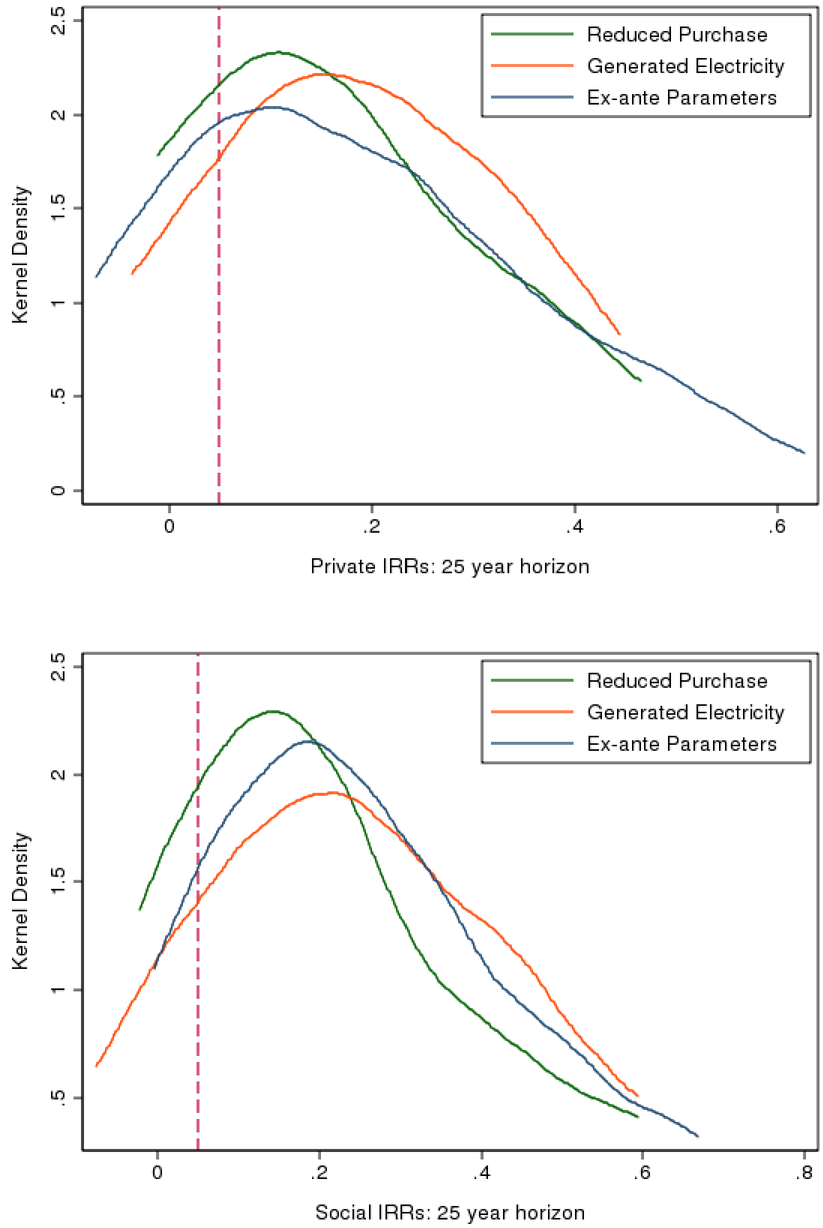
**Dependent Variable: Annual Cost of Fuel in Logs**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| $\pi_2$: time trend | 0.036*** | 0.002 | 0.177 | | |
| | (0.008) | (0.008) | (0.277) | | |
| $\pi_1$: $\mathbf{1}\{cogen\}$ | 0.198*** | 0.536*** | 0.718*** | **0.288*** | 0.578 |
| | (0.045) | (0.174) | (0.220) | (0.066) | (0.419) |
| $\pi_3$: $\mathbf{1}\{cogen\}\times$ | -0.014 | -0.035* | -0.32 | | |
| time trend | (0.011) | (0.021) | (0.291) | | |
| 5-year effect | 0.128 | 0.363*** | -0.882 | | |
| Plants (approx.) | 13,000 | 13,000 | 7,000 | 13,000 | 7,000 |
| Observations (approx.) | 157,000 | 157,000 | 20,000 | 157,000 | 20,000 |

Notes: Column (1) use two step procedure described in Chapter 5 (see equation 5.1 and 5.2), while column (2) - (3) use the analogous one step (5.3). Column (4) and (5) do not control for time trend or allow adoption effects to vary over time. Column (3) and (5) use the natural gas purchase quantity data from the MECS, while the rest columns use the ASM. All columns include plant fixed effects and survey year fixed effects. Standard errors are clustered at plant level. * p <0.1, ** p<0.05, *** p<0.01

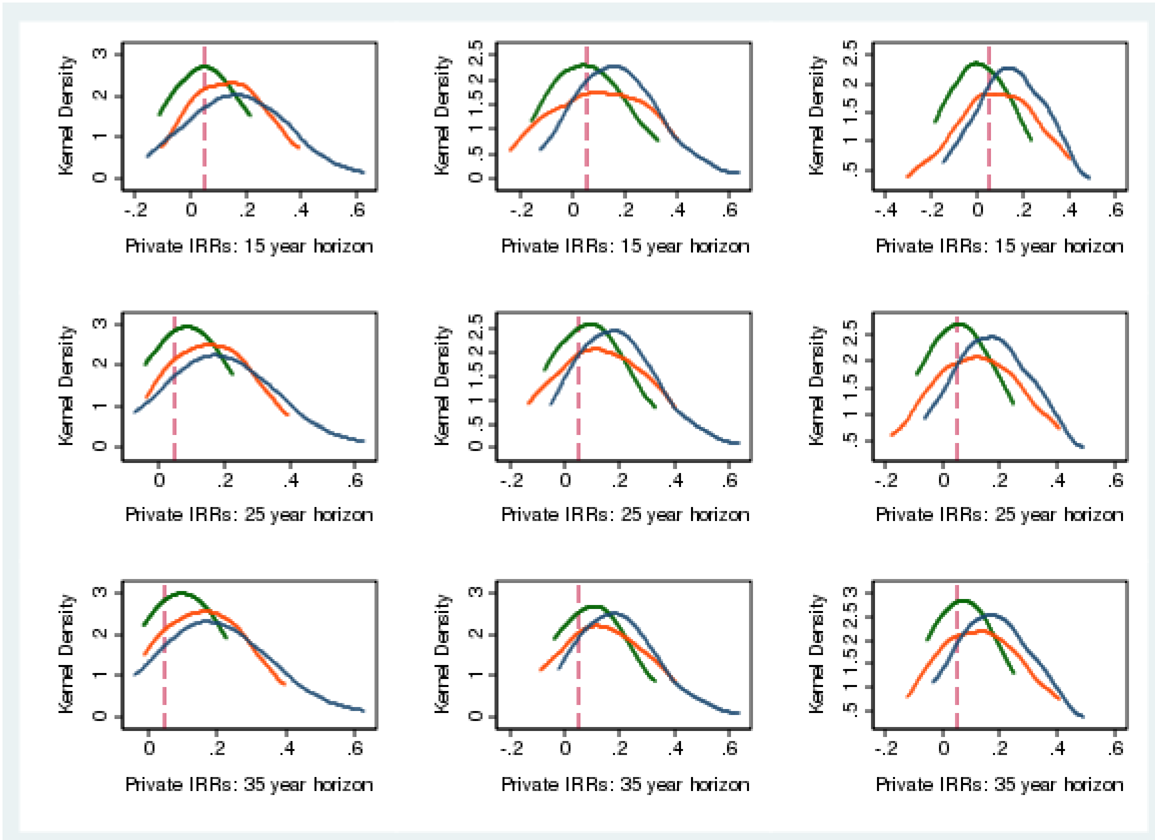
From previous discussion on computing annual savings, we use two different methods. One is less parametric and simply take the average pre and post adoption using the raw data. Two, we use the results from these difference-in-difference regressions. Under each method, we can compute savings from reduced electricity approach, cogenerated electricity approach, and ex ante projected. Figure 6.1 shows that using method one, the distribution of ex ante and ex post internal rate of return largely overlap, regardless if we use the reduced electricity purchase approach or generated electricity approach. This suggests the realized returns are within expectations and holds true also for 15 year, 35 year horizon. Figure 6.2 (private returns) and 6.3 (social returns) shows that using method two, the ex ante and ex post returns still overlapped quite a bit. The three columns in figure 6.2 and 6.3 differ based on how $e_0$, $n_0$, $p_e$, $p_n$ are computed. Column 1 uses the average across all pre-adoption years. Column 2 uses one year prior adoption. Column 3 uses average across seven pre-adoption years. Each row represents a different time horizon, 15, 25, 35 years. The results are largely similar (this is true using none regression method as well). Notice that using the reduced purchase approach (green line) shifts the return distribution to the left of ex ante projections, compared with that in figure 6.1. This is due to a combination of one, relative to control group, the savings are not as large as anticipated, and two, the average effect reflected in the regression coefficient underestimates the savings accrued to large plants since we use the same coefficient on all plants, which shifts the entire distribution towards the left. However, either way, the distribution of returns ex ante and ex post still largely overlapped, for both private and social returns.

**Figure 6.1**. Internal Rate of Return: 25 year horizon



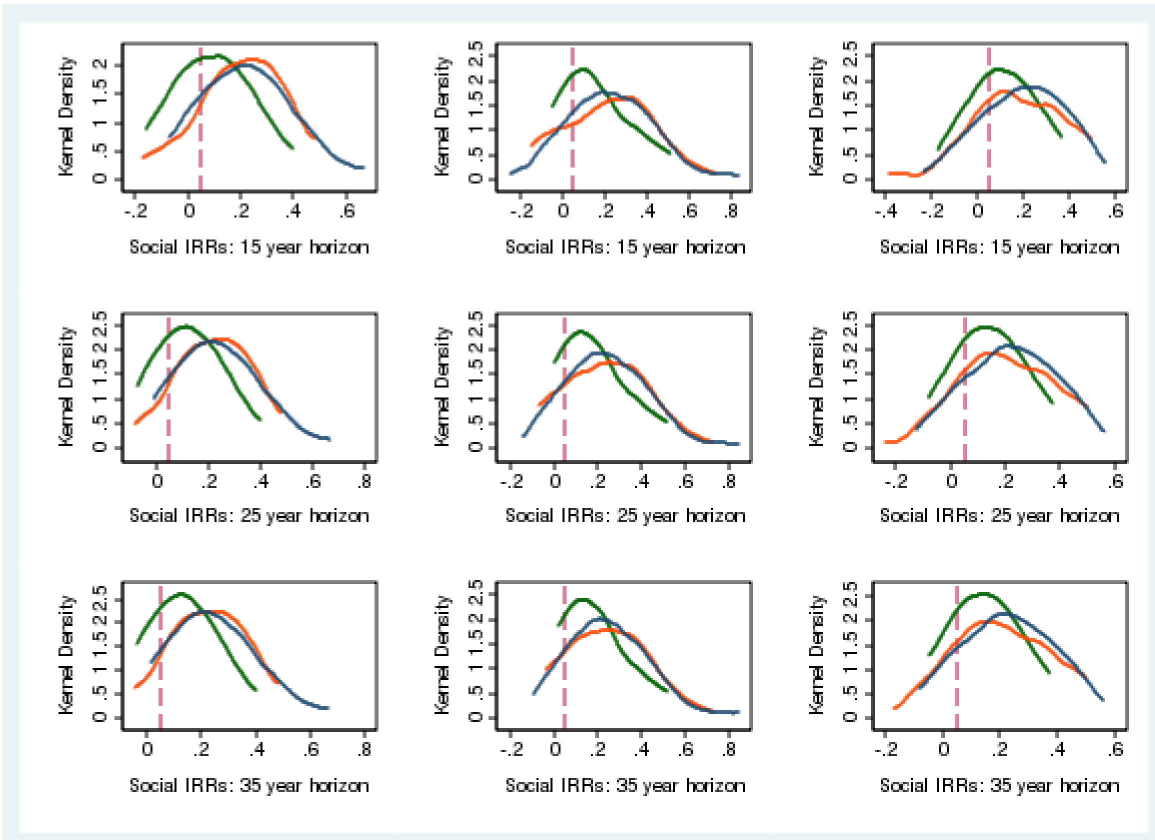

Notes: The first panel shows the distribution of private internal rate of returns computed using raw data, method one, described in Chapter 6.1. The second panel shows the distribution of social internal rate of returns using the same method as the first panel.

**Figure 6.2**. Internal Rate of Private Return




Notes: The figure shows the distribution of private internal rate of returns computed using regression method, method two, described in Chapter 6.1. First column uses the average pre adoption quantity to compute for savings. Second column uses the year immediately prior adoption. Third column uses the average of the seven years prior the adoption event.

**Figure 6.3**. Internal Rate of Social Return




Notes: The figure shows the distribution of social internal rate of returns computed using regression method, method two, described in Chapter 6.1. First column uses the average pre adoption quantity to compute for savings. Second column uses the year immediately prior adoption. Third column uses the average of the seven years prior the adoption event.

Table 6.3 reports the annualized internal rate of return to the median plant for 25 year horizon. Panel B are taken from first column of figure 6.2 and 6.3. Panel A is taken from figure 6.1. The none regression based approach has more or less the similar returns as the ex ante projected. The regression based approach, as discussed earlier, has smaller returns, but still within expectation. Also as expected, the reduced electricity approach consistently yields lower return than using cogenerated electricity. This is because the latter approach assumes all the cogenerated electricity were used to reduce purchase. Some plants could not sell the electricity they generated to the grid due to resistance from the central power plants and may end up wasting some electricity. Since the implicit assumption we make is that plants can always sell to the grid in this approach, we could be overestimating the benefits.

We also tested the assumption that a cogeneration system has 75% load factor in computing the ex ante projected. Our data suggests the the load factor is between 55-65%, which is not far from the assumption. In other words, cogeneration utilization rate is about what we expect. Hence, if we compute the returns based on cogeneration generating capacity or cogenerated electricity quantity, the ex post and ex ante returns should be similar.

In summary, from energy savings perspective, cogeneration delivers fairly well.

Table 6.3: Returns to the Median Plant

| For 25 year horizon | Private IRR | Social IRR |
|---|---|---|
| **Panel A: None Regression Based** | | |
| Reduced electricity approach | 11% | 14% |
| Cogenerated electricity approach | 17% | 20% |
| | | |
| **Panel B: Regression Based** | | |
| Reduced electricity approach | 7% | 13% |
| Cogenerated electricity approach | 10% | 17% |
| | | |
| **Panel C: Ex ante Projected** | 18% | 23% |

Notes: Table reports the annual internal rate of return to the median plant using both regression and none regression based approaches, as well as ex ante projected. Pre- and post-adoption price and quantity averages are taken across all the years.

## 6.2 Effects of Adoption on Manufacturing Production

In terms of helping with manufacturing production, however, adopting a cogeneration seems to put a plant at serious disadvantage with its competitors. Table 6.4 shows the effects of cogeneration adoption on various manufacturing activities. It reports regression results from equation 5.4, changing the dependent variable to a measure of the manufacturing activity. All dependent variables are in logs. All specifications include plant fixed effects and year effects. We observe a sizable decline in real output and TFP.

If there is any significant efficiency gain induced re-optimization, it should be reflected in a plant's manufacturing output. With an increase in energy efficiency, steam and electricity (intermediate input to the final good production) are cheaper than before. As a plant re-optimize, it will likely increase its production output to take advantage of this drop in intermediate input price. But we instead observe significant decline in output and TFP after the technology adoption (see also figure 6.4). Electricity demanded on site (i.e., electricity consumed on site) increased with the adoption, but not at the same level as the decline in output or TFP. The manufacturing production side of business seems to respond very poorly with the adoption of cogeneration.

We also see declines in total employment, total cost of materials, and total cost of energy (see figures 6.6 and 6.7). All the manufacturing inputs declined with the adoption of cogeneration. We use equation 5.1 to produce more event study graphs on this investigation and find that prior adoption of cogeneration, adopting plants and control group face almost parallel trend. After the adoption, similarly as the electricity purchase figure, a large drop happens within first few years of adoption, and persists at a permanent level 7 years down the road. Again, log TFP is computed as $\ln TFP_{ijt} = \ln q_{it} - \alpha_{jl} \ln l_{it} - \alpha_{jk} \ln k_{it} - \alpha_{jm} \ln m_{it} - \alpha_{je} \ln energy_{it}$, where $q_{it}$ is the real output of plant $i$ at year $t$, $\alpha_{jl}$ is the industry level labor cost share, $\alpha_{jk}$ is the industry level capital cost share, $\alpha_{jm}$ is the industry level materials cost share, $\alpha_{je}$ is the industry level energy cost share. $l_{it}$, $k_{it}$, $m_{it}$, $energy_{it}$ are the real labor, capital, material, and energy cost. When all input costs decline, holding output constant, TFP should go up. However, in the case of cogen adoption, output declined more than the costs, total TFP declined significantly.

Table 6.4: Manufacturing Activities Response to Cogeneration Adoption

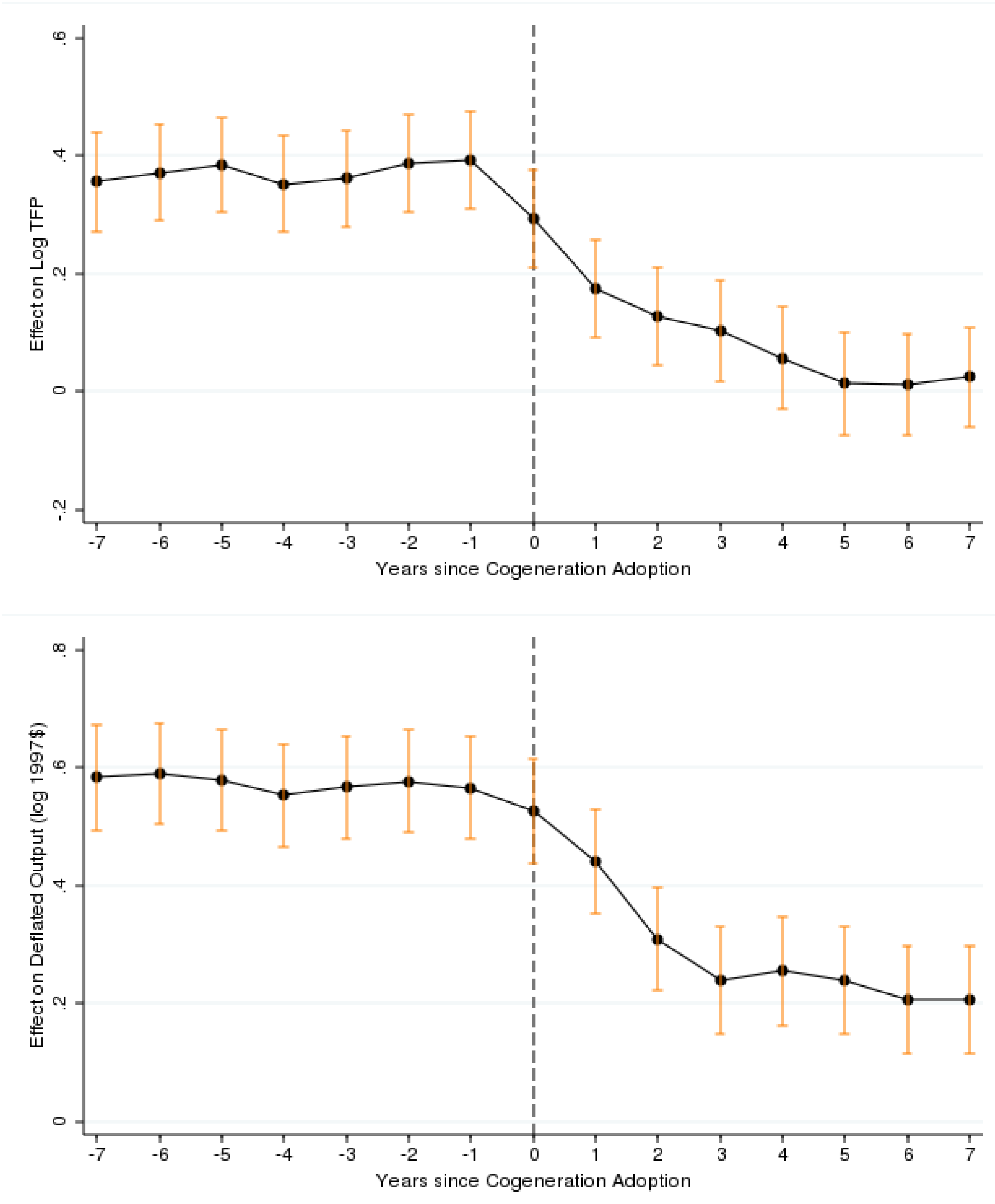
| | Electricity Demanded | Real Output | Log TFP | Energy Cost per output |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\mathbf{1}\{cogen\}_t$ | 0.11* | -0.43* | -0.31** | 0.68*** |
| | (0.07) | (0.23) | (0.14) | (0.21) |
| Adjusted R-squared | 0.91 | 0.92 | 0.64 | 0.80 |
| Plants (approx.) | 8,000 | 13,000 | 13,000 | 13,000 |
| Observations (approx.) | 24,000 | 170,000 | 170,000 | 157,000 |

Notes: Data is from U.S. Census Bureau and Energy Information Administration. Equation 5.4 is estimated. Standard errors (in parentheses) are clustered at plant level. * p <0.1, ** p<0.05, *** p<0.01

Figure 6.5 confirms that the peak in new machinery expenditure or capital expenditure occur at our defined adoption time. Since the adoption event time is defined by merging EIA data unto the Census data, it is comforting to see the Census data is in line with what we would expect, ensuring our data quality is reasonable.

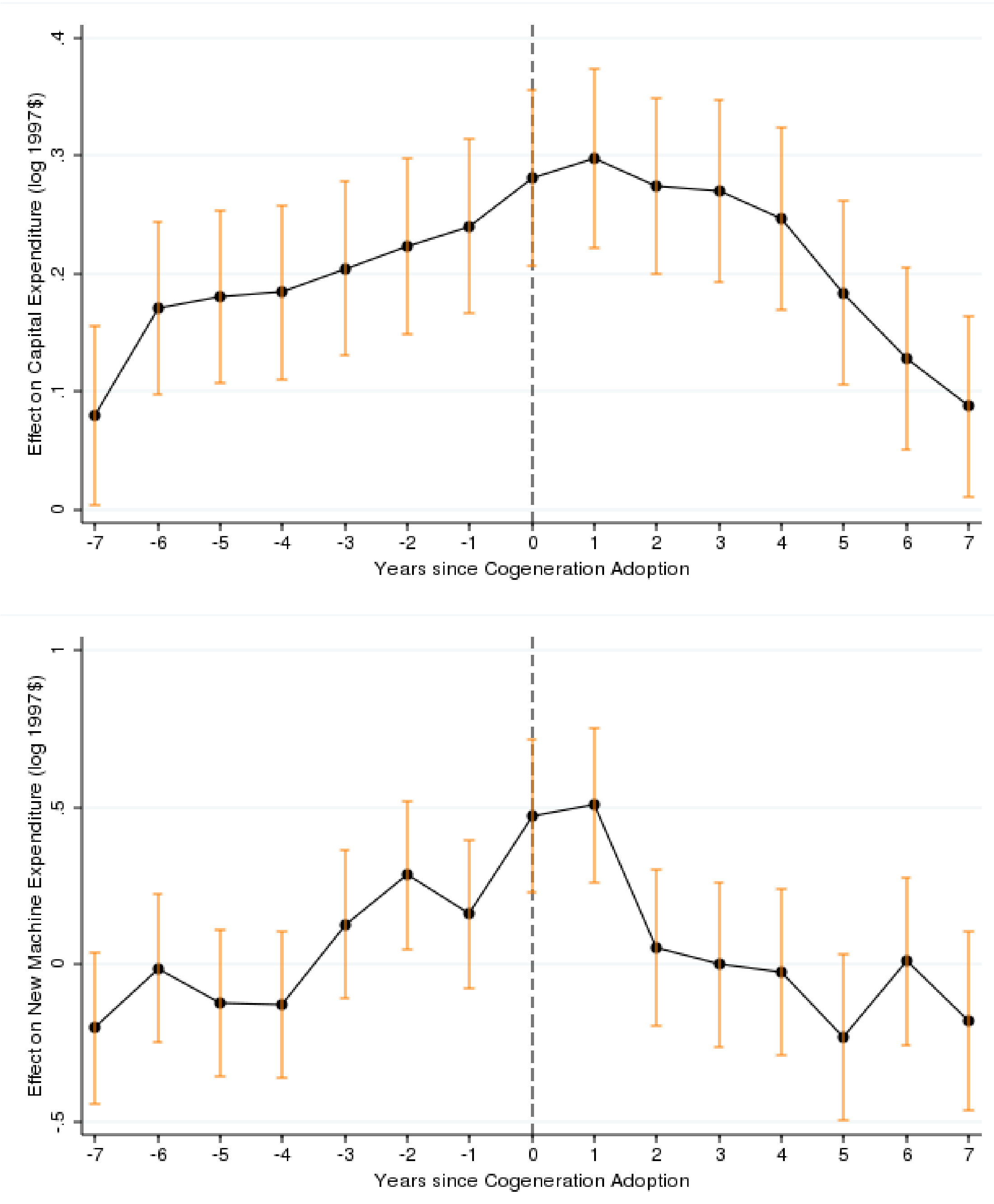
The summary statistics table 4.2 shows the average annual real output for cogen plants is $202,602 = exp(12.22)$ thousand 1997 dollars, or roughly 200 million. A 40% decline would lead to roughly 80 million. This wipes clean all the energy savings and push the total returns into very negative realm. A direct evidence on this decline in output and TFP is the life expectancy of a cogen plant versus a control group plant. Although the lifespan of a cogen plant in the summary statistics table is longer than the control group, this is not the case when we control for birth year and industry. We find strong and significant evidence that a cogen plant survive less years than those none cogen plants born on the same year within the same three digit NAICS industry. This is done by running $lifespan_{ijt} = cogen_{ijt} + \gamma_{jt}$, where $lifespan_{ijt}$ is the lifespan of plant $i$ in industry $j$ (3-digit NAICS) with birth year $t$, $cogen_{ijt}$ is the indicator whether plant $i$ adopted cogen in its life time, $\gamma_{jt}$ is industry by birth year fixed effect. An unit of observation in this regression is a plant. We also find that limiting our sample to a fully balanced panel, in which both control and treatment groups are balanced, the raw summary statistics show treatment plants live 4 years shorter than control group (32 versus 36).

**Figure 6.4**. Production Side: TFP and Output



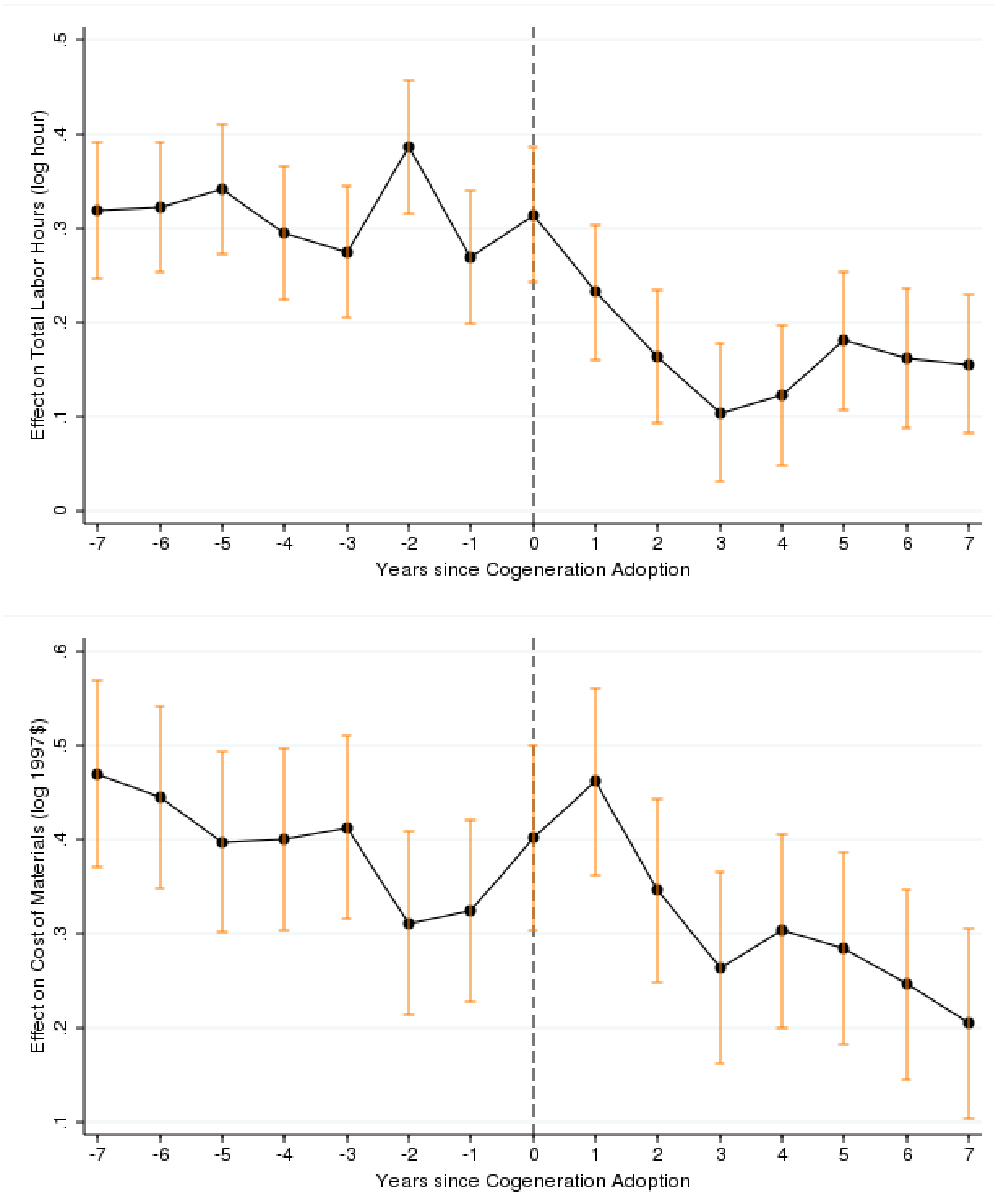

Notes: Data is from the EIA and Census Bureau. The first panel shows the change in log TFP prior and after the adoption of cogeneration. The second panel shows the change in real output prior and after the adoption of cogeneration. Event time is zero when a plant reports to have a cogenerator on site for the first time. Data covers from 1982 to 2010. *N* is roughly 60K with 2K unique establishments.

**Figure 6.5**. Production Side: Capital Expenditure and New Machinery Expenditure



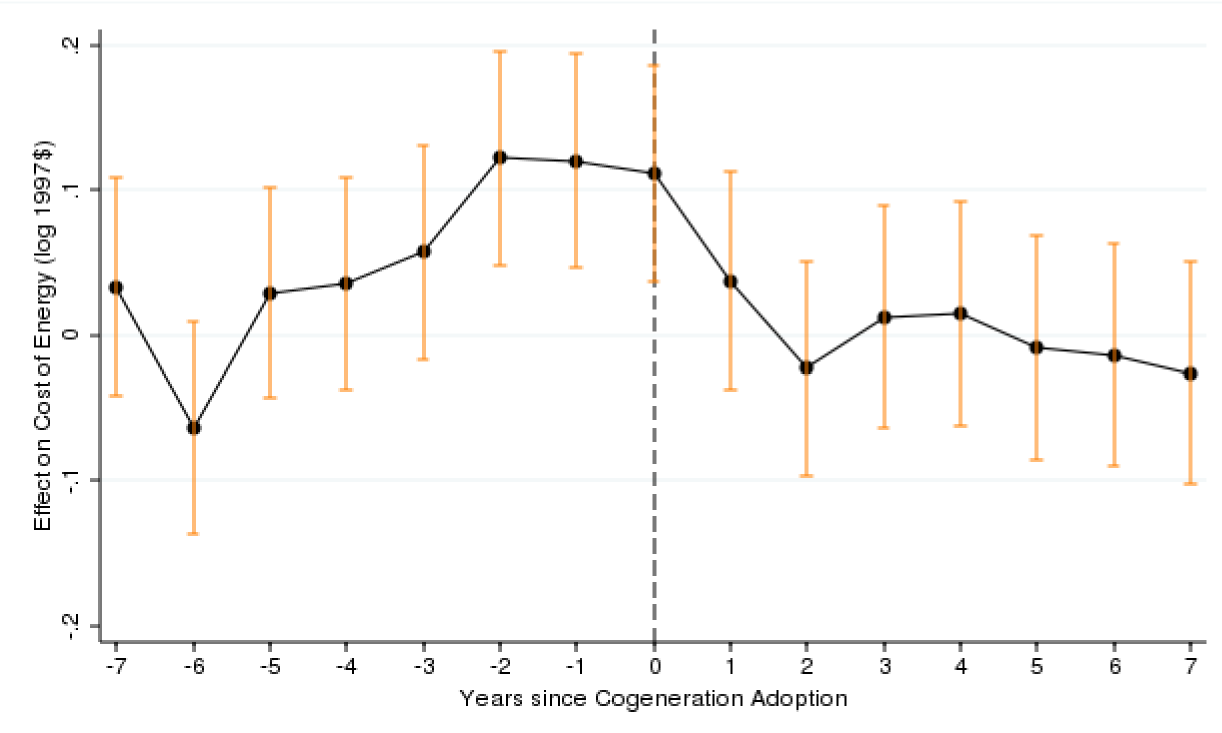

Notes: Data is from the EIA and the Census Bureau. The first panel shows the change in capital expenditure prior and after the adoption of cogeneration. The second panel shows the change in new machinery expenditure prior and after the adoption of cogeneration. Event time is zero when a plant reports to have a cogenerator on site for the first time. Data covers from 1982 to 2010. *N* is roughly 60K with 2K unique establishments.

**Figure 6.6**. Production Side: Total Labor Hours and Cost of Materials




Notes: Data is from EIA and the Census Bureau. The first panel shows the change in total labor hours prior and after the adoption of cogeneration. The second panel shows the change in cost of materials prior and after the adoption of cogeneration. Event time is zero when a plant reports to have a cogenerator on site for the first time. Data covers from 1982 to 2010. *N* is roughly 60K with 2K unique establishments.

**Figure 6.7**. Production Side: Total Energy Expenditure




Notes: Data is from EIA and the Census Bureau. This figure shows the change in total energy expenditure prior and after the adoption of cogeneration. Event time is zero when a plant reports to have a cogenerator on site for the first time. Data covers from 1982 to 2010. *N* is roughly 60K with 2K unique establishments.

## 6.3 Robustness Checks

While the findings are surprisingly, they appear to be robust across various attempts to disprove. Three main attempts were one, check different samples; two, focus on different control groups; and three, use instrumental variable strategy.

The figures were produced using a balanced sample while the tables were produced using an unbalanced panel. We re-produce the event study figures and re-estimate the difference-in-difference estimator using all the data–unbalanced, semi-balanced, and fully-balanced. Unbalanced panel is what has been used in the previous tables. Since our data span from 1982-2010, 29 years, we drop plants that have less than 15 years of obs to create a semi-balanced panel. This gives us roughly 130,000 plant-year obs and reduce the control group number of plants from 13,000 to 5,000. We keep plants with exactly 29 years of obs to create a fully-balanced panel. This gives us roughly 60,000 plant-year obs and reduce the control group further down to less than 2,000. We also create samples with just the top 3 cogen usage industries. The coefficients and figures are solid across these samples, although standard errors increase with the decrease in sample size, particularly with industry case studies. We also check on different event window size for event study figures. The patterns hold true across 3 year, 5 year, and 10 year window size, compared with our baseline 7 year window size. Since we make no attempt to match on plant characteristics in selecting control groups, we perform a propensity matching analysis and compare the results with our baseline. We create propensity scores based on plant size, age, and energy consumption quantity and use these propensity scores as weights in our otherwise identical baseline specification. See table 6.6 for a summary of our robustness checks.

While industry case studies are in a way selecting better control groups, we go further and match plants based on cohort, size (shipment and employment), and industry. We do this none-parametrically. For each treatment plant $i$ that adopted cogeneration at year $\tau$, we identify suitable control plants based on birth cohort, employment size in year $\tau$, and industry. In our sample, the earliest birth year is 1975. Any plants with birth year between 1975-1980 would be in the same birth cohort. We split the entire sample by 5-year gap birth cohort groups into 7 groups in total, 1975-1980, 1980-1985, 1985-1990, 1990-1995, 1995-2000, 2000-2005, and 2005-2010. For each year and industry, employment size can be split into three categories: small, median, and large. Plants in the lowest 25 percentile are in the small category, 25-75 median, and 75-100 large. For industry, we use 3-digit NAICS. Once we identify control plants for each treatment plant, we track the TFP or energy cost per output or electricity purchase quantity differences between these control plants and treatment plants over time. In other words, the control plants are identified at event time zero (adoption year), and we track the performance of these plants relative to the treatment plant across event time, from pre-adoption periods to post. Graphing out these difference over event years gives us a none-parametric event study figure. We found a small drop in the TFP using this nonparametric approach. The pre and post adoption trends look differently than our parametric approach, but nonetheless generates a drop of TFP by 8% over the 7 year post adoption horizon. We also found a smaller increase in energy cost per output relative to the baseline, but still very strong and significant. Over a 5 year horizon post adoption, energy cost per output increases 43% using this nonparametric approach. Without the time trend or allowing the adoption effect to vary over time, energy cost per output increases 20% using this nonparametric approach. The electricity purchase quantity acts as a validation for our nonparametric approach. We found a 60% reduction in both nonparametric matching approach and our baseline approach. Our baseline results using never-adopters by the end of our sample period, 2010, as suitable control plants. We also define controls as plants that did not adopt at the treatment year to include plants that may or may not install cogeneration in a later year, and plants that already have cogeneration. All the results described previously hold true across different definition of "suitable controls".

Table 6.5: Non parametric matching results

| **Dependent Variable:** | Electricity Purchase Quantity (1) | Energy Cost per output (2) | TFP (3) |
|---|---|---|---|
| $\pi_2$: time trend | -0.029 | -0.025* | 0.020*** |
| | (0.027) | (0.010) | (0.005) |
| $\pi_1$: $\mathbf{1}\{cogen\}$ | -0.520** | -0.072 | 0.025 |
| | (0.149) | (0.057) | (0.028) |
| $\pi_3$: $\mathbf{1}\{cogen\}\times$ time trend | -0.017 | 0.071*** | -0.022*** |
| | (0.035) | (0.013) | (0.007) |
| 5-year effect | -0.606*** | 0.426*** | -0.085* |
| | (0.230) | (0.088) | (0.044) |

Notes: Column (1) – (3) use two step procedure described in Chapter 5 (see equation 5.1 and 5.2), all control for time trend or allow adoption effects to vary over time. Step 1 here is to obtain point estimates for the difference in control and treatment group using non parametric matching, analogous to Chapter 5 event study regression. Non parametric matching matches on 3-digit NAICS industry, birth cohort, and employment size. Standard errors are clustered at plant level. * p <0.1, ** p<0.05, *** p<0.01

We push our attempts for instrument variable strategy into the following subsection.

### *6.3.1 Instrumental Variable Strategy*

Among the instruments listed in Chapter 5.5, none is ideal, but some work better than others. First, state level policies do not have strong predictive power in the first stage. In fact, neither the binary nor percentage coding can move the partial F-stat above 3. We also tried to code up the policies from alternative sources. None can do better. This does not come as a complete surprise when utilities fight hard against distributed power generation and most of the environmental policies target renewable technologies or clean energy. Industrial cogeneration still mostly uses fossil fuel (natural gas). Another important reason is that two important federal regulation passed: the Public Utility Regulatory Policies Act (PURPA) in 1978 and the Energy Policy Act 2005 that already removed some of the important institu-

Table 6.6: Robustness check

| | Unbalanced | Semi-balanced | Fully-balanced | Industry-Case | Parametric Matching |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Energy cost per output | 0.68*** | 0.67*** | 0.66*** | 0.47*** | 0.28* |
| | (0.21) | (0.21) | (0.20) | (0.12) | (0.14) |
| TFP | -0.31** | -0.29** | -0.28** | -0.15 | -0.08 |
| | (0.14) | (0.13) | (0.13) | (0.12) | (0.13) |
| Electricity Quantity | -0.65*** | -0.64*** | -0.63*** | -0.65*** | -0.70*** |
| | (0.11) | (0.11) | (0.10) | (0.17) | (0.18) |

Notes: Data is from U.S. Census Bureau and Energy Information Administration. Equation 5.4 is estimated using different sample and weightings. Column (1) is our baseline. Column (2) keeps plants with more than 15 years of observation (roughly 5000 plants). Column (3) keeps plants with exactly 29 years of observation (2000 plants). Column (4) keeps plants within the top 3 3-digit NAICS industries with the most cogenerated electricity in 2010. Column (5) use the entire sample as baseline, with propensity score as weights. Propensity score matching is matched on plant size, age, and energy usage. Standard errors (in parentheses) are clustered at plant level. * p <0.1, ** p<0.05, *** p<0.01

tional obstacles such as lowering standby rates and setting up interconnection rules (Burns et. al., 2014 [4]).

Out of the four within firm instruments, the first two, using same firm (or same firm same industry) out-of-state adoption to predict plant adoption, work the best. The last two use same firm out-of-industry adoption predict adoption and have very low predictive power in the first stage. However, unlike the baseline rock solid OLS results, the performance of the first two instruments depends on the sample. Fully balanced panel produce better results in terms of smaller standard errors and more reasonable second stage results, see table 6.7. Across all samples, with strong predictive power, more out-of-state adoption is associated with less likelihood of adoption. We find negative effect on TFP, negative effects on purchased electricity quantity, and positive effects on energy cost per output. While these are in line with the baseline, the standard errors are too large to be conclusive.

In summary, neither of these instrumental variable strategies is great. We have a weak instrument for all these IVs. It is also difficult to convincingly argue these multi-million investments can be moved by the exogenous factor we listed. Nonetheless, the IV point estimates do have the right signs relative to the baseline.

Table 6.7: Instrumental Variable Results

| | OLS<br>(1) | State Policy IV<br>(2) | Within firm out-of-state IV<br>(3) |
|---|---|---|---|
| Energy cost per output | 0.68*** | 2.13 | 0.02 |
| | (0.21) | (14.04) | (0.96) |
| TFP | -0.31** | -11 | -0.75 |
| | (0.14) | (12.10) | (0.87) |
| Elec. Q | -0.65*** | -4.77 | -1.95** |
| | (0.11) | (6.14) | (0.80) |
| First stage | | 0.004 | -0.013 |
| | | (0.005) | (0.01) |

Notes: Data is from U.S. Census Bureau and Energy Information Administration. Column (1) is our baseline result. Equation 5.5 is estimated for column (2). Equation 5.6 is estimated for column (3). Standard errors (in parentheses) are clustered at plant level. * p <0.1, ** p<0.05, *** p<0.01

## 6.4 Summary

Cogeneration is a technology that essentially trades off purchased electricity by incremental natural gas consumption. We first show that plants with cogeneration on site indeed face higher electricity natural gas price ratio. A series of event study figures also demonstrate that purchased electricity quantity drop significantly upon adoption and natural gas purchase increased somewhat. These event study figures portraits very limited differential trends with the control group prior adoption. Trend break analysis shows that majority of the change due to adoption occurs in the year or within two years of adoption. After the trend break year, plants stay at the same level consistently through the next 7 years. Due to these results, we design our methods to compute for annual savings.

Annual energy savings can be computed through two different methods. Raw data approach and regression based approach. Since we observe most variables needed to compute for savings, we can simply take the average prior and post adoption as a first cut to compare with the ex ante projection. We find that under different time horizon, the distribution of returns largely overlap between ex ante projected and ex post realized. We find similar results using regression based approach.

Although energy savings are within expectation, a surprising result we found is that adopting plant's manufacturing real output and TFP decrease significantly after the technology adoption. The decline in output makes it such that energy cost per output increases 20% after the adoption event. This holds true across different robustness checks–industry specific study, different event window size, and different definition of technology adoption. We also use different control groups, and match our treatment plants none parametrically to study the effects. There is still a 8% TFP decline, although less in magnitude and significance than our parametric event study figures. This is counter-intuitive, but in line with other recent findings that studies green technology adoption in Germany. We also find that adopting plants cut down in employment size and material input, along with cutting down the total energy input. Capital expenditure and new machinery expenditure peaked at adoption year, confirming that our data quality is reasonable.

Acknowledging the endogeneity of adoption event, we continue our study by constructing instrumental variables that plausibly motivate plants to adopt cogeneration for exogenous reasons such as state regulatory changes and tax incentives, or adoptions within the same firm but in different states. We find that government policies, tax incentives and subsidies, are not an important driver for cogeneration adoption decisions, and thus cannot be used as an instrument convincingly. Instrumenting adoption decisions by number of out-of-state adoptions within the same firm have some predictive power in the first stage. These

IV methods also generate a decline in the TFP and an increase in the energy cost per output after cogeneration adoption.

# APPENDIX A

# ADDITION INFORMATION ON COGENERATION

## A.1 DOE method in computing the annual benefits of cogneration

For a cogeneration system with 2679 kw capacity.

- Annual purchased electricity savings: 2679 KW * 8760 hours * 75% load factor (assumed CHP fleet average ) * $0.046/kwh (same unit price used in our empirically estimated savings calculation) = $809,647.38
- Annual incremental fuel cost: 2679 KW * 8760 hours * 75% load factor * 5.0 MMBtu/MWh (assumed incremental heat rate for electricity produced by CHP systems) * $3.60/MMBtu (same unit price used in our empirically estimated savings calculation ) /1000 KWh/MWh = $316,818.54
- Annual incremental O&M cost: 2679 KW * 8760 hours * 75% load factor *$0.0125/kWh O&M costs (average CHP system incremental O&M costs) = $220,012.88
- Annual savings to users: $809,647.38- $316,818.54 - $220,012.88 = $272,815.96

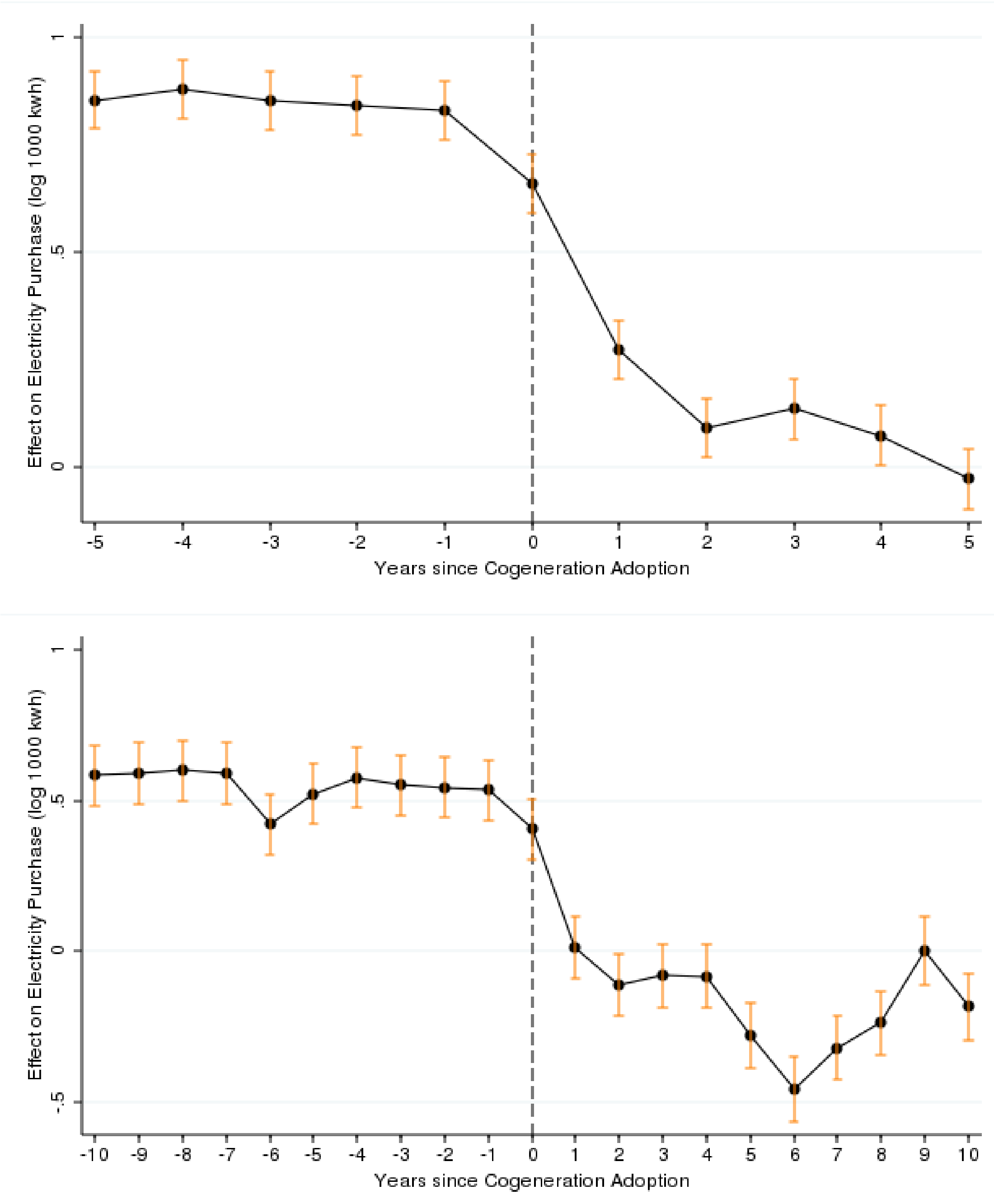
## A.2 Event Studies

We use a series of event study figures to help decide what approaches to take in computing annual savings used to compute the internal rate of return:

$$\ln(y_{it}) = \alpha + \sum_{\tau} \sigma_{\tau} D_{\tau,it} + \alpha_i + \alpha_t + \varepsilon_{it}$$

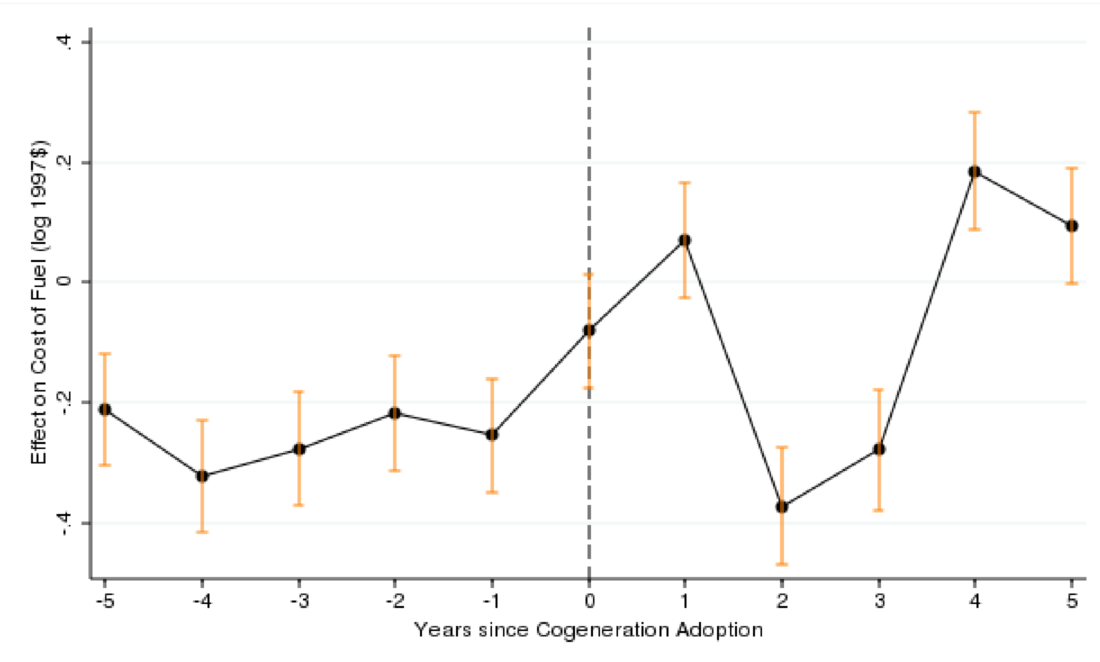
where $\ln(y_{it})$ is the natural log of fuel purchase quantity (natural gas, or electricity) at plant $i$ in year $t$. $D_{\tau,it}$ is an event indicator which turns on 1 at event time $\tau$ for plant $i$ in year $t$. Event time 0 is defined as the year EIA survey reports the plant's first cogenerator is installed. $\alpha_t$ is year fixed effects and $\alpha_i$ is plant fixed effects. We report various event window size here.

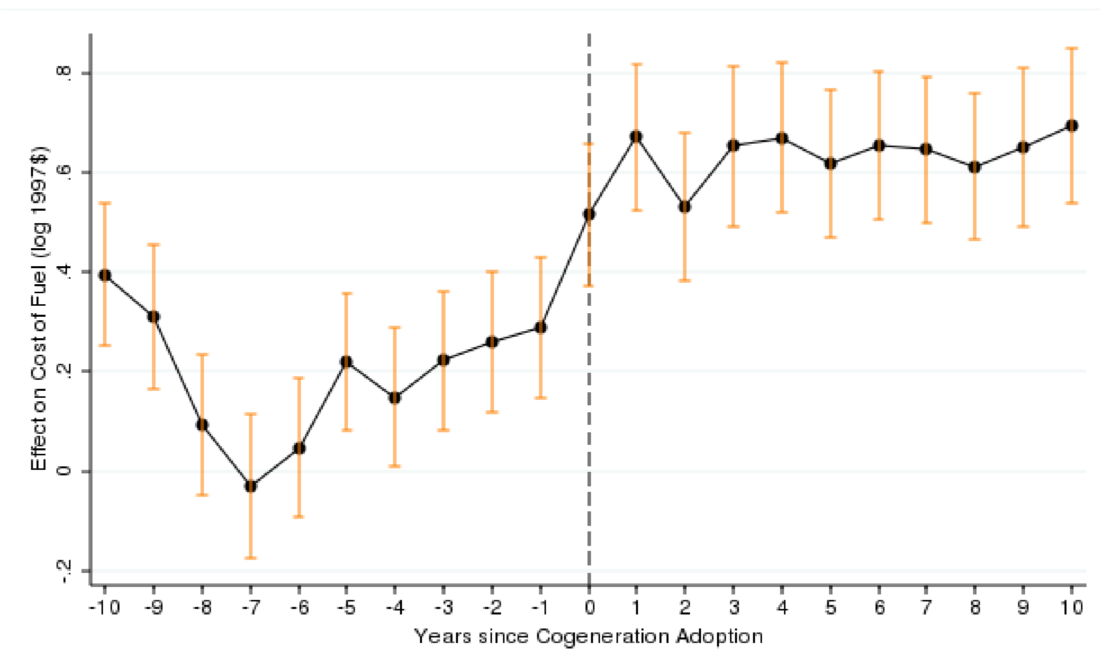
**Figure A.1**. Effect of Adoption on Electricity Purchase Quantity




Notes: Data is from the US Census Bureau and Energy Information Administration. Event time is zero when a plant reports to have cogeneration on site for the first time. Data covers from 1982 to 2010. *N* is roughly 174K with 13K unique establishments.

**Figure A.2**. Effect of Adoption on Cost of Fuel




Notes: Data is from the US Census Bureau and Energy Information Administration. Event time is zero when a plant reports to have cogeneration on site for the first time. Data covers from 1982 to 2010. $N$ is roughly 174K with 13K unique establishments.

## A.3 Penetration Ratio

Table A.1 shows the top ten 3-digit NAICS industries that cogenerated largest amount of electricity in year 1985 and 2010. The ranking has not changed much at all between the 15 years. In many of these industries where cogeneration technology were exploited the most, the penetration ratio (across different measures) was low in 1985 and remained low in 2010 (except for paper manufacturing, and petroleum and coal products manufacturing). This suggests that even among the most penetrated industries, there is still space for adoption. Outside of top three industries, no industry has a penetration ratio higher than 20 percent by all measures in 2010. From the technical side (plants with high steam load factor that could use the waste heat for electricity generation), there is ample room to grow.

## A.4 Installation Time

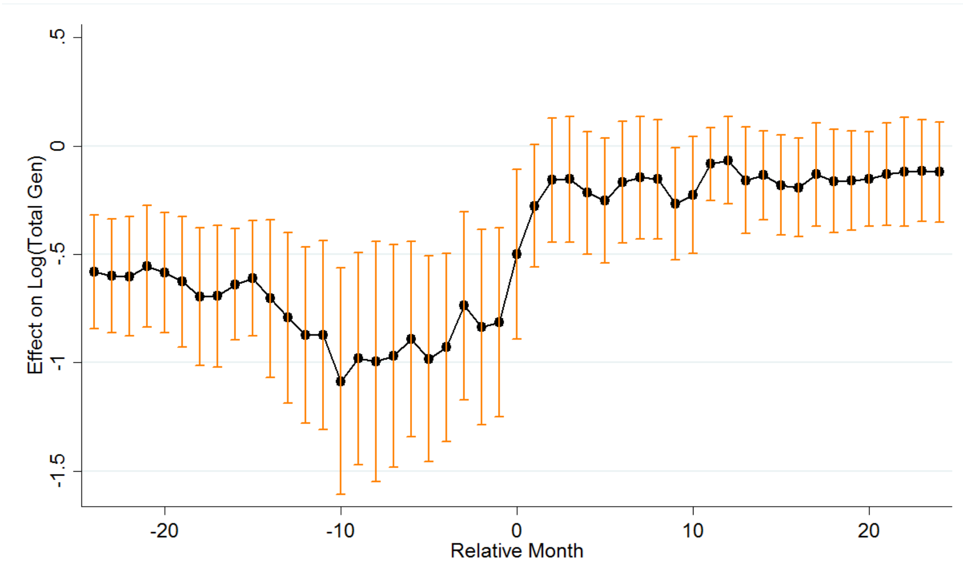
In Figure A.3, we produce an event study group with a balanced panel that have 24 pre and post adoption months. We show that when a power plant adopts cogeneration, we first observe a 15-month decline in total power generated prior the operation date of the cogeneration system and after operation date, total power generated increases to above the pre adoption level. This suggests that a cogeneration system takes about 15 months from installation to full operation. Ideally, we would like to do this for manufacturing plants. However, the EIA does not collect information prior a manufacturer install generators on site. Overall, power plants install larger cogenerators than manufacturers and would take them longer to install the system.

Table A.1: Penetration Ratio by Top Cogen Industries

| 3-digit NAICS Industry | 1985 Penetration Ratio | | | 3-digit NAICS Industry | 2010 Penetration Ratio | | |
|---|---|---|---|---|---|---|---|
| Manufacturing | (1) | (2) | (3) | Manufacturing | (1) | (2) | (3) |
| Paper | 0.2638 | 0.4698 | 0.2585 | Chemical | 0.2663 | 0.4291 | 0.2512 |
| Chemical | 0.0868 | 0.2544 | 0.0779 | Paper | 0.5520 | 0.7544 | 0.5462 |
| Petroleum and Coal Products | 0.1204 | 0.2982 | 0.1105 | Petroleum and Coal Products | 0.2884 | 0.7586 | 0.2254 |
| Primary Metal | 0.0424 | 0.1908 | 0.0391 | Primary Metal | 0.0743 | 0.1950 | 0.0672 |
| Food | 0.0629 | 0.1026 | 0.0645 | Food | 0.1229 | 0.1315 | 0.1224 |
| Beverage and Tobacco Product | 0.0759 | 0.1968 | 0.0735 | Wood Product | 0.1014 | 0.1515 | 0.10 |
| Transportation Equipment | 0.0116 | 0.0190 | 0.0113 | Transportation Equipment | 0.1219 | 0.1995 | 0.1119 |
| Wood Product | 0.0618 | 0.0994 | 0.0627 | Beverage and Tobacco Product | 0.1346 | 0.2369 | 0.1229 |
| Textile Mills | 0.0282 | 0.1063 | 0.0272 | Nonmetallic Mineral Product | 0.0454 | 0.0548 | 0.0430 |
| Nonmetallic Mineral Product | 0.0074 | 0.0271 | 0.0071 | Plastics and Rubber Products | 0.0907 | 0.1785 | 0.0917 |

Notes: Data is from the US Census Bureau. Ranking is the top ten 3-digit NAICS industries with largest amount of cogenerated electricity, 1 being the highest. Under column Penetration Ratio: Column 1 is measured by total value of shipment. Divide the total value of shipments from the plants with cogeneration technology (technology usage definition: cogenerated nonzero electricity on site) by total value of shipments from all the plants in a given year. Similarly, column 2 is measured by total employment. Column 3 is measured by number of establishments.

**Figure A.3**. Installation Time




Notes: Data is from the EIA860, 923 survey from 2001-2013. We include plant fixed effects and month-year fixed effects in our event study regression.

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