The Effects of State Energy Policy on Residential Electric Energy Burden

A thesis submitted by

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ABSTRACT

This thesis examines how state level energy efficiency resource standards (EERS), renewable portfolio standards (RPS), and electric sector deregulation have affected US households' energy burden. "Energy burden" represents the percentage of household income that is spent on energy for domestic use, and this analysis defines a related metric that is specific to electric purchases. The study posits that most policies have increased electric energy burden and employs fixed effects panel regression techniques to test this hypothesis across 105 private, investor-owned electric utilities and twenty-two years. Utilities' geographic service territories are the analytical units, and a typical household's electric energy burden is estimated for each utility in each year. The results suggest all three policies are associated with increases in electric energy burden over time, which corroborates previous research that examined electricity prices only. The study concludes with a discussion of avenues for future research that would expand upon these results.

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GLOSSARY

C&I: Commercial and Industrial

DSM: Demand Side Management

EERS: Energy Efficiency Resource Standard

ERCOT: Electric Reliability Council of Texas

FERC: Federal Energy Regulatory Commission

IOU: Investor-Owned Utility

ISO: Independent System Operator (equivalent to RTO)

LIHEAP: Low Income Home Energy Assistance Program

LMI: low- and moderate-income

LRAM: Lost Revenue Adjustment Mechanism

MWh: Megawatt-hour

OASIS: Open Access Same-Time Information System

PURPA: Public Utility Regulatory Policies Act of 1978

RPS: Renewable Portfolio Standard

RTO: Regional Transmission Operator (equivalent to ISO)

SBC: System Benefits Charge

T&D: Transmission and Distribution

WAP: Weatherization Assistance Program

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CHAPTER 1: INTRODUCTION

In the early 1990s, US states began to upend the traditional paradigm of electric service provision that had been in place for nearly a century. Spurred by regulatory changes on the federal level, as well as by a desire to promote cleaner energy sources and to introduce competition into the electric industry, states began adopting measures that altered longstanding business models, expanded the number of players in the sector, and allowed consumers greater control over their purchasing decisions. The most prominent new policies were energy efficiency resource standards (EERS), renewable portfolio standards (RPS), and deregulation of the power sector, which respectively promoted consumer energy efficiency, generation from renewable sources, and competition in electric generation and retailing. Numerous studies over the past two decades have analyzed the effects of these nationwide experiments, with results that often conflict ideologically, if not mathematically.

With respect to consumers, the literature focuses largely on how electric rates have changed in response to policy implementation. Yet It is not sufficient to consider only on how these policies have affected rates, since rates are only one piece in the larger puzzle of costs. Another metric that is particularly relevant to residential electricity consumers is “energy burden,” which measures the percentage of a household’s income that is devoted to energy purchases. In this study, I define a new measure of energy burden – median household electric burden (MHEB) – that specifically describes how much a typical household spends on electricity in a given year. I then perform a series of fixed effects econometric analyses to determine whether and how the policies described above have affected US households on average.

Public policy is about more than numbers and targets – it is about people. In this study, I attempt to merge the policy impacts and energy burden literatures to explore a new angle of the electric system upheaval of the past two decades. I focus on energy burden to show how documented changes in the costs faced by electric consumers relate to overall income, with a view towards the low- and median-income (LMI) consumers who, as previous research has shown, already tend to pay more for their electricity. If well-intentioned policies have inadvertently increased energy burden without providing relief for those consumers who are most drastically affected, then policymakers and regulators must recognize and address this disparity. I hope this analysis will illuminate pathways for future research that openly reviews the successes and failures of recent energy policy and, in doing so, points to solutions that address critical environmental needs while ensuring equitable access to energy for all members of society.

CHAPTER 2: LITERATURE REVIEW

This chapter describes the historical and political context of the state energy policies considered in this study, including the results of previous research exploring their effects on electric rates. The first three sections below consider each of the policies in turn. The fourth section outlines the concept of "energy burden," which is central to the main analysis in Chapter 4.

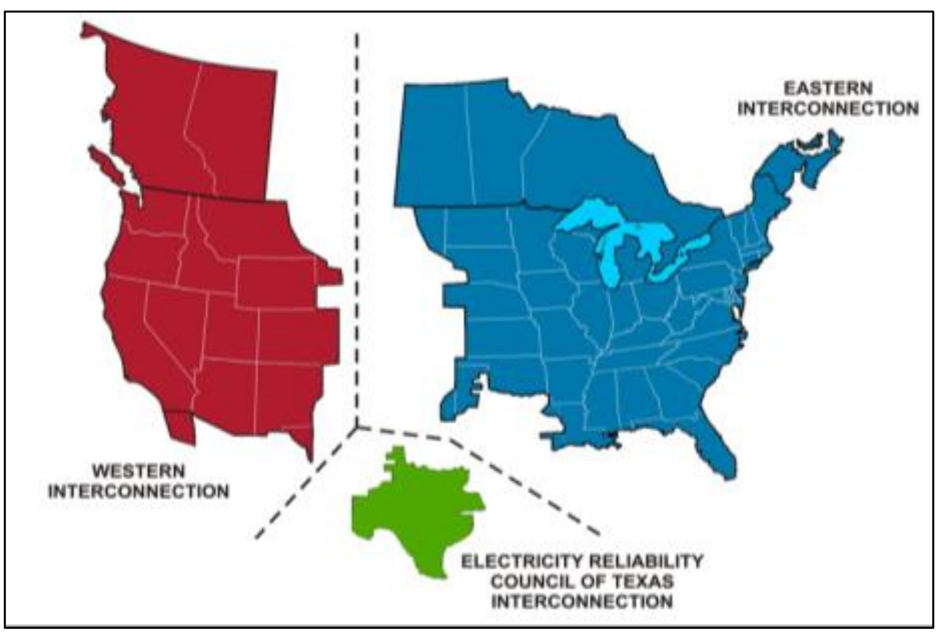
History of Electric Utility Regulation in the United States

Since electrification began in the early twentieth century, the primary model for electric service in the United States has been vertical integration. Under this system, a utility company owns and operates the entire electric infrastructure – from generating plants to intra- and interstate transmission lines to local distribution networks – within a defined geographic territory (Hickey and Carlson 2010), and it is the sole provider of electric service within that territory. This model stems from the nature of utilities as natural monopolies. Given economies of scale and the enormous amount of land and capital infrastructure involved in electric service provision, it is considerably more cost effective to grant one company exclusive jurisdiction than to allow several competitors to build parallel networks and attempt individual cost recovery (Ventosa, Linares, and Pérez-Arriaga 2013). Yet as natural monopolies, utilities are subject to the same pressure towards underproduction and overpricing faced by profit-maximizing monopoly firms in other markets.

Responsibility for regulating these monopolies – referred to as "investor-owned utilities (IOUs)" from now on – has traditionally fallen to the states (Joskow 2005). The state agencies with jurisdiction over electric utilities (and often over other monopoly network services such as natural gas, water, landline phones, and internet) generally have names such as "Public Utility Commission," "Public Service Commission," or "Commerce Commission" and are empowered to "[e]nsure that rates, terms, and conditions established for public service companies are just, reasonable, and transparent" (Maryland Public Service Commission 2017, 1). In so doing, they also allow utilities to recoup costs and therefore to remain financially stable enough to attract private investment (Hickey and Carlson 2010). Several other types of electric service provider have also come into being around the country, including federal generators and wholesalers (e.g. the Tennessee Valley Authority and the Bonneville Power Administration), state-owned service providers (e.g. the New York Power Authority), rural electric cooperatives, and municipal electric companies. Though these entities are subject to varying degrees of board or municipal oversight, they generally are not answerable to state utility commissions in the same way as IOUs.

The electric transmission system in the forty-eight contiguous states is divided between three separate grids – the Eastern, Western, and Texas (ERCOT) Interconnections – and each utility's service area represents a component of one of these grids (Joskow 2005). As shown in Figure 2.1, the Eastern and Western Interconnections span multiple states, as well as parts of Canada and Mexico, and interstate transactions on these grids are subject to federal regulation (FERC 2016). The Federal Energy Regulatory Commission (FERC) oversees electric transmission between states in accordance with the Federal Power Act of 1935 (Joskow 2005); FERC itself was originally constituted by the Federal Power Act of 1920 and received its current name in the 1977. FERC also has jurisdiction over *contracted* sales of power between utilities within and amongst states, which constituted the primary instruments of transmission between utility service territories prior to restructuring efforts that began in the late 1970s (Joskow 2005).

FIGURE 2.1: Electric Grids Covering the Contiguous United States



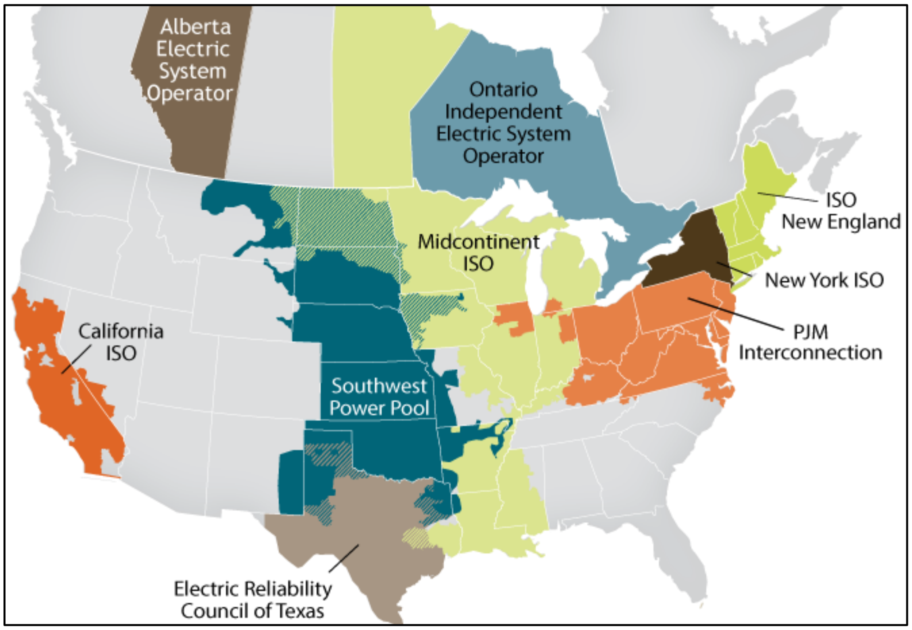
Source: John A. Dutton e-Education Institute (2017)

After a series of oil price shocks that rattled confidence in the prevailing electric system, Congress passed the Public Utility Regulatory Policies Act (PURPA) of 1978, which required that utilities buy power from the cheapest available sources, even if those sources were not their own generators (Union of Concerned Scientists 2016). These independent producers tended to be fossil fuel co-generation plants and renewable energy facilities (Joskow 2005). Congress further promoted restructuring with the Energy Policy Act of 1992, which loosened regulations on utilities owning independent generators and bolstered FERC's ability to require that utilities open their transmission infrastructure to others in support of trade (Joskow 2005, 102).

The trend towards a new paradigm for both electric and natural gas provision also found its way into state policy, starting with California in 1994 (Nadel and Kushler 2000). States began to require that electric utilities sell off their generation assets (power plants) to promote competition in electricity production (Hickey and Carlson 2010). Wielding its authority in support of PURPA and state level deregulation, FERC moved to enshrine greater access to transmission infrastructure in the US Code through its simultaneous rulemakings Order 888 and Order 889 in 1996 (Joskow 2005). The first of these required that utilities file tariffs with FERC that explicitly delineate the transmission services they will offer (and at what prices), whereas the second required that transmission owners develop Open Access Same-Time Information Systems (OASIS) – alone in conjunction with others – that would make both tariffs and system conditions publicly available in real time (Ibid.). Thus, FERC's intent was to inject transparency and consistency into services that utilities had been providing to each other for years, but which would now be opened to a much wider customer base.

Joskow (2005) notes that the creation of interstate wholesale markets for electricity was FERC's long-term goal, and after the passage of Orders 888 and 889, the agency strongly encouraged utilities in California and the Northeast to transform less formal sales agreements (power pools) in which they had participated since the 1960s into formal independent system operators (ISOs) with jurisdiction over load dispatch, planning, voluntary markets, and other areas (105). Utilities in these regions complied, followed by many in other parts of the country, and FERC issued Order 2000 in 1999 to set rules for ISOs that included development standards, operation of OASIS systems, and a requirement that participating utilities hand over operation of their transmission infrastructure to the ISO (Joskow 2005). Yet Joskow (2005) also stresses that the national electric system is still far from integrated, as neither states nor FERC have oversight over all transactions, ISOs have the authority to operate markets but do not necessarily own the relevant transmission infrastructure, and there are "no clear and coherent national laws that adopt a competitive wholesale and retail market model as national policy and that give federal authorities the tools to do the necessary restructuring and wholesale market design work required to make it work" (96). Figure 2.2 depicts the ISOs in existence today (also known as Regional Transmission Operators or RTOs), which cover many states that have deregulated their internal electric sectors and several that have not.

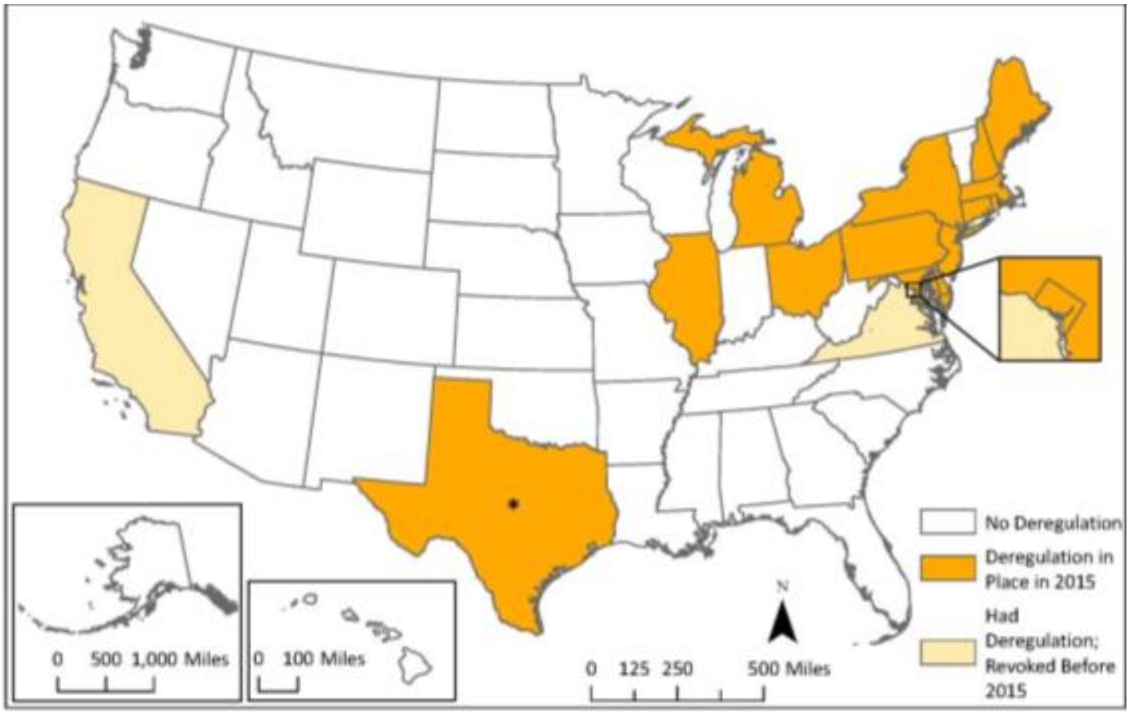
FIGURE 2.2: Independent System Operators of North America



Source: ISO/RTO Council (2015)

State level deregulation has generally pushed beyond divestment of generation assets (and participation in wholesale markets) to allow individual customers to choose their energy supplier. In such cases, rather than receiving "bundled" service from the utility that includes both energy and network (transmission and distribution) components, the customer may elect to purchase electricity from a third party while still paying the local utility to physically deliver that electricity through its network. Third parties might be power plants – if the consumer is large enough to sign a long-term contract – or they might be retailers participating in real-time wholesale markets (Woo et al. 2006). States that had deregulated their electric sectors by 2015 are depicted in Figure 2.3.

FIGURE 2.3: States with Deregulated Electric Sectors in 2015



*Deregulation in Texas only applies to IOUs within the ERCOT region (see Figure 2.1).
Map produced by author. Data sources: Electric Choice (2016), Stanford University (2003), Swadley and Yücel (2011)

Deregulation has not been a smooth process, and the results appear to be mixed. For one thing, actions by ENRON and other firms to artificially inflate prices in the California market caused a severe power crisis in that state during 2000 and 2001, which in turn curbed enthusiasm for deregulation in other states (Joskow 2005; Woo et al. 2006). Axelrod, DeRamus, and Cain (2006) argue that deregulation enabled efficiency improvements in plant construction and maintenance, as well as greater access to low-cost generation. Woo et al. (2006) point out, on the other hand, that efficiency gains were partly due to utility layoffs and that reliability (reserve capacity) requirements make arguments for cutting expenditures less realistic. Oppenheim and MacGregor (2003) similarly note that closures of utility field offices contributed to this efficiency gain.

For those consumers that choose to remain with their utility rather than shop for another retailer, the pass-through of prices depends largely on the local regulatory scheme. Traditional cost-of-service regulation generally allows distribution utilities to recoup all costs from ratepayers at a later date, whereas more recent "efficiency based" approaches, such as RPI-X, encourage efficiency and break the direct pipeline from costs to rates (for a comprehensive discussion of various regulatory approaches to distribution, see Gómez 2013). Yet particularly for those consumers who began choosing new suppliers, deregulation upended the standard ratemaking scheme. Axelrod, DeRamus, and Cain (2006) note that divestment of generation assets rightly transferred some cost risk from consumers to investors. This shift brought electric provision more in line with other (imperfectly) competitive sectors of the economy, where recent scholarship has shown that cost swings are only partially commuted from producers to consumers (Ganapati, Shapiro, and Walker 2016).

In the early years at least, the inelasticity of hourly demand for electricity caused large price swings in spot markets, which in combination with the spread of risk to investors raised concerns that generation investment would fall short of needs (Woo et al. 2006). In an attempt to shield consumers from anticipated price spikes upon switching to deregulated markets, many states imposed rate caps during the transition that hid a nationwide increase in natural gas prices; once caps were lifted, electricity prices jumped dramatically (Hickey and Carlson 2010; Swadley and Yücel 2011). Furthermore, the ability to switch to a third party – and thus to escape the old utility rate calculation model – was not open to all customer classes, as several third party providers indicated to utility commissioners that they had little intention of taking on less profitable low-income households (Oppenheim and MacGregor 2003).

Hickey and Carlson (2010) study changes in residential electric rates among states that did and did not deregulate in the 1990s and 2000s. They find that among fourteen states (and DC) that restructured their electric markets between 1990 and 2008, rates were generally higher than those in the remaining states both before and after the restructuring, though the *pace* of increases in several of these restructured states dropped below the pace in the remaining states. Swadley and Yücel (2011) also study the change in rates for all residential customers in sixteen states from 1990 to 2010, controlling for rate caps, lags in fuel prices, rates at which residential customers switched from utility service to third party service, and other variables. They find that increases in natural gas and coal prices had statistically significant positive effects on electricity rates, that rate caps did lower prices initially, and that deregulation did not necessarily decrease rates in the end. Yet they also find that an increase in the number of customers switching to third party service has a significant and negative long term effect on average rates. The researchers conclude that high rates of switchover to third parties may be necessary to lower retail rates in competitive markets. Nevertheless, these results speak to the average of rates faced by all consumers but do not identify the specific effect on rates for those who remain with utilities.

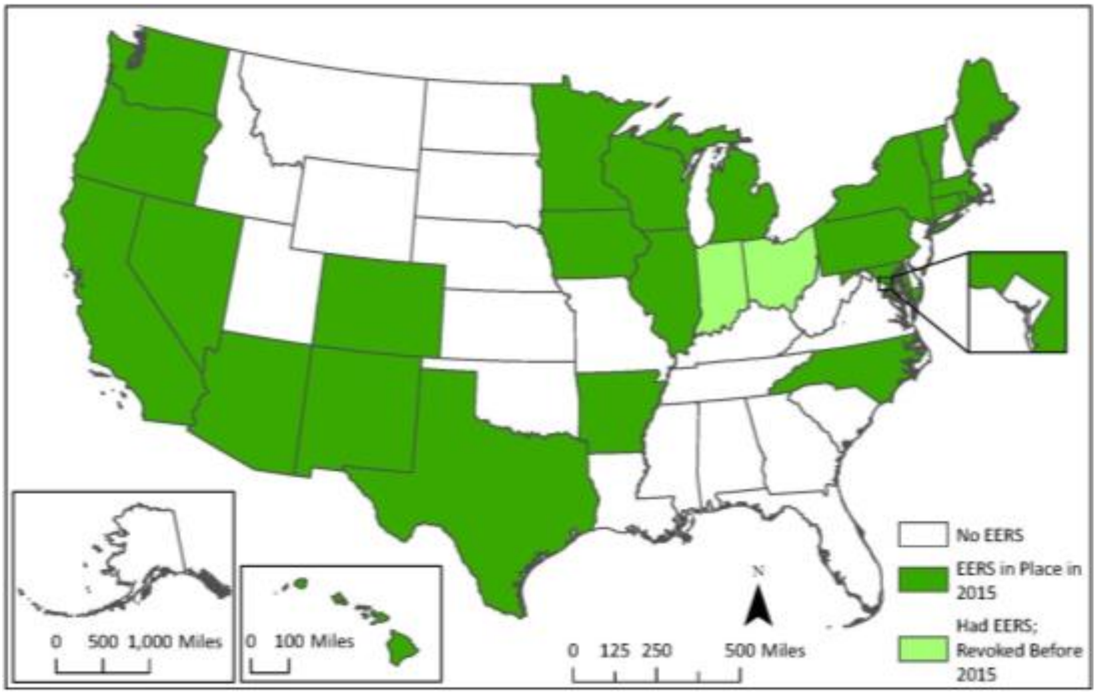
Energy Efficiency Resource Standards (EERS) and Decoupling

Deregulation is not the only major energy policy to have seen differential adoption among states over the past several decades. Although PURPA – and its successors – may have been "the single most effective measure in promoting renewable energy" (Union of Concerned Scientists 2016, 1), states have also pursued several other measures to that end. Electricity still cannot be economically stored on a large scale, which means that it must be used in real time as it is produced and that utilities must prepare to meet the highest projected load during their chosen planning horizon, even if that load only applies to a few hours out of the year (Brennan and Palmer 2013). Beginning in the 1970s, utilities in the Northwest and later in other regions of the country started implementing energy efficiency programs among their customer bases to ease high prices and to meet demand forecasts (Nadel and Kushler 2000). Programs are funded in several ways, most commonly through a “system benefits charge (SBC),” which is a standard number of mills per kilowatt-hour that is levied on all end use consumers statewide and used to reimburse utilities for their program costs (Ibid.). Over time, these programs grew from narrowly defined direct installation and purchase rebate programs to include comprehensive market transformation – that is, promoting greater efficiency among entire product fleets (Ibid.). Utilities across the country now run numerous types of efficiency programs geared towards electric and natural gas products and processes in all customer classes, ranging from standard appliance rebates to upstream marketing to behavior change (for example, see CEE 2016a).

Energy efficiency is consistently found to be highly cost effective relative to other energy resources (for example, see Arimura et al 2012 and Ettenson and Heavey 2015), although such calculations depend heavily on savings assumptions, discount rates, and included costs and benefits. Ettenson and Heavey (2015) argue that although California has among the highest electric *rates* in the country, efficiency has caused average *bills* to be among the lowest nationwide. Programs can help reduce peak load and therefore delay or avert expensive investment in power plants meant only to meet the highest peak (Brennan and Palmer 2013). They can also provide numerous tangential benefits to the most vulnerable communities. Ettenson and Heavey (2015) note that the benefits of energy efficiency to low-income communities include higher discretionary income, improved comfort and health, and even enhanced job opportunities where programs include local hiring requirements. Utility expenditures on energy efficiency programs were roughly $2 billion (in 2007 dollars) in 1993 (Arimura et al 2012) and grew to nearly $7.5 billion (in 2007 dollars) in 2014. These expenditures include roughly $6.1 billion on electric efficiency and roughly $1.5 billion on natural gas efficiency (CEE 2016b). This growth occurred despite a 43% drop in expenditures between 1993 and 1998 as the onset of deregulation placed pressure on utilities to cut costs and to eliminate efficiency programs (Nadel and Kushler 2000).

Since energy efficiency requires that an electric utility sell less of its product, states have implemented a handful of policies to incentivize utilities to pursue efficiency programs. One example is energy efficiency resource standards (EERS) that apply statewide and generally specify a demand target that must be met within a specific timeframe, the entities that will be required to exhibit performance, and the efficiency measures that are acceptable in pursuit of the target (Steinberg and Zinaman 2014, 5). Savings are usually defined either as a target percentage of a counterfactual baseline or as a percentage reduction beneath that baseline (Brennan and Palmer 2013). Thus, they act as an incentive – particularly for utilities – to boost their commitment to existing efficiency programs or to create new ones. Brennan and Palmer (2013) note that justifications for EERS often extend beyond simply promoting efficiency and reducing peak load to goals such as national security, reducing carbon emissions, and job creation. In considering whether EERS lead to lower emissions, however, Brennan and Palmer (2013) find that they are only optimal emissions reductions policies under very specific market circumstances and that even those EERS aimed at shaving peak demand generally reduce only a small fraction of peak use. States with an EERS in place in 2015 are depicted in Figure 2.4 below.

FIGURE 2.4: States with an Electric EERS in 2015

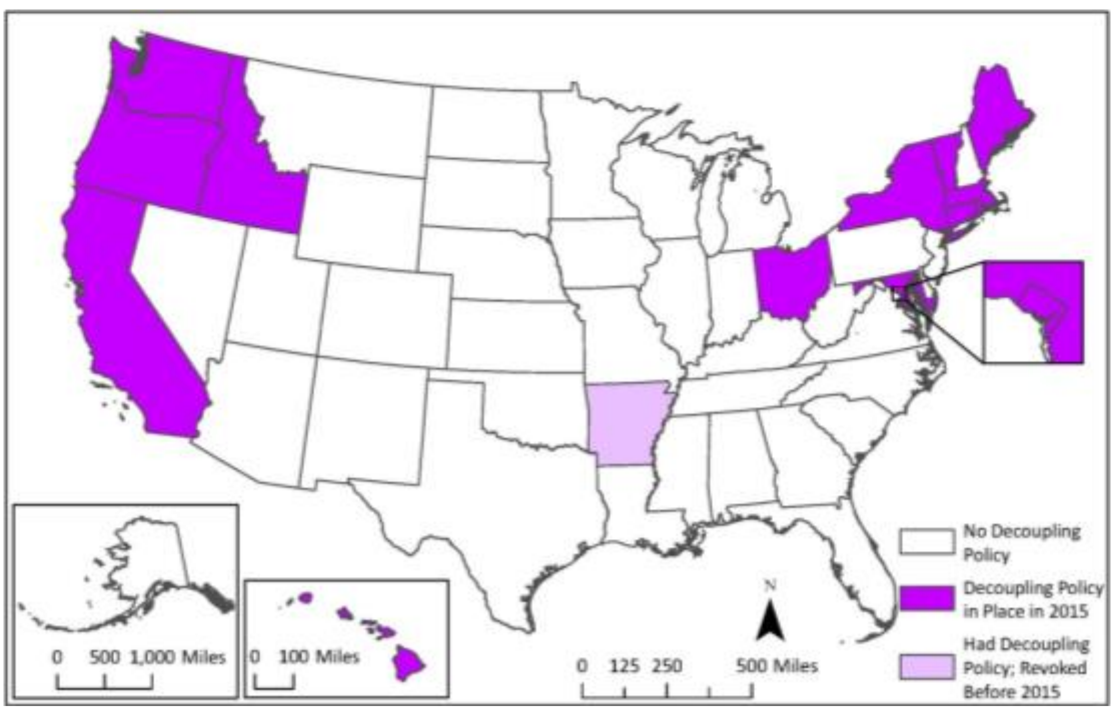


Map produced by author. Data source: ACEEE (2016a)

Another regulatory policy meant to encourage efficiency is revenue decoupling. Ratemaking procedures traditionally allow a utility to recover some fixed and variable costs through a per-kWh rate that links recovery directly to sales volume (Nissen and Williams 2016). "Decoupling" removes a major disincentive for pursuing efficiency programs by allowing the utility to recover an approved level of revenue regardless of sales (Ibid.). In fact, Nissen and Williams (2016) find that among three states in the Pacific Northwest that implemented decoupling after already having EERS in place for several years, expenditures and savings from utility efficiency programs increased. They stress that the correlation is not exact, as their data set is small and as two of these states had other policies conducive to efficiency programs in place at the same time. Nevertheless, they note that the primary electric utility in Idaho (which did not have any other conducive policies in place) experienced fourfold increases in efficiency expenditures and savings after decoupling was allowed. In their study of efficiency program savings, Arimura et al (2012) also find a positive – though insignificant – correlation between savings and the existence of a decoupling policy.

Decoupling entails revenue monitoring and regular rate adjustments that set remuneration back on track towards the approved amount (Lesh 2009). Adjustments are usually calculated for each customer class – which include residential, commercial, industrial, and possibly subclasses – and are often annual but may also be semiannual or monthly (Ibid.). Differences between projected and actual revenues, which trigger the adjustments, can occur because of variability in weather and consumer activity, though some electric utilities do account for the effect of weather in calculating the adjustment (Lesh 2009). States with decoupling in place in 2015 are depicted in Figure 2.5 below.

FIGURE 2.5: States with Electric Decoupling in 2015



Map produced by author. Data sources: ACEEE (2016b), IEE (2013), Williams (2016)

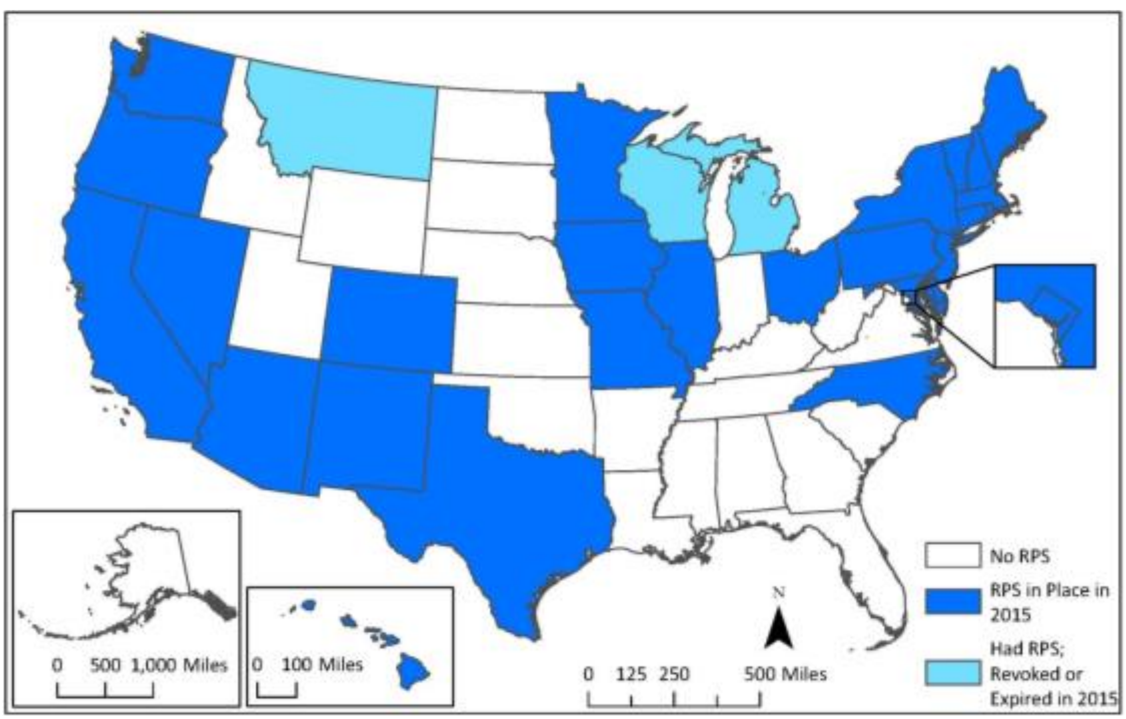
Lesh (2009) studies utility filings across the United States to determine how decoupling adjustments affect consumer rates overall. She finds that adjustments can be both positive and negative – as we would expect from the policy's definition – and that the majority are under one percent in either direction, which in the positive case translated to an extra two dollars on a monthly utility bill in 2007 (67). She obtained largely similar results in a follow up study three years later (see Morgan 2012). Lesh (2009) does note, however, that the overall effect of an adjustment on a customer's bill is dependent on the previous adjustment – a rebate this year will effectively translate into a rate hike if it is smaller than last year's rebate (69-70).

Other state policies intended to encourage utility energy efficiency programs include lost revenue adjustment mechanisms (LRAM), straight fixed-variable rates, and savings-sharing between customers and the IOU or between customers and the IOU's shareholders (IEE 2013 reviews certain policies in place by state in 2012). These policies do not generally represent as large a shift from traditional utility remuneration schemes as decoupling. Lesh (2009) defines a straight fixed-variable rate as one "in which the fixed monthly customer charge recovers all of the utility's fixed costs of service and the variable, energy-related charge only covers the variable cost of energy" (66-67). This is simply a reorganization of typical rate structures, in which some fixed costs may also be recovered through the volumetric energy charge (see Reneses, Rodríguez, and Pérez-Arriaga (2013) for a more thorough discussion). With regard to LRAM, Nissen and Williams (2016) note that previous research has considered this scheme inferior to decoupling on an equity basis, since LRAM allows positive rate adjustments to compensate utilities but does not entail negative rate adjustments to compensate consumers.

Renewable Portfolio Standards (RPS)

Several states have enacted renewable portfolio standards (RPS) in recent years to encourage the development of renewable energy generation. Renewable portfolio standards mandate that a certain percentage of electricity produced or consumed in the state must come from renewable sources (Fischer 2010), and they usually specify intermediate benchmarks leading up to the year in which the final goal must be met (Tra 2016). The definition of "renewable" may differ from state to state. Utilities meet the obligations either by operating their own renewable power plants (if the state regulatory regime allows them to own generation), by purchasing renewably sourced power from elsewhere, or by purchasing renewable energy certificates, which is possible in every state with an RPS except Hawaii and New York (Ibid.). States with an RPS in place in 2015 are depicted in Figure 2.6.

FIGURE 2.6: States with an RPS in 2015



Map produced by author. Data source: NCSL (2016)

Fischer (2010) shows mathematically that the effects of an RPS on electric retail rates will depend on the relative elasticities of the supply curve for renewable resources and the combined supply curve for incumbent fossil fuel generation, namely that rates should decrease if the combined fossil fuel supply curve is sufficiently steeper. She finds that increases in the stringency of the RPS should translate to higher rates ceteris paribus. Fischer (2010) also shows that the nature of an RPS as both a tax on fossil fuel generation and a subsidy to renewable generation engenders critical points at which the RPS is cheaper to meet by reducing overall demand rather than by increasing renewable capacity. Accordingly, she proposes that energy efficiency programs may mitigate positive price effects of an RPS by reducing demand – which will reduce retail rates and renewable energy certificate prices – or by making electricity demand more elastic, which could also mitigate rate increases (112). Finally, Fischer (2010) notes that her predictions are generally borne out in simulations. Palmer and Burtraw (2005) also find that in simulations on the Haiku energy model developed by Resources for the Future, the price effects of a hypothetical national RPS with an end year of 2020 are low up to a 15% mandate but increase sharply between 15% and 20%, as wind power replaces generation from nuclear and natural gas sources rather than from other fossil fuels.

Tra (2016) studies the effects of RPS enactment on residential and commercial electric rates between 2001 and 2012. He finds that after controlling for state-by-year fixed effects, residential rates are roughly three percent higher for utilities affected by an RPS but that marginal increases in RPS stringency, meaning smaller changes than those simulated by Palmer and Burtraw (2005), do not significantly affect rates. Tra (2016) concludes, therefore, that the costs imposed on utilities by an RPS are likely fixed rather than variable. Aside from the costs of

RPS compliance, which are passed on to consumers to varying degrees depending on the regulatory scheme in place, Linares, Batlle, and Pérez-Arriaga (2013) note that secondary effects may occur in wholesale markets as the penetration of renewables increases. These could be negligible if the renewable generation does not tend to set marginal prices, or they could be significant if the intermittency of renewables necessitates regular cycling of other generation technologies, thus increasing their operating costs (Ibid.).

Energy Burden and Low Income Assistance Initiatives

The concept of "energy burden" aims to quantify how much of a household's income is devoted to energy purchases and how changes in the price of residential energy sources affect household financial outcomes. Drehobl and Ross (2016) define energy burden as "total annual utility spending (electric, gas, and/or other heating fuel) as a percentage of total annual gross household income" (8). These researchers use 2011 and 2013 American Household Survey data to study the energy burden of households in forty-eight US metropolitan regions. They find that although low-income households (defined as those with income less than or equal to 80% of the local area median income) tend to spend less money on energy overall because they generally live in smaller spaces, the median energy burden of low-income households was three times that of households with higher incomes and twice the burden of the median household for their entire sample. Drehobl and Ross (2016) also find that the energy burden of low-income, African American, and renting households were highest in the Southeast and Midwest.

McIlmoil (2014) studies differential poverty rates and energy burdens in 2012 among electric utility service territories (IOUs, municipal utilities, and cooperatives) in the Southeastern United States. He notes that average energy expenditures in the South increased from $1,500 in 2001 to $2,000 in 2009, primarily because of increases in electric rates (2). McIlmoil (2014) also finds that the average burden of electricity costs in the Southeast in 2012 was 3% – compared to an average national burden for electricity *and* natural gas of 2.7% – and that the burden was higher for customers of municipal and cooperative utilities than for customers of IOUs. A study by the US Department of Health and Human Services (2014) puts the median energy burden nationwide in 2011 at 7%, with a median for low-income households (defined as those at or below 150% of the Department's income guidelines) of 13.4%.

Drehobl and Ross (2014) note that high energy burden is often the result of factors such as heating and appliance inefficiencies, renter status (that is, not owning the systems that use energy), lack of information about the availability of assistance, and changes in income or household size, among others (11). Accordingly, these researchers find that low-income, African-American, and renting households in their dataset often pay more for energy per square foot, which suggests less efficient housing (4). In a study of seventy-two low-income households (those at or below 150% of the poverty line) in Dorchester, Massachusetts, Hernández and Bird (2010) find that utility payments were a financial challenge for the vast majority of participants. These authors also argue for greater coordination between housing and utility energy efficiency programs, noting that even in cases where low-income households receive government assistance with rent that exceeds 30% of their income, energy costs often cause bills to far exceed this percentage (10). Drehobl and Ross (2016) echo the assertion of Ettenson and Heavey (2015) that low electric rates do not necessarily translate to low bills, noting that states with some of the highest average utility bills in 2014 had electric rates that were only around the national average (18).

The effects of high energy burden, particularly for low- and moderate-income (LMI) households, are stark and severe. Drehobl and Ross (2015) note that these effects include inadequate heating and light, unsafe living spaces, and stress, all of which contribute to health problems (13); Hernández and Bird (2010) add unstable housing to this list. Hernández and Bird (2010) also note that healthcare costs for low-income households stemming from a high energy burden are often shifted to state taxpayers at large. Oppenheim and MacGregor (2003) similarly point out that utility costs associated with these households, such as shutoff expenses, are generally recouped from other ratepayers. High energy burden, even if concentrated among LMI households, is thus a public policy issue with ramifications for all segments of society.

The federal government, states, and utilities do offer energy programs for LMI households, though they may not be sufficiently far reaching. The US Department of Health and Human Services established its Low Income Home Energy Assistance Program (LIHEAP), which covers a portion of energy bills, in 1981 (Hernández and Bird 2010). However, the percentage of eligible households participating in LIHEAP decreased from 36% in 1981 to just 19% in 2011 (US Department of Health and Human Services 2014). The US Department of Energy also runs a Weatherization Assistance Program (WAP), which helps low-income households save money through upgrades to building shell efficiency and is the largest such program in the country (US Department of Energy 2017).

Many utilities also run efficiency programs specifically for LMI customers, though these programs represented only about 7% of electric energy efficiency expenditures by US utilities in 2015 (CEE 2016a). Drehobl and Ross (2016) calculate that bringing the homes occupied by LMI households up to the efficiency of the median household in their sample would reduce their energy burden by 35%, yet they find that cities in their sample with the highest energy burdens also tended to have the lowest investment in efficiency programs. In addition, McIlmoil (2014) notes that only about one eighth of residents of the Southeastern US have adequate financial resources to cover the upfront costs of energy efficiency program participation (20). Even if efficiency improvements are available, Hernández and Bird (2010) point out that states often need to allow for special lease provisions that prevent evictions or rent hikes when housing values increase after the upgrades. Finally, many states offer rate discounts to LMI households in the form of fixed bill percentages or dollar amounts, or otherwise percentages that change depending on the level of consumption (Oppenheim and MacGregor 2003). Data regarding participation in these rate programs do not appear to be widely available, however.

CHAPTER 3: METHODS

The objective of this research effort is to determine whether state level energy policies have affected the energy burden of US residential electric customers over time. I focus specifically on customers who receive bundled service from an investor-owned utility, regardless of whether electric sector deregulation has occurred in the state. To conduct the analysis, I first define a new metric for electric energy burden and then use fixed effects regression techniques to analyze changes in this metric over time at the level of the electric utility. This chapter discusses the new metric, as well as assumptions and data handling procedures. The full analysis follows in the subsequent chapter.

Median Household Electric Burden (MHEB)

The dependent variable in this analysis is median household electric burden (MHEB), which I define as the average per-household revenue that an investor-owned utility (IOU) derives from residential electric sales divided by the median household income within its service territory. Put differently, MHEB asks the question, "What would the electric burden of a utility's median income customer (household) be if that customer spent the same amount of money annually for electric service as did the average residential customer of that utility?" MHEB is a measure of *electric* energy burden, not of the burden imposed by *all* household energy purchases, and it is therefore different from the fuel-agnostic definition of energy burden provided by Drehobl and Ross (2016). All else equal, MHEB should be lower than overall energy burden.

One immediate question that arises from the definition of MHEB is whether high-income households spend more in dollar terms than those at or below the median income, and if so, whether this artificially inflates average revenues and estimates of MHEB overall. As discussed previously, Drehobl and Ross (2016) find that the median energy burden of low-income households among forty-eight metro regions in the United States was over three times that of other households and was two times that of the median household for their entire sample. Therefore, as defined here, MHEB is more likely to approximate the burden of low and moderate-income (LMI) households than if it were defined solely using medians or averages. For this reason, I expect it to shed some light on the most economically vulnerable residential ratepayers. A more pragmatic reason to define MHEB in this way is that only average (not median) household electric purchases by utility are available from the Energy Information

Administration, and only estimates of median (not average) household income are available from the Census for years before 2005.

Regression Model and Analytical Approach

Equation 3.1 below presents the fixed effects regression model for the primary analyses in Chapter 4 of this paper:

$$\mathrm{MHEB}_{\mathrm{it}} = \beta_1 \mathrm{T}_{\mathrm{it}} + \boldsymbol{\beta_2 C_{it}} + \boldsymbol{\beta_3 I_{it}} + \boldsymbol{\upsilon_i} + \varepsilon_{\mathrm{it}} \tag{3.1}$$

where MHEB is the median household electric burden in percentage terms for a given utility service territory, T is the treatment policy of interest – energy efficiency resource standard (EERS), renewable portfolio standard (RPS), or deregulation – **C** is a vector of control variables that includes lags on the policy of interest, **I** is a vector of interaction terms, $\boldsymbol{\upsilon}$ is a vector of utility-specific fixed effects, and ε is a random error term. The subscripts *i* and *t* indicate a given IOU and a given year, respectively. This analysis considers the policies in combination before assessing each (and its lags) separately.

"Utilities" are defined here on a company-by-state basis, meaning that companies operating in several states are treated as a separate utility in each state. This aligns with the intention to test varying policy effects. A "multistate" utility must follow the policies in place in each individual state and is also regulated separately in each state, so its local subsidiaries should operate somewhat differently when energy policies diverge. I therefore disagree with Tra (2016) that including "multistate" utilities will prevent the identification of policy effects, and I have included these utilities in my analysis. The fixed effects approach is particularly advantageous given the definition of utility that I use here, since it will remove both attributes that remain constant for a company over time, as well as attributes that remain constant for a state over time.

A common approach to addressing the effects of time in fixed effects regression is to include dummy variables for each year or to interact year dummies with other independent variables. The appearance of dummies for various policies in this analysis, as well as of multiple lags on those dummies, raises the potential for significant multicollinearity between the policy and year dummies. Thus, it was necessary to find an alternative approach for dealing with the time component in this analysis. I instead made use of the tendency for time trends to induce autoregressive serial correlation in the errors of time series regressions. For each of the four analyses in Chapter 4, I first used the *xtregar* command (with fixed effects) in Stata to perform the regression in Equation 3.1, excluding any lagged variables to prevent multicollinearity. I then extracted ρ – the coefficient of AR(1) serial correlation estimated as a byproduct of *xtregar* – and used the transformation proposed by Prais and Winsten (1954) to remove serial correlation from all variables, including those that did not appear in the initial regression. I used *xtregar* to estimate ρ rather than using *xtreg* and simply regressing the residuals on their first order lags because *xtregar* utilizes the *prais* function to determine a convergent value of ρ through iteration (StataCorp 2015a, 2015b). Finally, I performed the main analytical regression using the *xtreg* function with fixed effects and including any appropriate lags. I instructed *xtreg* to calculate standard errors that were clustered by IOU; these clustered errors are known to be robust to arbitrary forms of heteroskedasticity and serial correlation (Wooldridge 2003). Thus, this process allowed me to remove estimated serial correlation from the data used in each analysis and therefore to increase the possibility that coefficient estimates would be unbiased by a time trend. In addition, the standard errors estimated by *xtreg* were themselves robust to any further correlation or heteroskedasticity, which enabled appropriate hypothesis testing.

Table 3.1 below lists the variables analyzed in Chapter 4, followed by a general discussion.

TABLE 3.1: Variables Included in Analysis

Variable Name	Description	Unit
mheb	Median household electric burden in service territory in year *t*	%
eers_policy	Dummy for EERS in year *t* (and up to five lags)	0/1
rps_policy	Dummy for RPS in year *t* (and up to five lags)	0/1
deregulation	Dummy for deregulation in year *t* (and up to five lags)	0/1
decoupling_policy	Dummy for a revenue decoupling policy in place in year *t*	0/1
c&i_revenues	Utility revenue from commercial and industrial (C&I) customers in year *t* (and up to two lags)	$Million
power_expenditures	Utility power expenditures, from generation and/or purchases, in year *t* (and up to two lags)	$Million
t&d_expenditures	Utility transmission and distribution expenditures in year *t* (and up to two lags)	$Million
heating_degree_days	Total heating degree days in service territory in year *t*	Degree-days
cooling_degree_days	Total cooling degree days in service territory in year *t*	Degree-days
median_income*	Up to four lags of median household income in service territory in year *t*	$Thousand
res_revenues*	Up to four lags of revenue received from residential customers in year *t*	$Million
res_customers*	Up to four lags of number of residential customers in year *t*	Thousand
employment_rate	Employment rate in service territory in year *t* (and up to four lags)	%
[*var1*]X[*var2*]…X[*varN*]	Interaction term between variables (dummy or otherwise)	Various
dsm_percust_annual_[*bound*]**	Dummies for categories of per-customer demand side management (DSM) expenditures *e* in year *t*	0/1
dsm_percust_4yrs_[*bound*]***	Dummies for categories of per-customer DSM expenditures *e* over the previous four years, using the current year residential customer base as the denominator	0/1

*See Appendix A and the section below on addressing endogeneity

**Bounds indicate the maximum expenditure per person (e) represented by the dummy variable. 25: 0<e≤25, 50: 25<e≤50, 75: 50<e≤75, 100: 75<e≤100, and max: e>100.

*** Same definition as above. 50: 0<e≤50; 100: 50<e≤100; 150: 100<e≤150, 200: 150<e≤200, and max: e>200.

The potential effect of an EERS and of related demand side management (DSM) spending on MHEB is somewhat ambiguous. Utility DSM expenditures translate into costs that must be recouped from customers, yet spending also induces participating customers to purchase less electricity in any given time period, all else equal. I hypothesize that the effects of EERS and DSM spending on MHEB will be negative overall, meaning that decreased use will lower average bills more than increased rates raise them, although this result is highly dependent upon the uptake of DSM programs. Total DSM spending (energy efficiency and demand response together) appears in this analysis instead of only energy efficiency spending because energy efficiency and demand response were reported together in Energy Information Administration (EIA) data for much of the relevant time period. Similarly, DSM expenditures per customer are calculated using residential bundled service customers as the denominator – despite the fact that DSM funding is generally also available to commercial and industrial customers – because the EIA data are not broken down into customer class for several years. Of course, energy efficiency and demand response programs are quite different, and an additional dollar will have different marginal effects depending on the program, the customer class, and the general energy-savviness of individual consumers. DSM expenditures per residential customer are therefore divided into dummy groups to provide wider bounds that characterize the impact of spending overall without attempting to identify marginal effects. DSM expenditures for prior years appear alongside annual expenditures in recognition of the finding by Arimura et al. (2012) that energy efficiency expenditures have significant effects on energy use up to fifteen years in the future. Rather than estimate expenditures in the 1980s as these authors do, I instead use a proxy of four years' worth of expenditures to capture some of the cumulative effects of expenditures. Four years is the chosen timeframe because 1990 is the earliest year for which relevant EIA data are available, and 1994 is the initial year in my analysis.

As noted previously, the effects of decoupling are also ambiguous, and I will not make a prediction here about their general direction. There appears to be somewhat more consensus about the effects of renewable portfolio standards (RPS) and deregulation policies, however. I expect that both will have an overall positive effect on MHEB through rates.

Policy variable dummies are coded as 1 for any year in which they were actually in place and 0 otherwise. Thus, if a policy was enacted by the state legislature in 1995 but did not come into force until 1997, then 1997 would be the first year marked as “1.” Similarly, in cases where a policy was rescinded, the final year in which it was in place for any amount of time is marked as “1.” Following Lesh (2009), revenue decoupling mechanisms do not include straight fixed-variable rates, nor do they include lost revenue adjustment mechanisms (LRAM). Thus, the included schemes entail both positive and negative adjustments – regardless of cadence – and do not assess a fixed fee for partial cost recovery. As discussed in Chapter 2, “deregulation” has generally involved two related components: utility divestment of generation assets and implementation of retail choice for customers. Retail choice governs the dummy variables in this analysis, though every deregulated state included here has also required or encouraged divestment at some point (often at the same time as retail choice). Thus, both effects are relevant.

I expect commercial and industrial (C&I) revenues to have a negative effect on MHEB when decoupling is in place because higher revenues from these customer classes reduce the need to raise rates on residential customers. This would be the case specifically when decoupling rate adjustments include all ratepayers, as they do in Massachusetts (Massachusetts DPU 2008), but it would not be the result where adjustments are made in for each ratepayer class individually. The present analysis does not distinguish between these approaches but instead takes a more holistic view. On the other hand, because they are costs that must be recouped from ratepayers, expenditures on power and on transmission and distribution (T&D) should have positive effects on MHEB. The former includes changes in the prices of generation fuels (coal, natural gas, oil, and uranium) by definition without seeking to determine the effects of individual fuel prices. Increases in cooling degree days and heating degree days should increase residential consumers' expenditures – and therefore MHEB – when they are associated with electric air conditioning and electric heating, respectively. Employment rates are included as a proxy for local economic activity; if unemployed workers are hired and incomes generally rise when the economy grows, then employment rates should correlate negatively with MHEB. Lags on median income itself, as well as on residential revenues, number of residential customers, and employment are discussed below in the section on addressing endogeneity.

Addressing Endogeneity

Two sources of potential endogeneity are apparent in the model in Equation 3.1. The first is that a utility might decide to increase rates for C&I customers – and thus to shift revenue recovery towards C&I – specifically because it detects a high energy burden for its residential consumers. In this case, MHEB would affect C&I revenues via an omitted variable that is related to policy formulation. This is unlikely in practice because of the nuances of regulatory processes. As a gross simplification, rates are generally determined for each ratepayer class based on its own contribution to overall costs. Yet the relative importance of C&I customers to a utility's bottom line may lead IOUs to purposefully recover some C&I-induced costs from the more numerous residential consumers, who may not notice this cross-subsidy (Reneses, Rodríguez, and Pérez-Arriaga 2013). Therefore, increases in C&I rates on behalf of residential consumers are neither consistent with standard ratemaking procedures nor are, in many cases, even possible from a customer relations perspective. This clarification does not contradict the previous discussion of decoupling. In a state like Massachusetts, where decoupling adjustments are calculated on a company wide basis, all customer classes are affected when revenues move above or below projections. This does not represent a transfer of wealth from one specific rate class to another, however, as would be the case if C&I rates were raised to benefit residential consumers.

The second potential source of endogeneity is that state policymakers may have chosen to implement certain policies in response to changes in MHEB, particularly if the policies were expected to reduce residential energy burden. Appendix A addresses this possibility in more detail. The overall conclusion is that policymakers are more likely to respond to the components of MHEB – residential bills and, on a more granular level, the number of residential consumers and the revenues derived from them – than to relatively new concepts such as MHEB or energy burden in general. Following the discussion in Appendix A, lags on median household income, residential revenues, number of residential customers, and local employment rates (see Table 3.1) appear as controls in the main analysis to correct for potential sources of endogeneity.

Data Sources and Data Handling Procedures

Annual IOU revenues by customer class, megawatt-hour (MWh) sales by customer class, and DSM expenditures were derived from the Energy Information Administration Form EIA-861 data (EIA 2016). Information on utility costs and expenditures was taken from the Federal Energy Regulatory Commission's annual Form 1 filings database (FERC 2017). Annual projections of median household income for each county in the continental United States were taken from the United States Census' Small Area Income and Poverty Estimates (US Census Bureau 2016), and annual estimates of county population were taken from the Census' Population and Housing Unit Estimates Tables (US Census Bureau 2017). Yearly projections of the number of households in each county were not available from the Census. Thus, median household income for each IOU in each year was estimated as follows: (1) multiplying the population of each county by the percentage of the county's land area covered by a given IOU service territory (in order to estimate the "served population"), followed by (2) averaging the median household income for all counties in which the service territory is located, using "covered population" as a weight. In all cases, monetary values were converted to 2015 dollars using the Bureau of Labor Statistics CPI Calculator (BLS 2017a).

The procedure for estimating median household income implicitly assumes that a county's residential population is distributed evenly. This is a gross but necessary simplification, and it will tend to "draw" urban incomes into the estimates for IOUs whose service territories cover, for example, only the rural areas of a county. If urban incomes are generally higher than rural incomes in a given state, this method will bias income estimates upward. Luckily, many service area boundaries throughout the country follow county lines or are otherwise vast enough that the bias may be miniscule. Furthermore, weighting ensures that counties with small populations – even if divided among several utilities – only marginally affect the income estimates. This analysis originally intended to compare estimates of median household income taken separately from the county and Census tract levels, the second of which would theoretically be more accurate because Census tracts are smaller in area. Unfortunately, this comparison was not possible because estimates of median household income by Census tract are not available for the majority of years in the study.

Following Arimura et al. (2012), IOUs with total annual sales of under 150,000 MWh were excluded from the analysis, as these utilities have not been required to report energy efficiency expenditures in Form EIA-861 since 1998 (see Arimura et al. 2012, footnote 14). Even so, DSM expenditures were not available for several IOUs in a handful of years. Where data were available for years on either side of the gap, missing entries were interpolated by averaging the difference over the missing years, assuming a constant rate of increase or decrease in each year. Utility DSM budgets and expenditures often ramp up and down depending upon the length of the regulatory cycle (CEE 2016a) – for example, expenditures will decrease as a five-year budget is expended and shoot up again once a new budget is approved by the regulator – but they very rarely drop to zero. Thus, this interpolation procedure is insufficient to catch minor swings in DSM spending but is necessary to handle erroneous data omissions. The need to project in this way is another reason why DSM expenditures per customer appear as discrete variables in the regression model. In the few cases where DSM data were not available on both ends of the gap, these entries were left alone. Aside from DSM expenditures, revenue or cost data were missing for a small number of other records and were estimated in the same way.

In several states, government entities or contracted organizations administer statewide DSM programs that supplement or replace those provided directly by utilities. The Form EIA-861 instructions request that utilities report DSM expenditures and savings for programs that they directly run or otherwise fund but, since 2011, they ask that respondents exclude DSM data for a short list of third parties that EIA surveys directly (EIA 2016). The seven third party organizations relevant to this analysis are Cape Light Compact (in Massachusetts), District of Columbia Sustainable Energy Utility, Efficiency Maine, Efficiency Vermont, Energy Trust of Oregon, New York State Energy Research and Development Authority (NYSERDA), and Wisconsin Focus on Energy. Funding administered by these organizations is generally available to all residents of a state, and I assigned their expenditures from 2011 to 2015 (except for Efficiency Vermont, as explained below) to IOUs within the associated states according to the number of residential customers receiving bundled service from each utility in the given year. This process incorporated all municipal utilities, cooperatives, and IOUs in the respective states – even those that were excluded from the analysis – so as not to grossly overestimate the funding available to the various IOUs. For years prior to 2011, I assumed that data from these third parties were included in utility-reported data per EIA's instructions; most of the organizations were not even founded until the middle years of the dataset. Although EIA does not collect separate data for Efficiency Vermont, responses by Vermont utilities between 2000 and 2010 do not appear to include Efficiency Vermont funding. Thus, I extracted data for Efficiency Vermont directly from the organization's annual reports for these years (Efficiency

Vermont 2016) and handled in the same way as other third parties. Finally, I added third party funding only after performing the missing data interpolations discussed above.

Data for heating degree days and cooling degree days by state climate division and by year were taken from the National Oceanic and Atmospheric Administration (NOAA 2017b). Heating and cooling degree days for each IOU in each year were calculated using averages for the climate divisions in which a given IOU's service territory is located, weighted by the percentage of the service territory that lies within each climate division. Employment data for each county in each year were taken from the Bureau of Labor Statistics (2017b). Employment rates were calculated for each IOU in each year by weighting the total number of employed laborers and the total labor force in each county by the percentage of that county's area covered by a given utility – again assuming equal population distribution – and calculating a new employment rate from these adjusted data.

Information regarding whether an IOU had various policies in place during a given year came from numerous sources. Where I used multiple sources for a particular policy, I compared information across the sources to verify that dates were accurate. EERS data were taken from the American Council for an Energy-Efficient Economy (2016a). Decoupling data were taken from the Edison Foundation Institute for Electric Efficiency (IEE 2013), the American Council for an Energy-Efficient Economy (2016b), and Williams (2016). Information on RPS policies was available from the National Conference of State Legislatures (2016). Finally, deregulation information was derived from Electric Choice (2016), Stanford University (2003), and Swadley and Yücel (2011). In the vast majority of cases, a given policy was instituted or revoked for all IOUs in a state at one time. Yet in several instances, deregulation and decoupling were instituted in different years for various IOUs as a result of legislative or regulatory actions. Start or end years for decoupling and deregulation in the dataset vary accordingly by IOU in the relevant states. See Appendix B for a table outlining the years in which certain policies were in place for states included in the analysis.

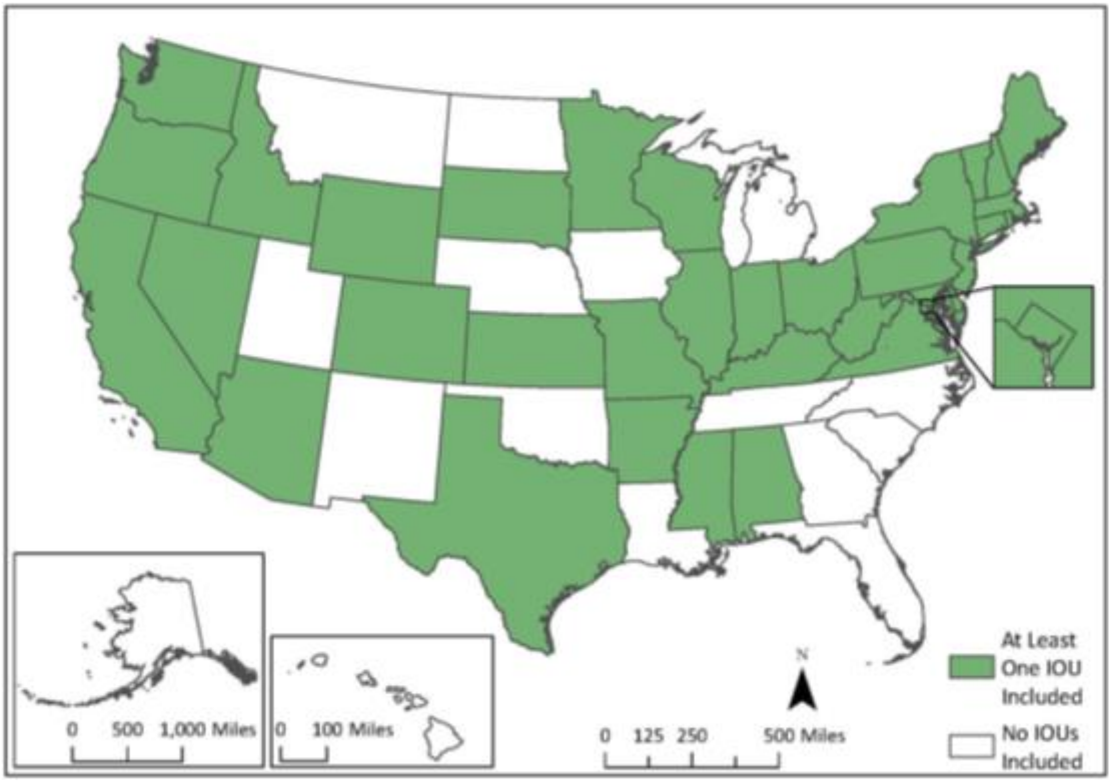
ArcGIS shapefiles for IOU service territories in fourteen states were publicly available from state utility commissions, and an additional three states were covered by a single file from ArcGIS Open Data (2016). For the remainder of included states, I created shapefiles for IOU service territories manually using PDF, JPEG, or service territory map files that were available from public utility commissions or from individual IOUs. Form EIA-861 requires that IOUs list the counties in which their service territories are located, and changes in the counties served are documented for several IOUs between 1994 and 2015. A cross-check of these changes with the most recent available service territory maps and with certain older maps indicated that in every case, the supposed changes were either (likely) incorrect or involved such small areas or counties with such small populations that the median household income, heating and cooling degree day, and employment calculations outlined above are unlikely to be significantly affected. County and state shapefiles were available from ArcGIS Online (2013), and shapefiles for state climate divisions were available from NOAA (2017a).

Several utility mergers occurred during the timeframe under consideration. In such cases, I treated the merged entity as one utility across all years, aggregating data for the component companies in years prior to their merger (while being careful not to double-count data after the merger). Yet in cases where formerly independent IOUs have merged but continue to market themselves as distinct entities (e.g. Nevada Power and Sierra Pacific Power), and where EIA has continued to collect separate data for each, I treated these entities as separate utilities. Again, I do not expect that financial dependence between such entities would significantly impact the variables I analyze here. A couple of utilities also disbanded into smaller entities during the years of the dataset. I performed the opposite calculation for these utilities, estimating individual shares of EIA or FERC data using residential customer counts. In this way, the number of IOUs remains constant over time, and calculations (for example, median income) for individual utilities are consistent.

The final dataset incorporates 105 IOUs across all or parts of 34 states and the District of Columbia, and the data span twenty-two years from 1994 to 2015. In addition to the IOUs removed from the dataset because their sales were under 150,000 MWh, several other individual IOUs were removed because of irreconcilable issues with their EIA or FERC data or because sufficiently detailed service territory maps were unavailable. Thus, not every IOU in every otherwise "included" state appears in this analysis. Two states – Nebraska and Tennessee – were excluded because they do not contain IOUs; an additional four (Louisiana, Michigan, North Carolina, and South Carolina) were excluded because their IOUs and rural electric cooperatives exhibit significant territory overlap, and it was therefore impossible to use them for calculating median household income and other metrics. Sufficiently detailed service territory maps were not available for the remainder of excluded states.

Figure 3.1 indicates the states for which at least one IOU was included in the analysis. According to data from Form EIA-861, the 105 utilities represented in this study served 45% of all US residential electric customers in 2015, including 67% of all residential customers who received bundled service from an IOU. Appendix B contains a table listing all IOUs included in this analysis, as well as a map of the associated service territories that also indicates major metropolitan areas that are fully or partially served by included IOUs.

FIGURE 3.1: States With At Least One IOU Included in Analysis



Map produced by author

CHAPTER 4: RESULTS

This chapter describes the results of the main analysis. The first section provides summary statistics for select variables, and the second and third sections describe the results of a combined policy analysis and individual policy analyses, respectively. As described in Chapter 3, the anticipated correlations between key variables and median household electric burden (MHEB) were as follows: negative for energy efficiency resource standards (EERS) and demand side management (DSM) expenditures per customer, positive for renewable portfolio standards (RPS), and positive for deregulation.

Summary Statistics

Median household income was $56,344 on average across all IOUs and all years, with minimum and maximum values of $33,232 and $92,553, respectively. The weighted average value of median household income grew from $59,353 in 1994 to $61,523 in 2015. Average annual household electric expenditures ranged from $389 to $2,366, with a mean value of $1,202. Table 4.1 below presents summary statistics for other select variables. Tables 4.2 to 4.4 separately provide statistics for these variables based on whether each of the three policies of interest was in place in a given year, including the results of Wilcoxon Rank-Sum Tests to examine median differences across variables when the policy is (or is not) in place. In all four tables, “dsm_expend_currentyr” refers to demand side management (DSM) spending per residential customer in the current year, and “dsm_expend_last4yrs” refers to total DSM spending per residential customer over the previous four years (the number of customers in the denominator is the number in the current year). Although different levels of DSM expenditures are represented as categorical dummy variables in the main analysis at the end of this chapter, Tables 4.1 through 4.4 present summary statistics on DSM expenditures as a continuous variable. Again, all monetary values are in real 2015 dollars.

TABLE 4.1: Summary Statistics

Variable	Units	Mean	Median	Std. Dev.	Min.	Max.
mheb	%	2.20	2.12	0.57	0.69	5.14
c&i_revenues	$Million	780.77	449.85	1,143.43	0.02	8,827.16
power_expenditures	$Million	868.85	507.82	1,104.22	-	11,803.59
t&d_expenditures	$Million	91.11	41.29	136.31	0.15	1,116.41
heating_degree_days	Degree-days	5,592.51	5,554.74	1,743.03	1,220.60	10,501.68
cooling_degree_days	Degree-days	922.01	734.04	644.99	44.85	3,552.26
employment_rate	%	94.22	94.67	2.08	84.11	98.30
dsm_expend_currentyr	$/person	33.40	17.26	41.71	-	367.04
dsm_expend_last4yrs	$/person	118.20	63.30	136.43	-	1,393.45

n = 2,310

MHEB was roughly 2.2% on average across the twenty-two years in the sample, with a median of 2.12% and a maximum value of 5.14%. The weighted average value of MHEB decreased from 2.17% in 1994 to 2.11% in 2015 (not shown in Table 4.1). These numbers are comparable to the 2012 electric-only energy burden of 3% that McIlmoil (2014) calculated for the Southeastern US, as well as to the overall national energy burden of 3.5% calculated by Drehobl and Ross (2016). Nevertheless, they are below the energy burdens for low- and moderate-income (LMI) consumers calculated in the latter study and by the US Department of Health and Human Services (2014). Therefore, although I expected MHEB to approximate LMI electric energy burden to a certain degree (as discussed in Chapter 3), the estimates in my analysis likely underestimate the burdens faced by LMI households and should be treated as a lower bound for this group.

Commercial and industrial (C&I) revenues and expenditures on power and on transmission and distribution (T&D) vary greatly but are clearly skewed to the right. The maximum annual power expenditure of nearly $12 billion is particularly surprising, but it is nevertheless accurate and is the result of a large swing in a particular investor-owned utility's

(IOU) nuclear fuel costs (American Electric Power 2001). Given this range, it is important to remember that the IOUs considered here vary greatly in size: across all 105 IOUs and 22 years, the number of residential consumers with either bundled or network-only service varied from 2,673 to 4,749,486, with an average of 550,885. Demand side management (DSM) expenditures per customer averaged $33 in any given year, with a maximum of $367, and DSM expenditures per customer in the previous four years varied by similar magnitudes.

TABLE 4.2: Summary Statistics by Existence of an EERS

		EERS_POLICY = 0 (n = 1,754)			EERS_POLICY = 1 (n = 556)		
Variable	**Units**	**Mean**	**Median**	**Std. Dev.**	**Mean**	**Median**	**Std. Dev.**
mheb	%	2.17	2.09***(-)	0.58	2.26	2.21	0.51
c&i_revenues	$Million	753.87	450.99(-)	1,046.29	865.64	440.91	1,404.35
power_expenditures	$Million	837.19	483.70***(-)	1,091.51	968.74	599.10	1,138.64
t&d_expenditures	$Million	60.74	26.76***(-)	89.30	186.92	112.39	200.00
heating_degree_days	Degree-days	5,671.18	5,534.82**	1,687.90	5,344.31	5,656.56	1,886.74
cooling_degree_days	Degree-days	886.98	742.22(-)	584.05	1,032.53	700.11	798.26
employment_rate	%	94.65	95.05***	1.85	92.87	93.07	2.19
dsm_expend_currentyr	$/person	24.79	11.36***(-)	33.48	60.55	48.67	52.22
dsm_expend_last4yrs	$/person	102.05	47.95***(-)	128.11	169.16	127.36	148.92

Results of Wilcoxon Rank-Sum Tests: * p ≤ 0.1; ** p ≤ 0.05;*** p ≤ 0.01; (-) indicates negative p-value (median lower when policy not in place)

TABLE 4.3: Summary Statistics by Existence of an RPS

		RPS_POLICY = 0 (n = 1,460)			RPS_POLICY = 1 (n = 850)		
Variable	**Units**	**Mean**	**Median**	**Std. Dev.**	**Mean**	**Median**	**Std. Dev.**
mheb	%	2.22	2.12*	0.60	2.15	2.11	0.51
c&i_revenues	$Million	734.86	439.20**(-)	1,030.14	859.64	467.65	1,312.36
power_expenditures	$Million	794.67	451.02***(-)	1,110.38	996.28	656.41	1,082.40
t&d_expenditures	$Million	53.11	24.95***(-)	76.84	156.38	82.04	183.40
heating_degree_days	Degree-days	5,617.31	5,459.75(-)	1,757.07	5,549.90	5,723.85	1,718.83
cooling_degree_days	Degree-days	924.72	765.95***	599.82	917.36	650.79	716.32
employment_rate	%	94.64	95.02***	1.87	93.50	93.97	2.23
dsm_expend_currentyr	$/person	24.39	10.90***(-)	33.65	48.86	37.49	49.07
dsm_expend_last4yrs	$/person	98.89	45.59***(-)	126.78	151.38	113.58	145.80

Results of Wilcoxon Rank-Sum Tests: * p ≤ 0.1; ** p ≤ 0.05;*** p ≤ 0.01; (-) indicates negative p-value (median lower when policy not in place)

TABLE 4.4: Summary Statistics by Existence of Deregulation

		DEREGULATION = 0 (n = 1,614)			DEREGULATION = 1 (n = 696)		
Variable	**Units**	**Mean**	**Median**	**Std. Dev.**	**Mean**	**Median**	**Std. Dev.**
mheb	%	2.26	2.16***	0.61	2.06	2.03	0.43
c&i_revenues	$Million	770.46	454.81(-)	1,180.86	804.68	432.27	1,051.97
power_expenditures	$Million	756.14	434.36***(-)	970.75	1,130.24	710.80	1,328.88
t&d_expenditures	$Million	76.06	30.88***(-)	124.69	126.00	70.16	154.59
heating_degree_days	Degree-days	5,483.47	5,381.35***(-)	1,963.06	5,845.36	5,813.59	1,028.74
cooling_degree_days	Degree-days	1,014.78	785.49***	716.69	706.88	642.49	351.71
employment_rate	%	94.25	94.75**	2.17	94.15	94.55	1.87
dsm_expend_currentyr	$/person	30.05	15.15***(-)	37.45	41.15	29.21	49.39
dsm_expend_last4yrs	$/person	111.13	57.32***(-)	131.69	134.59	87.63	145.63

Results of Wilcoxon Rank-Sum Tests: * p ≤ 0.1; ** p ≤ 0.05;*** p ≤ 0.01; (-) indicates negative p-value (median lower when policy not in place)

Notwithstanding the interactive effects between the various policies, median MHEB appears significantly higher when an EERS is in place than when it is not, but median MHEB is marginally lower when an RPS is in place and is significantly lower when deregulation is in place. This is the exact opposite of my predictions above with respect to directional effects. Median expenditures are significantly higher when any of the policies are in place; for power expenditures in particular, this may reflect the exogenous increase in gas prices during the late 1990s and early 2000s that was described in Chapter 3. Median C&I revenues are also higher under the three policies, though this difference is only significant for an RPS. An increase in C&I revenues could be due in part to increased expenditures: if regulators allow IOUs to pass higher fuel costs to consumers more easily in deregulated states than in regulated states, and if demand for electricity amongst C&I customers is sufficiently inelastic in the short term, then C&I revenues will increase as rates increase. Median DSM expenditures per customer are significantly higher under EERS policies, which is expected, although they are also significantly higher under either of the other two policies. These initial results raise interesting questions that I address in the following sections.

Combined Policy Effects

The first analysis combines all three primary policies together in order to study interactions between them. Unlike the analyses of individual policies that follow in the next section, this section focuses on contemporaneous interactions between the policies themselves, though it does include lags on control variables related to utility expenditures. Unlike data from the Energy Information Administration (EIA), which are available back to 1990, cost data from the Federal Energy Regulatory Commission (FERC) are only available starting in 1994. I must therefore drop one year of data for each lag on expenditures, which are more likely to affect rates in the current year than are contemporary expenditures, since rate changes generally occur on a yearly or longer basis (except in the case of intra-annual decoupling adjustments).

Table 4.5 below presents four models: model (1) is the analysis without lags on expenditures, model (3) is the same analysis including two lags on the expenditure variables and on C&I revenues, and models (2) and (4) are sensitivity analyses of models (1) and (3), respectively, that exclude any records for which I interpolated data (see Chapter 3 for a discussion). Each model is fitted and therefore includes only as many lags as are statistically significant on the margin. In order to save space, I have also excluded certain insignificant or marginally significant control variables from the tables. Unlike the marginal lags removed via the fitting procedure, these control variables are components of models (1) through (4). Appendix C presents regression outputs that contain the full list of variables, regardless of significance, as well as baseline models that also include the complete vector of lags before fitting. Tests for joint significance also appear in Appendix C. The values in parentheses in each table are clustered standard errors, which are robust to arbitrary forms of heteroskedasticity and serial correlation (Wooldridge 2003). Finally, the notes at the bottom of the table present the value of ρ used in the initial Prais-Winsten data transformation, along with other information.

Multicollinearity is generally a greater threat in the combined analysis because there is a high level of temporal overlap between some policies. For example, an RPS was in place for 89% of the utility-years in which an EERS was in place (this overlap is 59% the other way around), and an RPS was in place for 72% of utility-years in which deregulation was in place (again 59% the other way around). Serial correlation is also a greater threat in the combined analysis – or at least in the baseline models presented in Tables C.1 and C.3 in Appendix C – because I include lags on all three components of MHEB to correct for potential endogeneity. (Appendix A explains this threat in more detail.) After conducting the first Prais-Winsten transformation as outlined in Chapter 3, I used the *xtregar* command in Stata (with fixed effects) to regress *mheb* on the same independent variables plus four lags on median income, residential revenues, and residential customers and collected the residuals. I then regressed these residuals on their first-order lags to test whether the MHEB components would induce additional AR(1) serial correlation. The resulting point estimate of ρ was -0.0097, with a p-value of 0.411. Thus, I concluded that these lags were not inducing significant additional correlation and that it was not necessary to perform a second Prais-Winsten transformation before the full analysis.

TABLE 4.5: Combined Policy Regression Outputs

Variables	(1)	(2)	(3)	(4)
eers_policy	1.02e-01	7.53e-02	-1.82e-03	-1.87e-02
	(3.64e-02)***	(5.04e-02)	(3.57e-02)	(4.77e-02)
rps_policy	4.26e-02	5.13e-02	4.59e-02	5.97e-02
	(1.84e-02)**	(2.23e-02)**	(1.65e-02)***	(2.00e-02)***
deregulation	-7.74e-02	-8.66e-02	-5.20e-02	-5.80e-02
	(2.24e-02)***	(2.91e-02)***	(2.07e-02)**	(2.52e-02)**
eers_policyXdecoupling_policy	-1.26e-01	-1.27e-01	-5.82e-02	-6.27e-02
	(3.91e-02)***	(5.26e-02)**	(4.18e-02)	(5.23e-02)
eers_policyXrps_policyXderegulationXdecoupling_policy	1.82e-01	2.10e-01	1.44e-01	1.91e-01
	(6.16e-02)***	(7.00e-02)***	(6.18e-02)**	(7.05e-02)***
c&i_revenues	8.70e-05	8.95e-05	1.20e-04	1.20e-04
	(3.83e-05)**	(4.06e-05)**	(4.36e-05)***	(4.53e-05)***
c&i_revenuesXdecoupling_policy	-1.78e-05	-1.68e-05	-2.78e-06	4.46e-07
	(7.69e-06)**	(9.54e-06)*	(6.69e-06)	(8.27e-06)
t&d_expenditures	3.46e-04	2.93e-04	2.50e-04	2.03e-04
	(9.31e-05)***	(8.37e-05)***	(8.64e-05)***	(8.20e-05)**
t&d_expenditures_lag1			1.80e-04	2.17e-04
			(8.47e-05)**	(9.26e-05)**
heating_degree_days	9.88e-05	1.00e-04	8.95e-05	9.08e-05
	(9.42e-06)***	(1.07e-05)***	(7.80e-06)***	(9.21e-06)***
cooling_degree_days	3.47e-04	3.34e-04	3.20e-04	3.04e-04
	(2.46e-05)***	(2.81e-05)***	(2.49e-05)***	(3.08e-05)***
median_income_lag1	2.95e-03	2.67e-03	1.17e-02	1.31e-02
	(3.24e-03)	(3.63e-03)	(3.22e-03)***	(3.76e-03)***
median_income_lag2	-1.13e-02	-1.42e-02	-5.22e-03	-7.19e-03
	(3.16e-03)***	(3.58e-03)***	(3.03e-03)*	(3.51e-03)**
median_income_lag3	-9.48e-03	-1.05e-02	-1.17e-02	-1.15e-02
	(3.31e-03)***	(3.88e-03)***	(3.04e-03)***	(3.52e-03)***
median_income_lag4	-4.33e-03		-1.21e-02	-1.01e-02
	(2.35e-03)*		(2.53e-03)***	(2.94e-03)***
residential_revenue_lag2	1.35e-04	1.43e-04		
	(5.85e-05)**	(6.49e-05)**		
residential_revenue_lag3	2.38e-04	2.22e-04		
	(5.97e-05)***	(6.17e-05)***		
residential_revenue_lag4	1.21e-04	1.08e-04		
	(4.31e-05)***	(4.27e-05)**		
residential_customers_lag2	-3.19e-04	-3.67e-04		
	(1.14e-04)***	(1.58e-04)**		
residential_customers_lag3	-2.52e-04	-2.64e-04		
	(1.11e-04)**	(1.68e-04)		
residential_customers_lag4	-3.92e-04	-3.50e-04		
	(7.90e-05)***	(9.08e-05)***		
employment_rate	-3.59e-03	-2.99e-03	-2.76e-02	-2.56e-02
	(3.93e-03)	(4.06e-03)	(4.31e-03)***	(4.56e-03)***
employment_rate_lag1	-1.76e-02	-1.88e-02	-3.89e-02	-4.23e-02
	(5.50e-03)***	(6.18e-03)***	(5.26e-03)***	(5.92e-03)***
employment_rate_lag2	1.55e-02	1.34e-02		
	(4.34e-03)***	(4.31e-03)***		
employment_rate_lag3	1.40e-02	1.74e-02		
	(5.54e-03)**	(5.94e-03)***		
employment_rate_lag4	1.86e-02	1.80e-02		
	(5.05e-03)***	(5.41e-03)***		
_constant	-2.75e-03	-1.25e-03	1.80e+00	1.80e+00
	(1.24e-02)	(1.27e-02)	(1.23e-01)***	(1.28e-01)***
R2 Within	0.6257	0.6570	0.2352	0.2320
R2 Between	0.3304	0.3885	0.1340	0.1242
R2 Overall	0.5765	0.6050	0.1966	0.1806
Observations	2,310	1,852	2,100	1,646
Groups	105	105	105	105

* *p*<0.1; ** *p*<0.05; *** *p*<0.01; Parentheses contain clustered std. errors; Model 1: Fitted (NCL); Model 2: No Projected Data (NCL); Some insignificant or marginally significant control variables have been removed from the table (see Appendix C for the full results); *ρ*=0.790

As shown in Table 4.5, the contemporaneous effects of all three main policies are significant in model (1), and this significance holds across models for *rps_policy* and *deregulation*. The estimated coefficients on *eers_policy* (in the first model) and on *rps_policy* are positive, which suggests that these policies have increased electric rates for IOU customers to a greater extent than any increase in incomes over time. Although the result for *eers_policy* is unexpected, the estimate for *rps_policy* corroborates the findings of Tra (2016) that RPS policies have increased residential electric rates. Nevertheless, the effect on *mheb* here is much smaller than the 3% increase in residential electric rates calculated by Tra (2016). Using the average median household income of $56,344 from the sample, the coefficients on *eers_policy* and *rps_policy* in model (1) correspond to respective average increases in annual household electric expenditures of $56 (0.1 *mheb* percentage points) and $23 (0.043 *mheb* percentage points), all else equal. Alternatively, the negative coefficient estimate on *deregulation* suggests that deregulation has had the opposite effect and corresponds to an average, ceteris paribus decrease in annual household electric expenditures of $45 (0.077 *mheb* percentage points). The magnitude of this effect is similar to but smaller than the contemporaneous, state-specific effects of deregulation on retail rates calculated by Swadley and Yücel (2011). Most of the interaction terms are insignificant, and they are excluded from Table 4.5, though the negative coefficient on *eers_policyXdecoupling_policy* suggests that decoupling restrains the rate increases associated with an EERS. The opposite appears true when all three policies and decoupling are in place: the coefficient on the interaction of all four policies is significant and positive, which suggests that decoupling may not help keep rates down in this instance.

The estimated coefficients on *c&i_revenues* are positive and significant, which is the opposite of my prediction in Chapter 3, though it may indicate that rates tend to increase for all customer classes at the same time (so C&I rates and C&I revenues will increase as *mheb* increases). Notably, the positive coefficient on the interaction between *c&i_revenues* and *decoupling_policy* provides further evidence that decoupling limits rate increases that might otherwise occur. The coefficients on *t&d_expenditures*, *heating_degree_days*, and *cooling_degree_days* are generally positive and significant, as expected. The estimated coefficients on the components of *mheb* (*median_income*, *residential_revenues*, and *residential_customers*) follow their mathematical relationship with *mheb*: those in the *mheb* numerator have positive coefficients, and those in the denominator have negative coefficients. The lags on *employment_rate* of two or more years have positive estimated coefficients, which is also consistent with the expectation that incomes rise with employment. The negative coefficients on the contemporaneous *employment_rate* and on its one-year lag – as well as the positive coefficient on *median_income_lag1* – are unexpected, though they may signify an initial income effect that promotes additional electricity use (e.g. purchase of new appliances) when incomes rise.

Unfortunately, none of the estimated coefficients on DSM expenditures per customer are significant, and these variables are excluded from the table. Table C.1 shows that the estimated coefficients for most of these variables, at least in models (1) and (2), are positive. We could partially infer this from the coefficient on *eers_policy* itself, since we would expect an EERS to lead to greater DSM expenditures over time. Finally, coefficients tend to have similar signs and magnitudes for given variables between models (1) and (2) and between models (3) and (4) when they are significant, which suggests that data interpolation methods were not a major source of error. Even where the differences are more substantial, they are mere tenths or hundredths of an MHEB point and are therefore small in a practical sense.

Individual Policy Effects

The following three analyses focus on each policy individually, and in particular on the effects of lags of the policies and of various control variables. The control variables include contemporaneous interactions with the other two major policies (as well as with *decoupling_policy*) to address some of the temporal overlap between policies in a given state. Tables 4.6 to 4.8 below provide the regression outputs for the fixed effects model in Equation 3.1, with *eers_policy*, *rps_policy*, and *deregulation* respectively serving as the policy variable of interest. For each, models (1) through (4) are defined the same way as in the combined analysis above. Again, the values in parentheses in each table are clustered standard errors, which are robust to arbitrary forms of heteroskedasticity and serial correlation (Wooldridge 2003). The value of ρ used in the initial Prais-Winsten data transformation for each of the analyses appears beneath the associated table, along with other information.

TABLE 4.6: EERS Regression Outputs

Variables	(1)	(2)	(3)	(4)
eers_policy	6.48e-02	5.13e-02	-2.94e-02	-3.98e-02
	(3.70e-02)*	(5.54e-02)	(3.56e-02)	(5.06e-02)
eers_policy_lag1	7.40e-02	7.82e-02	3.87e-02	4.49e-02
	(2.24e-02)***	(2.31e-02)***	(2.13e-02)*	(2.22e-02)**
eers_policy_lag2	5.73e-02	5.89e-02		
	(1.99e-02)***	(2.30e-02)**		
eers_policy_lag3	5.42e-02	5.51e-02		
	(2.47e-02)**	(2.79e-02)*		
eers_policyXrps_policy	-6.61e-03	9.73e-05	4.21e-02	5.03e-02
	(4.55e-02)	(6.73e-02)	(4.57e-02)	(6.38e-02)
eers_policyXderegulation	-3.39e-02	-1.08e-02	-1.78e-02	7.07e-03
	(4.21e-02)	(5.04e-02)	(4.11e-02)	(4.86e-02)
decoupling_policy	5.48e-02	5.60e-02	2.24e-02	1.05e-02
	(3.76e-02)	(5.66e-02)	(3.50e-02)	(4.96e-02)
eers_policyXdecoupling_policy	-1.05e-02	-8.03e-04	2.53e-02	3.91e-02
	(3.45e-02)	(4.80e-02)	(3.27e-02)	(4.22e-02)
c&i_revenues	8.06e-05	7.58e-05	1.19e-04	1.15e-04
	(3.30e-05)**	(3.18e-05)**	(4.32e-05)***	(4.63e-05)**
c&i_revenues_lag1			3.14e-05	4.21e-05
			(2.13e-05)	(1.99e-05)**
c&i_revenues_lag2			2.67e-05	
			(1.54e-05)*	
c&i_revenuesXdecoupling_policy	-2.16e-05	-2.20e-05	-1.05e-05	-1.12e-05
	(7.81e-06)***	(9.33e-06)**	(7.52e-06)	(8.55e-06)
t&d_expenditures	3.13e-04	2.56e-04	2.61e-04	2.08e-04
	(9.66e-05)***	(8.78e-05)***	(8.70e-05)***	(7.99e-05)**
t&d_expenditures_lag1			1.89e-04	2.24e-04
			(8.87e-05)**	(9.74e-05)**
heating_degree_days	9.19e-05	9.22e-05	8.88e-05	9.07e-05
	(9.34e-06)***	(1.04e-05)***	(7.83e-06)***	(9.42e-06)***
cooling_degree_days	3.40e-04	3.24e-04	3.19e-04	3.07e-04
	(2.44e-05)***	(2.70e-05)***	(2.49e-05)***	(3.12e-05)***
median_income_lag1	2.91e-03	2.85e-03	1.18e-02	1.32e-02
	(3.33e-03)	(3.72e-03)	(3.25e-03)***	(3.79e-03)***
median_income_lag2	-1.12e-02	-1.27e-02	-5.40e-03	-7.52e-03
	(3.12e-03)***	(3.65e-03)***	(3.07e-03)*	(3.57e-03)**
median_income_lag3	-8.67e-03	-8.31e-03	-1.20e-02	-1.11e-02
	(3.23e-03)***	(3.86e-03)**	(3.01e-03)***	(3.50e-03)***
median_income_lag4			-1.19e-02	-9.63e-03
			(2.49e-03)***	(2.90e-03)***
employment_rate	-5.66e-03	-4.54e-03	-2.68e-02	-2.47e-02
	(3.67e-03)	(3.87e-03)	(4.28e-03)***	(4.45e-03)***
employment_rate_lag1	-1.60e-02	-1.77e-02	-3.91e-02	-4.21e-02
	(5.42e-03)***	(6.22e-03)***	(5.23e-03)***	(5.89e-03)***
employment_rate_lag2	1.62e-02	1.38e-02		
	(4.54e-03)***	(4.55e-03)***		
employment_rate_lag3	1.60e-02	1.86e-02		
	(5.68e-03)***	(6.16e-03)***		
employment_rate_lag4	1.44e-02	1.57e-02		
	(5.14e-03)***	(5.67e-03)***		
_constant	-4.05e-02	-3.92e-02	1.75e+00	1.74e+00
	(1.30e-02)***	(1.35e-02)***	(1.20e-01)***	(1.23e-01)***
R2 Within	0.6176	0.6495	0.2318	0.2270
R2 Between	0.1012	0.1753	0.0857	0.0822
R2 Overall	0.5290	0.5580	0.1681	0.1540
Observations	2,310	1,852	2,100	1,646
Groups	105	105	105	105

* *p*<0.1; ** *p*<0.05; *** *p*<0.01; Parentheses contain clustered std. errors; Model 1: Fitted (NCL); Model 2: No Projected Data (NCL); Model 3: Fitted (CL); Model 4: No Projected Data (CL); Some insignificant or marginally significant control variables have been removed from the table (see Appendix C for the full results); ρ=0.793

As in the combined analysis, the contemporaneous effect of *eers_policy* on *mheb* appears to be positive and significant (at least in model (1)). The effects of lags on *eers_policy* are also positive and significant up to three years out, with coefficients becoming gradually smaller over time. The estimated effect of *eers_policy* in model (1) corresponds to an average and ceteris paribus increase in annual electric expenditures of about $37 (0.065 *mheb* percentage points); this increases to $42 (0.074 *mheb* percentage points) after one year and then begins to decline again. The interactions with *eers_policy* are insignificant across all four models, though the negative and significant coefficient estimates on *c&i_revenuesXdecoupling_policy* again suggest that decoupling policies decrease the magnitude of rate hikes that would occur for other reasons. Coefficients on the categorical dummies for DSM expenditures per household are again insignificant across models, and they are excluded from Table 4.6. As shown in Table C.5, these insignificant coefficients are generally positive as the dollar amounts increase, which loosely supports the finding of positive and significant effects of an EERS policy on *mheb*. Nevertheless, these coefficients switch sign in Table C.7 (models (3) and (4)), which suggests that correlation between DSM expenditures and other (lagged) expenditures is confounding the analysis of DSM spending.

Where significant, the coefficients on control variables are similar to those in the combined analysis. Coefficients on *median_income_lag1*, *employment_rate*, and *employment_rate_lag1* again have the opposite sign from the one expected, which may signal initial income effects that promote increased electricity use. Once more, significant coefficients tend to have similar signs and magnitudes across models, and the primary (though small) differences that do exist appear to result from inclusion of the expenditure lags in models (3) and (4) rather than from exclusion of projected data.

TABLE 4.6: RPS Regression Outputs

Variables	(1)	(2)
rps_policy	5.82e-02	4.94e-02
	(2.45e-02)**	(2.71e-02)*
rps_policy_lag1	4.25e-02	3.79e-02
	(1.93e-02)**	(1.88e-02)**
rps_policy_lag2	5.77e-02	4.34e-02
	(3.10e-02)*	(3.89e-02)
rps_policy_lag3	5.21e-02	3.15e-02
	(2.54e-02)**	(2.77e-02)
rps_policy_lag4	6.57e-02	7.15e-02
	(2.20e-02)***	(2.47e-02)***
rps_policy_lag5	3.99e-02	4.37e-02
	(2.08e-02)*	(2.23e-02)*
eers_policyXrps_policy	-4.52e-03	1.71e-02
	(2.53e-02)	(2.97e-02)
rps_policyXderegulation	-4.98e-02	-2.83e-02
	(3.08e-02)	(3.66e-02)
c&i_revenues	1.14e-04	1.09e-04
	(3.92e-05)***	(4.20e-05)**
c&i_revenuesXdecoupling_policy	-2.19e-05	-2.47e-05
	(8.51e-06)**	(1.02e-05)**
power_expenditures	1.59e-05	2.51e-05
	(9.38e-06)*	(1.79e-05)
t&d_expenditures	2.44e-04	2.02e-04
	(1.00e-04)**	(9.14e-05)**
heating_degree_days	9.73e-05	9.86e-05
	(9.33e-06)***	(1.07e-05)***
cooling_degree_days	3.46e-04	3.31e-04
	(2.38e-05)***	(2.75e-05)***
median_income_lag2	-1.16e-02	-1.30e-02
	(3.01e-03)***	(3.48e-03)***
median_income_lag3	-9.34e-03	-9.23e-03
	(3.28e-03)***	(3.88e-03)**
residential_revenues_lag2	1.27e-04	1.38e-04
	(5.62e-05)**	(6.31e-05)**
residential_revenues_lag3	2.28e-04	2.22e-04
	(5.94e-05)***	(6.31e-05)***
residential_revenues_lag4	1.05e-04	9.81e-05
	(4.38e-05)**	(4.57e-05)**
residential_customers_lag2	-3.07e-04	-3.56e-04
	(1.13e-04)***	(1.49e-04)**
residential_customers_lag3	-2.61e-04	-2.67e-04
	(1.16e-04)**	(1.77e-04)
residential_customers_lag4	-4.11e-04	-3.71e-04
	(9.09e-05)***	(1.01e-04)***
employment_rate_lag1	-1.80e-02	-1.91e-02
	(5.32e-03)***	(6.17e-03)***
employment_rate_lag2	1.67e-02	1.35e-02
	(4.28e-03)***	(4.20e-03)***
employment_rate_lag3	1.50e-02	1.81e-02
	(5.49e-03)***	(5.98e-03)***
employment_rate_lag4	1.32e-02	1.42e-02
	(4.96e-03)***	(5.44e-03)**
_constant	-3.71e-02	-3.30e-02
	(1.36e-02)***	(1.43e-02)**
R2 Within	0.6279	0.6574
R2 Between	0.2691	0.3484
R2 Overall	0.5692	0.5981
Observations	2,310	1,852
Groups	105	105

* p<0.1; ** p<0.05; *** p<0.01; Parentheses contain clustered std. errors; Model 1: Fitted (NCL); Model 2: No Projected Data (NCL); Some insignificant or marginally significant control variables have been removed from the table (see Appendix C for the full results); ρ=0.794

Following the discussion in Appendix A, all three components of *mheb* (*median_income*, *residential_revenues*, and *residential_customers*) appear in the RPS analysis. Thus, it was again necessary to test for any additional AR(1) serial correlation that might arise due to the interaction of these variables with *mheb*. After performing the first Prais-Winsten transformation according to the procedure in Chapter 3, I ran another regression using the *xtregar* command in Stata and collected the residuals. I then regressed the residuals on their first-order lags; the resulting estimate of ρ was -0.0163, with a p-value of 0.136. This is insufficient evidence for AR(1) serial correlation, and a second Prais-Winsten transformation was not necessary. Another peculiarity of the RPS analysis was that the expenditure lags in models (3) and (4) were not significant and were removed during the lag fitting procedure. Therefore, I only include models (1) and (2) in Table 4.7 and in Appendix C.

The contemporaneous and lagged effects of *rps_policy* on *mheb* are generally positive and significant, though there is no clear trend in the magnitude of coefficients over time. The coefficient on *rps_policy* in model (1) corresponds to an average and ceteris paribus increase in annual household electric expenditures of $33 (0.058 *mheb* percentage points) when an RPS is in place. This again supports the findings of Tra (2016) that RPS policies have led to residential rate increases over time, though as in the combined policy analysis above, the estimated effect is smaller here. Interactions are once more insignificant except for *c&i_revenuesXdecoupling_policy*, whose estimated coefficient is negative and significant, as in the EERS and combined analyses above. Other control variables follow the same patterns as in the EERS and combined analyses, including the negative coefficient on the first-degree lag of *employment_rate*, and all categorical dummies for DSM spending per household are insignificant. Once again, significant coefficients have similar magnitudes between models (1) and (2), which suggests that the data interpolation method did not significantly affect results.

TABLE 4.7: Deregulation Regression Outputs

Variables	(1)	(2)
deregulation	-1.23e-01	-1.00e-01
	(2.80e-02)***	(2.11e-02)***
deregulation_lag1	-8.20e-02	-6.49e-02
	(5.41e-02)	(3.39e-02)*
deregulation_lag2	-2.32e-02	-3.39e-02
	(3.11e-02)	(2.46e-02)
deregulation_lag3	8.76e-02	8.07e-02
	(4.29e-02)**	(3.10e-02)**
eers_policyXderegulation	3.23e-02	5.78e-03
	(3.87e-02)	(2.85e-02)
rps_policyXderegulation	4.98e-02	3.22e-02
	(2.69e-02)*	(2.12e-02)
decoupling_policy	5.56e-03	1.16e-03
	(5.55e-02)	(4.10e-02)
deregulationXdecoupling_policy	7.75e-02	6.71e-02
	(2.76e-02)***	(2.69e-02)**
c&i_revenues	5.94e-05	6.34e-05
	(3.15e-05)*	(3.26e-05)*
c&i_revenuesXdecoupling_policy	-1.25e-05	-9.95e-06
	(9.62e-06)	(7.84e-06)
power_expenditures	2.39e-05	1.39e-05
	(1.72e-05)	(8.86e-06)
t&d_expenditures	3.18e-04	3.75e-04
	(8.59e-05)***	(9.53e-05)***
heating_degree_days	9.49e-05	9.48e-05
	(1.04e-05)***	(9.39e-06)***
cooling_degree_days	3.19e-04	3.34e-04
	(2.73e-05)***	(2.45e-05)***
median_income_lag1	2.21e-03	2.76e-03
	(3.59e-03)	(3.30e-03)
median_income_lag2	-1.36e-02	-1.03e-02
	(3.57e-03)***	(3.17e-03)***
median_income_lag3	-9.29e-03	-8.24e-03
	(3.86e-03)**	(3.28e-03)**
median_income_lag4		-4.97e-03
		(2.41e-03)**
employment_rate	-3.58e-03	-3.57e-03
	(3.89e-03)	(3.79e-03)
employment_rate_lag1	-1.95e-02	-1.89e-02
	(6.12e-03)***	(5.38e-03)***
employment_rate_lag2	1.31e-02	1.50e-02
	(4.29e-03)***	(4.17e-03)***
employment_rate_lag3	1.91e-02	1.55e-02
	(5.82e-03)***	(5.43e-03)***
employment_rate_lag4	1.73e-02	1.82e-02
	(5.31e-03)***	(5.06e-03)***
_constant	-8.92e-03	-8.86e-03
	(1.43e-02)	(1.40e-02)
R2 Within	0.6502	0.6189
R2 Between	0.2148	0.1565
R2 Overall	0.5673	0.5406
Observations	1,852	2,310
Groups	105	105

* p<0.1; ** p<0.05; *** p<0.01; Parentheses contain clustered std. errors; Model 1: Fitted (NCL); Model 2: No Projected Data (NCL); Model 3: Fitted (CL); Model 4: No Projected Data (CL); Some insignificant or marginally significant control variables have been removed from the table (see Appendix C for the full results); ρ=0.793

The lag fitting procedure again removed all lags on expenditures and on *c&i_revenues* in models (3) and (4), which are therefore excluded here and in Appendix C. The estimated coefficient on *deregulation* in Table 4.7 is negative and significant, which is consistent with the combined analysis in the previous section. The coefficient corresponds with an average and ceteris paribus drop in *mheb* of 0.12 percentage points when deregulation is in place in the current year – as compared to years in which deregulation is not in place – which translates to roughly $68 fewer dollars spent on electricity in a given year. This coefficient is similar in magnitude to some of the contemporaneous, state-specific effects of deregulation on residential electric rates determined by Swadley and Yücel (2011). It is also a notable estimate, given that the analysis focuses specifically on those residential customers who stuck with IOUs under deregulation. Yet this coefficient may also reflect the effect of rate caps implemented by many states in the first years of deregulation, which Hickey and Carlson (2010) and Swadley and Yücel (2011) both find depressed electric rates and bills initially. Although most lags on *deregulation* are statistically insignificant, Tables 4.7 and C.11 indicate an apparent trend towards positive values over time. The coefficient on *deregulation_lag3* in particular is both positive and significant, which suggests that deregulation has actually increased the electric energy burden of IOU customers over time, whether due to the removal of price caps (Hickey and Carlson 2010) or to the need for IOUs to recoup capacity investment costs from a dwindling customer base. This effect is masked in the finding by Swadley and Yücel (2011) that residential prices *overall* (including for customers who switched to third party providers) decreased as competitive retail markets matured under deregulation. Future research should clarify this finding by examining additional lags.

Aside from this, the estimated coefficients for the remaining control variables are similar in sign and magnitude to those in the EERS and RPS models. Here again, *decoupling_policy* has insignificant effects on its own, as well as an insignificant (though negative, as expected) effect in its interaction with *c&i_revenues*. Interestingly, *decoupling_policy* has a significant and *positive* effect in its interaction with *deregulation*. There are two plausible explanations for this effect. One is that deregulated IOUs have under-recovered the revenue levels agreed with regulators under decoupling policies, which has led to consistently positive rate adjustments. Table 1 in Swadley and Yücel (2011) reports that rate caps lasted from two to over ten years and were removed in various states between 2001 and 2011. Table B.2 in Appendix B of this paper shows that decoupling often began around ten years after deregulation in states with both policies. Thus, another explanation for the positive coefficient on *deregulationXdecoupling_policy* is that the beginning of revenue decoupling in many states coincided with the removal of price caps, and the interaction is actually picking up the effect of cap removals. Future research may attempt to discern which explanation holds more sway. Finally, coefficient estimates on other control variables follow the patterns identified in the individual and combined policy analyses above, and statistically significant coefficients again have similar signs and magnitudes across the two models.

CHAPTER 5: DISCUSSION AND OPPORTUNITIES FOR FUTURE RESEARCH

On the whole, this analysis (at least loosely) corroborates the findings of prior research. After controlling for factors related to utility finances, weather, and economic activity, it appears that median household electric burden (MHEB) has increased over time among the investor-owned utilities (IOUs) studied and that at least part of this increase can be attributed to various state level energy policies enacted since the early 1990s. Put differently, as time has progressed and as states have implemented policies to shape the electric sector with various motives, the amount of money an average household spends on electricity has grown faster than median income among those who rely on local IOUs for all aspects of their electric service.

These findings are particularly apparent with regard to electric sector deregulation. MHEB mirrors the response of electric rates to price caps that were enacted by states and later eased, as described by both Hickey and Carlson (2010) and Swadley and Yücel (2011), and the long term effect appears to be an increase in IOU customers' electric burden. The results for renewable portfolio standards (RPS) provide support to the findings of Tra (2016), namely that rates have also risen for these customers over time as a result of RPS implementation. The results for energy efficiency resource standards (EERS) are statistically significant and positive and suggest that EERS policies are also associated with increases in MHEB, even though it was not possible to identify significant effects of different DSM spending levels through this analysis. Decoupling of utility revenues from sales appears to have a somewhat small (though statistically insignificant) effect on MHEB across all analyses – in line with the small magnitude of decoupling adjustments identified by Lesh (2009) – but it generally appears to constrain exogenous rate hikes. Control variables such as heating degree days and lags on median income have some of the most consistent effects across all four analyses, which at least lends credence to their inclusion.

In reviewing these results, it is critical to remember that MHEB and electric rates are not equivalent, even if they appear to move in sync. MHEB is a more "fundamental" metric than electric rates in that it accounts for income as well as expenditures. If electric rates increase at a pace equal to or less than that of income, then rate increases are not an immediate problem. If rates increase more quickly than incomes, however, then MHEB will increase as long as consumers cannot change their electric consumption behaviors sufficiently in the short term. This has real distributional effects in society, despite the seemingly small coefficients estimated in Chapter 4. An increase in annual electricity expenditures of any amount or income percentage will mean much more to low- and moderate income (LMI) households than to wealthy households. Furthermore, although MHEB is an imperfect proxy for LMI electric energy burden and does not reflect the wide spectrum of energy burden values identified in studies such as Drehobl and Ross (2016) and McIlmoil (2014).

Regional disparities noted by these same authors reappear in the current analysis: the states with the highest MHEB values in 2015 – weighted by number of bundled service customers for each IOU – were Alabama (3.77%), Mississippi (3.57%), West Virginia (3.14%), and Arkansas (3.05%), whereas jurisdictions with the lowest values were in Illinois (1.59%), the District of Columbia (1.48%), Minnesota (1.42%), and Colorado (1.34%). The first three states are notably ones that did not implement any of the three primary policies discussed here, whereas the latter five all implemented various combinations of these policies. According to data from the US Census Bureau (2016), the states with the highest MHEB values in 2015 were also amongst the most impoverished, with Mississippi having the highest percentage of its population living in poverty (22.1%) and West Virginia having the seventh highest (18%). Poverty estimates were more mixed for the states with low MHEB values in 2015: DC had the eighth highest poverty level (17.7%), whereas Minnesota had the third lowest (10.2%). Thus, it is not enough to say that certain state level energy policies are associated with increases in electric burden over time, since fundamental differences still exist between states that did and did not implement these policies. These differences complicate the analysis of whether energy policies have been "good" or "bad" for consumers overall (particularly since not all benefits and costs are included here), and they are likely rooted in overarching historical, political, and economic factors that have interacted with electric sector development but that have much broader social ramifications.

In short, the results of this analysis are nuanced. Perhaps the most significant takeaway is that distributional impacts are still very important in electric policy, and policymakers must remain vigilant in ensuring that they do not create new problems as they attempt to solve existing ones. Well-intentioned policy can lead to unintended consequences, such as increased energy burden for electric consumers who stick with their local utilities, and both potential consequences and the methods for addressing them must appear in the cost-benefit calculus. Adequate solutions are not always apparent. For example, can and should deregulated states force electric consumers to choose a service provider rather than sticking with the local IOU by default, given the findings of Swadley and Yücel (2011) that average rates decrease as large numbers of consumers switch to third parties? Should energy efficiency programs target high-income consumers who use a lot of electricity, even if all consumers pay the costs of these programs? These are the types of questions that will define our future energy system.

This study has attempted to provide a "big picture" to frame the discussion of how EERS, RPS, and deregulation have affected residential consumer electric energy burden. Yet there are numerous issues that I have either not addressed or have only partially addressed here, and these represent avenues of future research that would more fully develop the present analysis. One such possibility is to attempt more granular calculations of MHEB using, for example, median incomes on the Census tract or municipality level. This would enable better approximations of MHEB for utilities in the absence of adequate household level data. If household data were available, an even better option would be to perform the analysis specifically for LMI households while controlling for the effects of discounted electric rates and energy assistance programs that they may take advantage of. Candidates for other control variables include the existence of regional electric wholesale markets, customer participation in distributed energy resource programs such as solar net metering, and the local prevalence of electric (versus natural gas) heating. It would also be useful to differentiate demand side management expenditures into separate energy efficiency and demand response categories (and to further differentiate each by customer class), as well as to include other outside sources of energy efficiency funding, such as the Regional Greenhouse Gas Initiative in the Northeast or any regional efficiency organizations that IOUs do not incorporate into their annual data submissions to the Energy Information Administration. Researchers might address the confounding influence of temporal overlap between policies by performing quantitative and qualitative analyses of state-specific program nuances, such as the timing of rate cap implementation and removal and the specific technologies included in an RPS. Finally, future research should attempt expanded regional comparisons and, in particular, should ensure adequate representation from the US Southeast.

CHAPTER 6: CONCLUSION

This study has attempted to join the energy policy impacts and energy burden literatures to assess whether and how state level energy policies have affected residential consumers’ energy burden in the United States over the past two decades. Specifically, I have addressed the impacts of energy efficiency resource standards (EERS), renewable portfolio standards (RPS), and electric sector deregulation – as well as decoupling of utility revenues from sales of electricity. I have found that median household electric burden (MHEB), which I defined specifically for this analysis, has largely followed the movements of electric rates that numerous previous studies have identified. The effects of deregulation are the most significant and suggest that despite short-term rate decreases in response to rate cap implementation, the electric burden of residential customers that stick with their local investor-owned utility (IOU) has increased over time. The results for RPS are less obvious but provide weak evidence of an increase in MHEB. The results for EERS are similarly weak, but IOU expenditures on demand side management (DSM) – a primary result of EERS policies – do appear to increase MHEB over time. Decoupling has very small impacts overall, but it appears to mitigate the effects of rate increases on MHEB.

The results of this analysis provide a wide berth for additional research, particularly studies that would delve deeper into the differences among similar policies enacted from state to state. Regardless, the primary takeaway is that otherwise well-intentioned energy policies may be engendering unintended negative consequences; this finding is, of course, nothing new to the energy burden literature. As the US electric system becomes more integrated and data-driven, and as state and local governments continue to push towards emissions reductions and other responses to climate change, it is critical that we account for the impact of these regulatory adjustments on vulnerable low-income electricity consumers.

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APPENDIX A: ADJUSTMENTS FOR ENDOGENEITY

A major source of potential endogeneity in Equation 3.1 stems from the interaction between the median household electric burden (MHEB) and the policy variables of interest: energy efficiency resource standards (EERS), renewable portfolio standards (RPS), and deregulation. If state regulators first implement these policies in response to perceived changes in MHEB, then I cannot treat the policies as independent variables with respect to MHEB, and it is necessary either to find suitable instrumental variables for the policies or to address endogeneity some other way. Unfortunately, it is challenging to identify instruments for binary variables, particularly when they overlap to a significant degree. Even the most promising candidate for an instrument – a political variable such as total votes for Democrats or Republicans in a utility service territory over the past several election cycles – will not do because the policies considered in this analysis were implemented in states with different political leanings and because voting is possibly correlated with electric rates or incomes, which are components of MHEB. I have therefore chosen to address endogeneity in a different way.

Whether defined as MHEB or otherwise, energy burden itself is a somewhat new and abstract concept, and for that reason, it is not likely to affect policy decisions directly. I have defined MHEB as the average per-household revenue that an investor-owned utility (IOU) derives from residential electric sales divided by the median household income within its service territory. Put differently, MHEB is the average annual electric bill for a household (AB) divided by median household income (MI):

$$\mathrm{MHEB} = \mathrm{AB} \,/\, \mathrm{MI} \qquad \text{(A.1)}$$

Average bills, in turn, are calculated by dividing an IOU's annual residential revenues (RR) by the number of households – or residential consumers (RC) – in a given IOU service territory in a given year. Thus, the equation for MHEB breaks down further as follows:

$$\mathrm{MHEB} = (\mathrm{RR} \,/\, \mathrm{RC}) \,/\, \mathrm{MI} = \mathrm{RR} \,/\, (\mathrm{RC} * \mathrm{MI}) \qquad \text{(A.2)}$$

I suggest that these three components of MHEB – residential revenues, number of residential customers, and median household income – are more digestible and relevant than MHEB itself and that they are the variables which might truly predict policy implementation.

I used random effects probit regression analyses to test whether these variables can predict implementation of the three policies of interest, or of revenue decoupling. Although the main analysis in Chapter 4 uses fixed effects, a sufficient method for analyzing probit models with fixed effects does not exist (StataCorp 2015b). Fixed effects and random effects models make different assumptions regarding the degree of correlation between the "effect" and the explanatory variables; these assumptions are mutually exclusive and cannot both hold in a single analysis. Nevertheless, I use the random effects probit model here because I am only interested in showing the possibility of endogeneity and in identifying a method to reduce the potential for error, rather than in determining exact correlations. I continue to assume fixed effects in the main analysis.

The data for these probit analyses consisted of records for each IOU up to and including the year the policy was first implemented, as well as all years for any IOU for which the policy was never implemented. This unbalanced panel enabled me to test whether the dependent variables were moving in any common direction before a policy was implemented for a given IOU (usually for an entire state), relative to IOUs where the policy never appeared. As in the main analyses in Chapter 4, I first used the *xtregar* command in Stata to perform a random effects regression for each policy according to Equation A.3 below:

$$\mathrm{policy\_start\_year_{it}} = \beta_1 \mathrm{median\_income_{it-1}} + \beta_2 \mathrm{residential\_revenues_{it-1}} + \beta_3 \mathrm{residential\_customers_{it-1}} + \beta_4 \mathrm{employment\_rate_{it-1}} + \alpha_i + \varepsilon_{it} \tag{A.3}$$

where *policy_start_year* is a dummy variable indicating whether the given policy was initiated in the given year for the given IOU, *median_income* is a one-year lag on median income in the service territory, *residential_revenues* is a one-year lag on residential revenues to the utility, *residential_customers* is a one-year lag on residential customers in the service territory, *employment_rate* is a one-year lag on the employment rate in the service territory, α is the random effects operator, and ε is a random error term. The subscripts *i* and *t* indicate a given IOU and a given year, respectively. I used random effects here, rather than fixed effects, for the reasons noted above.

To remove the effects of correlation over time, I then used the estimated ρ – the coefficient of AR(1) serial correlation calculated as a byproduct of *xtregar* – to transform the data using the Prais-Winsten procedure (Prais and Winsten 1954). One concern is that the lags in this particular model may pick up some of the time effect and therefore distort the estimate of ρ. Again, I set aside this concern because I am interested in outlining a plausible method to deal with endogeneity and am not interested in estimating exact values. The estimated value of ρ will remove some time effects and will therefore improve the accuracy of the estimates below.

Next, I used the *xtprobit* command in Stata to perform a random effects probit regression of the demeaned data, again according to Equation A.3. Finally, I selected significant variables from this initial analysis and performed a second probit regression that included them along with a one-year lag on *mheb*, following Equation A.4 below:

$$\mathrm{policy\_start\_year}_{\mathrm{it}} = \beta_1 \mathrm{mheb}_{\mathrm{it}-1} + \beta_{\mathbf{2}} \mathbf{V}_{\mathbf{it-1}} + \alpha_{\mathrm{i}} + \varepsilon_{\mathrm{it}} \qquad \text{(A.4)}$$

where *policy_start_year* is a dummy variable indicating whether the given policy was initiated in the given year for the given IOU, *mheb* is a one-year lag on median household electric burden in the service territory, ***V*** is a vector of one-year lags on the significant variables identified through the initial regression, α is the random effects operator, and ε is a random error term. Again, the subscripts *i* and *t* respectively indicate a given IOU and a given year.

The "significant" variables always included at least one MHEB component. I did not include all three MHEB components when all were significant, however, since doing so would be statistically similar to duplicating the lag on *mheb* that appears in Equation A.4. I discuss why this would be a problem at the end of this appendix.

The results of the probit analyses are presented in Tables A.1 to A.9 below, along with a discussion of their application to the full analysis in Chapter 4. Notes at the bottom of Tables A.1, A.3, A.5, and A.8 contain the ρ values used in the Prais-Winsten transformations for the given policies.

TABLE A.1: Random Effects Probit Analysis of EERS Start Year, Model 1

Dep. Var. / Metrics	Indep. Var.	Model 1
eers_start_year	median_income_lag1	2.53e-02
		(1.33e-02)*
	residential_revenues_lag1	-1.19e-04
		(5.73e-04)
	residential_customers_lag1	3.46e-04
		(6.22e-04)
	employment_rate_lag1	-2.67e-01
		(8.45e-02)***
	_constant	1.10e+01
		(3.95e+00)***
lnsig2u	_constant	-1.55e+01
		(7.75e+05)
Observations		1,810

* *p*<0.1; ** *p*<0.05; *** *p*<0.01; Parentheses contain robust std. errors; *ρ*=0.458

TABLE A.2: Random Effects Probit Analysis of EERS Start Year, Model 2

Dep. Var. / Metrics	Indep. Var.	Model 2
eers_start_year	mheb_lag1	-8.73e-02
		(1.30e-01)
	median_income_lag1	2.52e-02
		(1.49e-02)*
	employment_rate_lag1	-2.77e-01
		(7.05e-02)***
	_constant	1.18e+01
		(3.27e+00)***
lnsig2u	_constant	-1.49e+01
		(3.51e+05)
Observations		1,810

* *p*<0.1; ** *p*<0.05; *** *p*<0.01; Parentheses contain robust std. errors

The most significant dependent variables in model 1 are *employment_rate_lag1* and *median_income_lag1*, which are subsequently included in model 2. As the results indicate, *mheb_lag1* does not significantly predict *eers_start_year* when these controls are included. The same will hold true for further lags on MHEB if equivalent lags on the MHEB components are also included.

TABLE A.3: Random Effects Probit Analysis of Decoupling Start Year, Model 1

Dep. Var. / Metrics	Indep. Var.	Model 1
decoupling_start_year	median_income_lag1	3.09e-02
		(1.22e-02)**
	residential_revenues_lag1	2.56e-04
		(6.24e-04)
	residential_customers_lag1	-4.81e-05
		(6.96e-04)
	employment_rate_lag1	-6.74e-02
		(3.01e-02)**
	_constant	2.62e-01
		(1.29e+00)
lnsig2u	_constant	-1.56e+01
		(1.03e+06)
Observations		2,089

* *p*<0.1; ** *p*<0.05; *** *p*<0.01; Parentheses contain robust std. errors; *ρ*=0.458

TABLE A.4: Random Effects Probit Analysis of Decoupling Start Year, Model 2

Dep. Var. / Metrics	Indep. Var.	Model 2
decoupling_start_year	mheb_lag1	6.39e-02
		(2.08e-01)
	median_income_lag1	3.85e-02
		(2.32e-02)*
	employment_rate_lag1	-7.31e-02
		(4.55e-02)
	_constant	2.61e-01
		(1.59e+00)
lnsig2u	_constant	-1.57e+01
		(2.06e+06)
Observations		2,089

* *p*<0.1; ** *p*<0.05; *** *p*<0.01; Parentheses contain robust std. errors

The most significant dependent variables in model 1 for decoupling (Table A.3) are again *employment_rate_lag1* and *median_income _lag1*, which are subsequently included in model 2. Once more, *mheb_lag1* does not significantly predict *decoupling_start_year* when these controls are included, and an analogous argument will hold for further lags on MHEB.

TABLE A.5: Random Effects Probit Analysis of RPS Start Year, Model 1

Dep. Var. / Metrics	Indep. Var.	Model 1
rps_start_year	median_income_lag1	3.99e-02
		(9.92e-03)***
	residential_revenues_lag1	-1.04e-03
		(5.32e-04)*
	residential_customers_lag1	1.38e-03
		(5.96e-04)**
	employment_rate_lag1	-7.30e-02
		(1.23e-02)***
	_constant	9.69e-01
		(4.58e-01)**
lnsig2u	_constant	-1.46e+01
		(2.86e+05)
Observations		1,528

* *p*<0.1; ** *p*<0.05; *** *p*<0.01; Parentheses contain robust std. errors; *ρ*=0.424

TABLE A.6: Random Effects Probit Analysis of RPS Start Year, Model 2

Dep. Var. / Metrics	Indep. Var.	Model 2
rps_start_year	mheb_lag1	-3.04e-01
		(1.33e-01)**
	median_income_lag1	2.86e-02
		(1.09e-02)***
	employment_rate_lag1	-7.53e-02
		(1.73e-02)***
	_constant	2.15e+00
		(8.75e-01)**
lnsig2u	_constant	-1.37e+01
		(6.80e+04)
Observations		1,528

* *p*<0.1; ** *p*<0.05; *** *p*<0.01; Parentheses contain robust std. errors

The most significant dependent variables in model 1 for RPS (Table A.5) are again *median_income_lag1* and *employment_rate_lag1*, which are subsequently included in model 2. Unfortunately, model 2 indicates that a one-year lag on MHEB does still significantly predict the start year of an RPS policy. Table A.7 below presents a model that expands upon Equation A.4. I began with four lags on each MHEB component variable (and *employment_rate*) and iteratively removed insignificant lags until all remaining variables had significant coefficient estimates.

TABLE A.7: Random Effects Probit Analysis of RPS Start Year, Model 3

Dep. Var. / Metrics	Indep. Var.	Model 3
rps_start_year	mheb_lag1	-2.22e-01
		(1.73e-01)
	median_income_lag3	-2.28e-01
		(4.75e-02)***
	median_income_lag4	2.63e-01
		(4.51e-02)***
	residential_revenues_lag1	3.17e-03
		(9.15e-04)***
	residential_revenues_lag3	-2.45e-03
		(8.37e-04)***
	residential_revenues_lag4	-2.34e-03
		(7.73e-04)***
	residential_customers_lag1	1.94e-03
		(6.86e-04)***
	employment_rate_lag1	1.04e-01
		(4.24e-02)**
	employment_rate_lag4	-1.77e-01
		(3.87e-02)***
	_constant	1.42e+00
		(8.79e-01)
lnsig2u	_constant	-1.30e+01
		(3.26e+04)
Observations		1,528

* *p*<0.1; ** *p*<0.05; *** *p*<0.01; Parentheses contain robust std. errors; Some insignificant lags have been removed to save space

As Table A.7 shows, *mheb_lag1* is no longer a statistically significant predictor of *rps_start_year* when several lags on the various MHEB components and on *employment_rate* are included. Again, this should also hold true for subsequent lags on MHEB when equivalent lags on the MHEB component variables are included. Notably, the model does not contain the same lags for all three MHEB components, which means that *mheb_lag1* is not duplicated.

TABLE A.8: Random Effects Probit Analysis of Deregulation Start Year, Model 1

Dep. Var. / Metrics	Indep. Var.	Model 1
deregulation_start_year	median_income_lag1	8.84e-02
		(1.23e-02)***
	residential_revenue_lag1	-1.89e-03
		(9.58e-04)**
	residential_customers_lag1	2.81e-03
		(1.18e-03)**
	employment_rate_lag1	-1.01e-01
		(9.50e-03)***
	_constant	6.45e-01
		(2.69e-01)**
lnsig2u	_constant	-1.21e+00
		(3.77e-01)***
Observations		1,588

* *p*<0.1; ** *p*<0.05; *** *p*<0.01; Parentheses contain robust std. errors; *ρ*=0.377

TABLE A.9: Random Effects Probit Analysis of Deregulation Start Year, Model 2

Dep. Var. / Metrics	Indep. Var.	Model 2
deregulation_start_year	mheb_lag1	-3.08e-01
		(2.52e-01)
	median_income_lag1	8.17e-02
		(1.33e-02)***
	employment_rate_lag1	-9.72e-02
		(1.05e-02)***
	_constant	1.51e+00
		(5.94e-01)**
lnsig2u	_constant	-1.10e+00
		(4.22e-01)***
Observations		1,588

* *p*<0.1; ** *p*<0.05; *** *p*<0.01; Parentheses contain robust std. errors

The most significant dependent variables in model 1 for deregulation (Table A.8) are once more *employment_rate_lag1* and *median_income_lag1*, which are subsequently included in model 2. As with the analyses of *eers_start_year* and *decoupling_start_year* above, *mheb_lag1* no longer significantly predicts *deregulation_start_year* when these components are included. The same should hold true for further lags on MHEB.

The primary takeaway from this analysis is that including lags on employment rates and/or relevant MHEB components in the primary fixed effects analysis in this study should largely account for the endogeneity that would result if policymakers tend to implement EERS, RPS, deregulation, or decoupling policies based on changes in MHEB. Identical lags for all three MHEB component variables – median income, residential revenues, and residential customers – should not be included at the same time, however, as doing so would be similar to including lags on MHEB itself. This would pose a problem in the primary fixed effects analysis because autoregressive models with panel data induce serial correlation in the errors by definition. Luckily, it appears from the analysis in this appendix that doing so would not be necessary in most cases. The full analysis in Chapter 4 therefore incorporates several lags on the variables identified above for each individual policy, and the models are fitted to the appropriate number of lags. Yet as this analysis identifies that all three MHEB components are significant predictors of an RPS policy start year, all three must be included in the individual analysis of RPS policies in Chapter 4, as well as in the combined analysis that considers the effects of all three policies simultaneously. I address the resulting potential AR(1) serial correlation in the full analysis in Chapter 4.

APPENDIX B: SUPPLEMENTAL CHARTS AND FIGURES

TABLE B.1: Policy Implementation by State

State	Deregulation	RPS	EERS	Decoupling
Alabama				
Alaska				
Arizona		2006	2010	
Arkansas			2010	2007 (2010)
California	1998 (2001)	2002	2004	1982 (1996); 2004
Colorado		2004	2007	
Connecticut	2000	1998	1998	2007*
Delaware	2000	2005		
District of Columbia	2001	2005		2009
Florida				
Georgia				
Hawaii		2001	2009	2010
Idaho				2013*
Illinois	1999	2007	2007	
Indiana			2010 (2014)	
Iowa		1983	2008	
Kansas				
Kentucky				
Louisiana				
Maine	2000	1999	2012	2014*
Maryland	2000	2004	2008	2007
Massachusetts	1998	1997	2008	2011*
Michigan	1998	2008 (2015)	2008	
Minnesota		2007	2007	
Mississippi				
Missouri		2007		
Montana		2005 (2015)		
Nebraska				
Nevada		1997	2005	
New Hampshire	1998*	2007		
New Jersey	1999	1999		
New Mexico		2002	2008	
New York	1998	2004	2008	2007
North Carolina		2008	2008	
North Dakota				

State	Deregulation	RPS	EERS	Decoupling
Ohio	2001	2008	2008 (2014)	2011*
Oklahoma				
Oregon		2007	2010	2009*
Pennsylvania	1999	2004	2012	
Rhode Island	1998	2004	2006	2011
South Carolina				
South Dakota				
Tennessee				
Texas	2002*	1999	1999	
Utah				
Vermont		2015	2007	2006
Virginia	2002 (2007)			
Washington		2006	2006	2014*
West Virginia				
Wisconsin		1998 (2015)	2010	
Wyoming				

States that were included in the analysis are in ***bold italics***. Parentheses indicate years in which policies were revoked or expired. Following the main analysis, this table indicates the year in which a given policy was actually implemented (or revoked), not the year in which it was approved by the state legislature or public utility commission. Where a state policy was implemented for different IOUs in different years, an asterisk (*) indicates the year in which the policy was first implemented for at least one IOU.
Sources: ACEEE (2016a), ACEEE (2016b), Electric Choice (2016), IEE (2013), NCSL (2016), Stanford University (2003), Swadley and Yücel (2011), Williams (2016)

TABLE B.2: Included IOUs by State

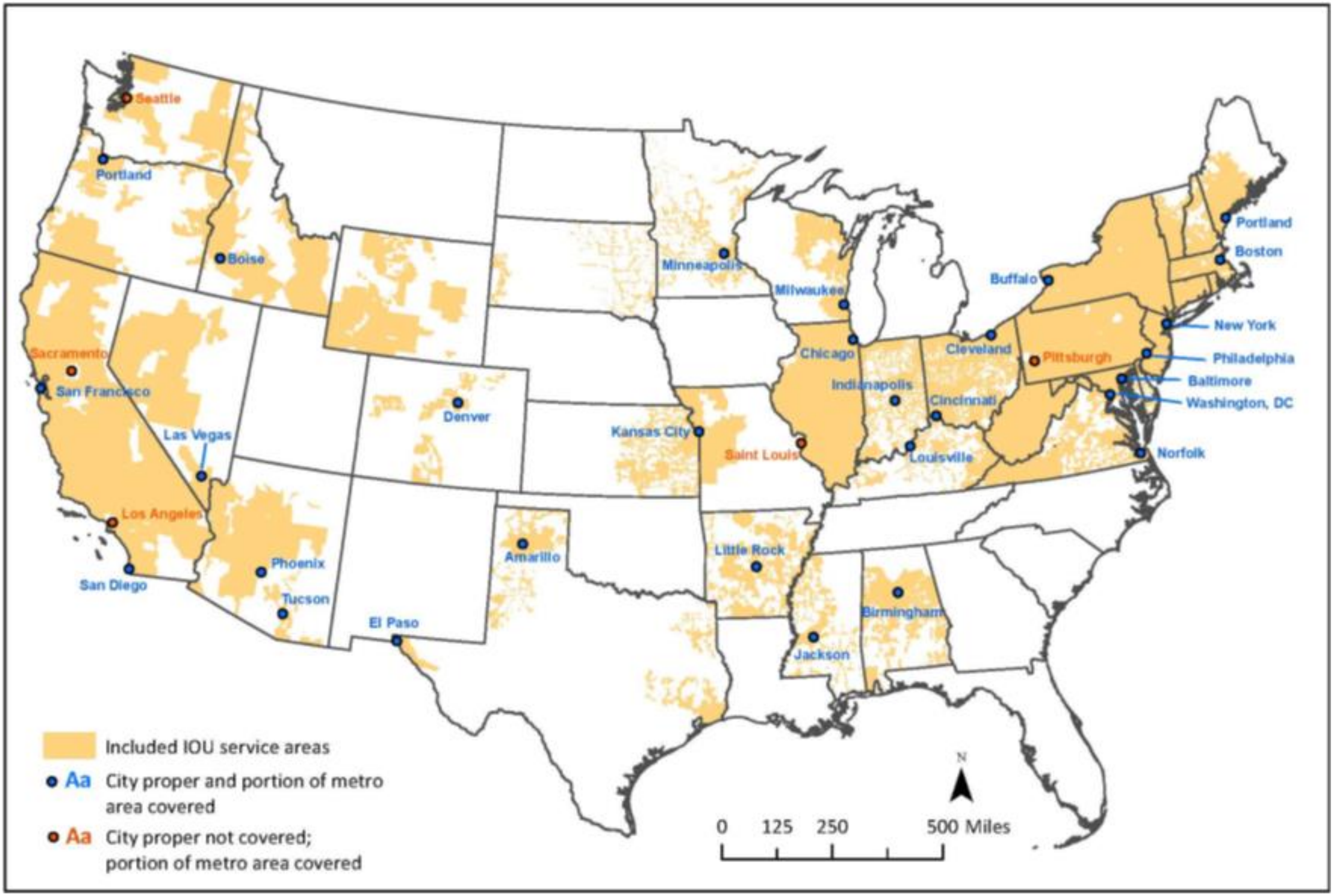
State	IOU (Common Name)	Avg. Residential Customers (Bundled Service)
Alabama	Alabama Power	1,164,774
Arizona	Arizona Public Service (APS)	859,571
	Tucson Electric Power (TEP)	332,488
	UNS Electric	69,119
Arkansas	Empire District Electric	3,254
	Entergy Arkansas	559,441
	Oklahoma Gas & Electric	52,274
	Southwestern Electric Power (SWEPCO)	89,534
California	Pacific Gas & Electric (PG&E)	4,259,052
	PacifiCorp	34,038
	San Diego Gas & Electric (SDG&E)	1,150,082
	Southern California Edison (SCE)	4,034,370
Colorado	Xcel Energy	1,067,142
Connecticut	Connecticut Light & Power (CL&P)	937,459
	United Illuminating (UI)	249,410
Delaware	Delmarva Power	245,972
District of Columbia	Potomac Electric Power (PEPCO)	200,487
Idaho	Avista	95,233
	Idaho Power	347,371
	PacifiCorp	50,442
Illinois	Ameren Illinois	920,820
	Commonwealth Edison (ComEd)	2,970,190
Indiana	Duke Energy Indiana	642,231
	Indiana Michigan Power	391,528
	Indianapolis Power & Light	400,813
	Northern Indiana Public Service (NIPSCO)	386,375
	Southern Indiana Gas & Electric	119,061
Kansas	Empire District Electric	8,610
	Kansas City Power & Light (KCP&L)	193,828
	Kansas Gas & Electric	266,305
	Westar Energy	306,586
Kentucky	Duke Energy Kentucky	113,951
	Kentucky Power	142,300
	Kentucky Utilities (KU)	395,238
	Louisville Gas & Electric (LGE)	335,059

State	IOU (Common Name)	Avg. Residential Customers (Bundled Service)
Maine	Central Maine Power	150,745
Maryland	Baltimore Gas & Electric	988,962
	Delmarva Power	155,043
	Potomac Edison	195,902
	Potomac Electric Power (PEPCO)	414,681
Massachusetts	Eversource	842,937
	National Grid	977,498
	Unitil (Fitchburg Gas & Elec Light)	23,032
	Western Massachusetts Electric Company (WMECO)	177,493
Minnesota	Allete	113,962
	Otter Tail Power	46,469
	Xcel Energy	1,039,958
Mississippi	Entergy Mississippi	348,827
	Mississippi Power	154,318
Missouri	Kansas City Power & Light (KCP&L)	233,206
	KCP&L Greater Missouri Operations	234,569
Nevada	Nevada Power	615,032
	Sierra Pacific Power	248,229
New Hampshire	Liberty Utilities (Granite State Electric)	33,063
	Public Service of New Hampshire (PSNH)	381,995
New Jersey	Atlantic City Electric	439,241
	Jersey Central Power & Light	880,007
	Public Service Elec & Gas (PSEG)	1,734,439
	Rockland Electric	60,297
New York	Central Hudson Gas & Electric	233,161
	Consolidated Edison (Con Ed)	2,467,339
	National Grid	1,314,418
	New York State Electric & Gas (NYSEG)	670,099
	Orange & Rockland Utilities	143,710
	Rochester Gas & Electric	276,245
Ohio	AEP Ohio	1,175,933
	Cleveland Electric Illuminating	443,635
	Dayton Power & Light	416,932
	Duke Energy Ohio	518,227
	Ohio Edison	657,570
	Toledo Edison	191,736
Oregon	Idaho Power	13,017
	PacifiCorp	439,912

State	IOU (Common Name)	Avg. Residential Customers (Bundled Service)
Oregon	Portland General Electric	665,974
Pennsylvania	Metropolitan Edison (MetEd)	426,879
	PECO Energy	1,224,759
	Pennsylvania Electric (Penelec)	466,212
	Pennsylvania Power	122,571
	PPL Electric Utilities	1,031,073
	West Penn Power	572,410
Rhode Island	National Grid	382,919
South Dakota	Black Hills Power	49,037
	Montana-Dakota Utilities	6,726
	NorthWestern Energy	47,279
	Otter Tail Power	8,776
	Xcel Energy	65,052
Texas	El Paso Electric	227,655
	Entergy Texas	325,743
	Southwestern Electric Power (SWEPCO)	138,160
	Xcel Energy	214,423
Vermont	Green Mountain Power	206,256
Virginia	Appalachian Power	424,772
	Dominion	1,893,924
	Kentucky Utilities (KU)	24,857
Washington	Avista	195,851
	PacifiCorp	99,406
	Puget Sound Energy	870,271
West Virginia	Appalachian Power	365,335
	Monongahela Power (Mon Power)	312,708
	Potomac Edison	101,996
	Wheeling Power	35,632
Wisconsin	Wisconsin Electric Power	928,944
	Wisconsin Public Service	355,041
Wyoming	Montana-Dakota Utilities	11,719
	PacifiCorp	102,423

Source: EIA (2016)

FIGURE B.1: Service Territories of Included IOUs and Metro Area Coverage



Map produced by author. Data sources: ArcGIS Online (2013), ArcGIS Open Data (2016), service territory shapefiles and graphic files from state public utility commissions and individual utilities

APPENDIX C: FULL REGRESSION RESULTS AND TESTS FOR JOINT SIGNIFICANCE

The tables in this appendix supplement the results in Chapter 4. Tables C.1 to C.4 correspond to the combined policy analysis in Table 4.5, Tables C.5 to C.8 correspond to the individual energy efficiency resource standard (EERS) analysis in Table 4.6, Tables C.9 and C.10 correspond to the individual renewable portfolio standard (RPS) analysis in Table 4.7, and Tables C.11 and C.12 correspond to the individual deregulation analysis in Table 4.8. Again, I defined four models for each policy and for the combined analysis. Model (1) excludes lags on expenditures, model (3) includes two lags on the expenditure variables and on commercial and industrial (C&I) revenues, and models (2) and (4) are sensitivity analyses of models (1) and (3), respectively, that exclude any records for which I interpolated data.

For each analysis below, the first table provides the baseline model that does not include lags on the expenditure variables, as well as the full versions of models (1) and (2) derived from this baseline. The table includes any variables that I removed in Chapter 4 to save space. The second table presents the results of tests for joint significance: one test of coefficients in the baseline model that are individually insignificant at the 10% level, one test of coefficients in model (1) that are individually insignificant at the 10% level, and one test of coefficients in model (2) that are individually insignificant at the 10% level. The third table provides the same information as the first, but for the models that include lags on expenditures variables (models (3) and (4)). The fourth table provides tests of joint significance for these models. The notes beneath the first and third tables for each analysis include the value of ρ used in the initial Prais-Winsten data transformation, along with other information.

One notable result of the analysis in this appendix is that *individually* insignificant coefficients in some models are *jointly* significant at the 10% level or lower. This indicates multicollinearity between the variables, though it does not alter the analysis in Chapter 4.

TABLE C.1: Baseline and Complete Fitted Models for Combined Analysis, Without Cost Lags

Variables	Baseline	(1)	(2)
eers_policy	1.02e-01	1.02e-01	7.53e-02
	(3.64e-02)***	(3.64e-02)***	(5.04e-02)
rps_policy	4.26e-02	4.26e-02	5.13e-02
	(1.84e-02)**	(1.84e-02)**	(2.23e-02)**
Deregulation	-7.74e-02	-7.74e-02	-8.66e-02
	(2.24e-02)***	(2.24e-02)***	(2.91e-02)***
eers_policyXrps_policy	-4.84e-02	-4.84e-02	-3.13e-02
	(4.65e-02)	(4.65e-02)	(6.37e-02)
eers_policyXrps_policyXderegulation	-4.51e-02	-4.51e-02	-4.38e-03
	(4.49e-02)	(4.49e-02)	(5.15e-02)
decoupling_policy	6.01e-02	6.01e-02	5.95e-02
	(3.73e-02)	(3.73e-02)	(5.80e-02)
eers_policyXdecoupling_policy	-1.26e-01	-1.26e-01	-1.27e-01
	(3.91e-02)***	(3.91e-02)***	(5.26e-02)**
eers_policyXrps_policyXderegulationXdecoupling_policy	1.82e-01	1.82e-01	2.10e-01
	(6.16e-02)***	(6.16e-02)***	(7.00e-02)***
c&i_revenues	8.70e-05	8.70e-05	8.95e-05
	(3.83e-05)**	(3.83e-05)**	(4.06e-05)**
c&i_revenuesXdecoupling_policy	-1.78e-05	-1.78e-05	-1.68e-05
	(7.69e-06)**	(7.69e-06)**	(9.54e-06)*
power_expenditures	1.65e-05	1.65e-05	2.65e-05
	(8.98e-06)*	(8.98e-06)*	(1.81e-05)
t&d_expenditures	3.46e-04	3.46e-04	2.93e-04
	(9.31e-05)***	(9.31e-05)***	(8.37e-05)***
heating_degree_days	9.88e-05	9.88e-05	1.00e-04
	(9.42e-06)***	(9.42e-06)***	(1.07e-05)***
cooling_degree_days	3.47e-04	3.47e-04	3.34e-04
	(2.46e-05)***	(2.46e-05)***	(2.81e-05)***
median_income_lag1	2.95e-03	2.95e-03	2.67e-03
	(3.24e-03)	(3.24e-03)	(3.63e-03)
median_income_lag2	-1.13e-02	-1.13e-02	-1.42e-02
	(3.16e-03)***	(3.16e-03)***	(3.58e-03)***
median_income_lag3	-9.48e-03	-9.48e-03	-1.05e-02
	(3.31e-03)***	(3.31e-03)***	(3.88e-03)***
median_income_lag4	-4.33e-03	-4.33e-03	
	(2.35e-03)*	(2.35e-03)*	
residential_revenues_lag1	9.75e-05	9.75e-05	9.35e-05
	(5.20e-05)*	(5.20e-05)*	(5.37e-05)*
residential_revenues_lag2	1.35e-04	1.35e-04	1.43e-04
	(5.85e-05)**	(5.85e-05)**	(6.49e-05)**
residential_revenues_lag3	2.38e-04	2.38e-04	2.22e-04
	(5.97e-05)***	(5.97e-05)***	(6.17e-05)***

residential_revenues_lag4	1.21e-04	1.21e-04	1.08e-04
	(4.31e-05)***	(4.31e-05)***	(4.27e-05)**
residential_customers_lag1	8.01e-05	8.01e-05	1.05e-04
	(1.21e-04)	(1.21e-04)	(1.28e-04)
residential_customers_lag2	-3.19e-04	-3.19e-04	-3.67e-04
	(1.14e-04)***	(1.14e-04)***	(1.58e-04)**
residential_customers_lag3	-2.52e-04	-2.52e-04	-2.64e-04
	(1.11e-04)**	(1.11e-04)**	(1.68e-04)
residential_customers_lag4	-3.92e-04	-3.92e-04	-3.50e-04
	(7.90e-05)***	(7.90e-05)***	(9.08e-05)***
employment_rate	-3.59e-03	-3.59e-03	-2.99e-03
	(3.93e-03)	(3.93e-03)	(4.06e-03)
employment_rate_lag1	-1.76e-02	-1.76e-02	-1.88e-02
	(5.50e-03)***	(5.50e-03)***	(6.18e-03)***
employment_rate_lag2	1.55e-02	1.55e-02	1.34e-02
	(4.34e-03)***	(4.34e-03)***	(4.31e-03)***
employment_rate_lag3	1.40e-02	1.40e-02	1.74e-02
	(5.54e-03)**	(5.54e-03)**	(5.94e-03)***
employment_rate_lag4	1.86e-02	1.86e-02	1.80e-02
	(5.05e-03)***	(5.05e-03)***	(5.41e-03)***
dsm_percust_annual_25	-5.63e-03	-5.63e-03	-1.50e-02
	(4.36e-02)	(4.36e-02)	(4.51e-02)
dsm_percust_annual_50	-2.24e-03	-2.24e-03	-1.69e-02
	(5.09e-02)	(5.09e-02)	(5.28e-02)
dsm_percust_annual_75	1.84e-02	1.84e-02	9.33e-03
	(5.13e-02)	(5.13e-02)	(5.30e-02)
dsm_percust_annual_100	2.76e-02	2.76e-02	1.68e-02
	(5.21e-02)	(5.21e-02)	(5.38e-02)
dsm_percust_annual_max	4.97e-02	4.97e-02	3.89e-02
	(5.87e-02)	(5.87e-02)	(6.18e-02)
dsm_percust_4yrs_50	2.02e-02	2.02e-02	1.06e-02
	(6.91e-02)	(6.91e-02)	(6.75e-02)
dsm_percust_4yrs_100	3.41e-02	3.41e-02	3.00e-02
	(7.02e-02)	(7.02e-02)	(6.83e-02)
dsm_percust_4yrs_150	2.69e-02	2.69e-02	2.07e-02
	(7.21e-02)	(7.21e-02)	(7.07e-02)
dsm_percust_4yrs_200	5.38e-02	5.38e-02	4.96e-02
	(7.19e-02)	(7.19e-02)	(7.00e-02)
dsm_percust_4yrs_max	3.74e-02	3.74e-02	3.42e-02
	(7.26e-02)	(7.26e-02)	(7.11e-02)
_constant	-2.75e-03	-2.75e-03	-1.25e-03
	(1.24e-02)	(1.24e-02)	(1.27e-02)
R2 Within	0.6257	0.6257	0.6570
R2 Between	0.3304	0.3304	0.3885
R2 Overall	0.5765	0.5765	0.6050
Observations	2,310	2,310	1,852
Groups	105	105	105

* p<0.1; ** p<0.05; *** p<0.01; Parentheses contain clustered std. errors; ρ=0.790

TABLE C.2: Tests for Joint Significance in Combined Analysis, Without Cost Lags

Baseline and Model (1)	Model (2)
F(16, 104) = 1.22	F(19, 104) = 1.37
Prob > F = 0.2622	Prob > F = 0.1592

TABLE C.3: Baseline and Complete Fitted Models for Combined Analysis, With Cost Lags

Variables	Baseline	(3)	(4)
eers_policy	-1.64e-02	-1.82e-03	-1.87e-02
	(3.64e-02)	(3.57e-02)	(4.77e-02)
rps_policy	4.69e-02	4.59e-02	5.97e-02
	(1.80e-02)**	(1.65e-02)***	(2.00e-02)***
Deregulation	-4.17e-02	-5.20e-02	-5.80e-02
	(2.31e-02)*	(2.07e-02)**	(2.52e-02)**
eers_policyXrps_policy	1.07e-02	6.52e-03	1.26e-02
	(4.73e-02)	(4.58e-02)	(6.12e-02)
eers_policyXrps_policyXderegulation	-3.01e-02	-4.33e-02	-9.81e-03
	(4.45e-02)	(4.36e-02)	(4.90e-02)
decoupling_policy	1.63e-02	1.43e-02	-9.76e-03
	(3.44e-02)	(3.49e-02)	(4.92e-02)
eers_policyXdecoupling_policy	-5.04e-02	-5.82e-02	-6.27e-02
	(4.24e-02)	(4.18e-02)	(5.23e-02)
eers_policyXrps_policyXderegulationXdecoupling_policy	1.27e-01	1.44e-01	1.91e-01
	(6.13e-02)**	(6.18e-02)**	(7.05e-02)***
c&i_revenues	1.21e-04	1.20e-04	1.20e-04
	(4.62e-05)**	(4.36e-05)***	(4.53e-05)***
c&i_revenues_lag1	-3.90e-06		
	(3.26e-05)		
c&i_revenues_lag2	3.57e-05		
	(1.97e-05)*		
c&i_revenuesXdecoupling_policy	-8.32e-06	-2.78e-06	4.46e-07
	(8.86e-06)	(6.69e-06)	(8.27e-06)
power_expenditures	1.68e-05	1.79e-05	2.76e-05
	(1.07e-05)	(1.07e-05)*	(1.97e-05)
exppower_lag1	7.66e-06		
	(5.51e-06)		
exppower_lag2	4.53e-07		
	(4.16e-06)		
t&d_expenditures	2.21e-04	2.50e-04	2.03e-04
	(8.69e-05)**	(8.64e-05)***	(8.20e-05)**
t&d_expenditures_lag1	1.65e-04	1.80e-04	2.17e-04
	(8.48e-05)*	(8.47e-05)**	(9.26e-05)**
t&d_expenditures_lag2	-3.77e-07		
	(8.08e-05)		
heating_degree_days	9.07e-05	8.95e-05	9.08e-05
	(9.11e-06)***	(7.80e-06)***	(9.21e-06)***
cooling_degree_days	3.18e-04	3.20e-04	3.04e-04
	(2.84e-05)***	(2.49e-05)***	(3.08e-05)***
median_income_lag1	1.54e-02	1.17e-02	1.31e-02
	(3.42e-03)***	(3.22e-03)***	(3.76e-03)***

median_income_lag2	-1.64e-03	-5.22e-03	-7.19e-03
	(3.18e-03)	(3.03e-03)*	(3.51e-03)**
median_income_lag3	-1.07e-02	-1.17e-02	-1.15e-02
	(3.37e-03)***	(3.04e-03)***	(3.52e-03)***
median_income_lag4	-1.13e-02	-1.21e-02	-1.01e-02
	(2.47e-03)***	(2.53e-03)***	(2.94e-03)***
residential_revenues_lag1	-1.30e-05		
	(6.21e-05)		
residential_revenues_lag2	-3.04e-05		
	(5.27e-05)		
residential_revenues_lag3	7.62e-05		
	(4.75e-05)		
residential_revenues_lag4	-2.47e-05		
	(4.23e-05)		
residential_customers_lag1	2.86e-04		
	(1.58e-04)*		
residential_customers_lag2	-1.49e-04		
	(1.15e-04)		
residential_customers_lag3	4.96e-05		
	(1.10e-04)		
residential_customers_lag4	-1.24e-04		
	(8.09e-05)		
employment_rate	-2.80e-02	-2.76e-02	-2.56e-02
	(4.85e-03)***	(4.31e-03)***	(4.56e-03)***
employment_rate_lag1	-4.15e-02	-3.89e-02	-4.23e-02
	(6.07e-03)***	(5.26e-03)***	(5.92e-03)***
employment_rate_lag2	-6.38e-03		
	(4.91e-03)		
employment_rate_lag3	-2.33e-03		
	(6.04e-03)		
employment_rate_lag4	-1.23e-02		
	(7.15e-03)*		
dsm_percust_annual_25	-3.18e-02	-3.12e-02	-4.49e-02
	(5.37e-02)	(5.28e-02)	(5.49e-02)
dsm_percust_annual_50	-3.99e-02	-3.91e-02	-5.89e-02
	(6.16e-02)	(6.05e-02)	(6.29e-02)
dsm_percust_annual_75	-1.75e-02	-1.70e-02	-3.18e-02
	(6.26e-02)	(6.17e-02)	(6.42e-02)
dsm_percust_annual_100	-5.71e-03	-7.02e-03	-2.20e-02
	(6.41e-02)	(6.29e-02)	(6.53e-02)
dsm_percust_annual_max	1.50e-02	2.48e-02	9.53e-03
	(7.29e-02)	(7.30e-02)	(7.70e-02)
dsm_percust_4yrs_50	-2.23e-02	-2.72e-02	-3.27e-02
	(4.97e-02)	(5.15e-02)	(5.24e-02)
dsm_percust_4yrs_100	-1.96e-02	-2.27e-02	-1.76e-02
	(5.11e-02)	(5.23e-02)	(5.30e-02)
dsm_percust_4yrs_150	-3.82e-02	-3.64e-02	-3.21e-02
	(5.47e-02)	(5.53e-02)	(5.63e-02)
dsm_percust_4yrs_200	-1.05e-02	-1.15e-02	8.90e-04
	(5.46e-02)	(5.51e-02)	(5.59e-02)
dsm_percust_4yrs_max	-2.99e-02	-2.92e-02	-1.37e-02
	(5.57e-02)	(5.60e-02)	(5.71e-02)
_constant	2.15e+00	1.80e+00	1.80e+00

	(1.98e-01)***	(1.23e-01)***	(1.28e-01)***
R2 Within	0.2480	0.2352	0.2320
R2 Between	0.0177	0.1340	0.1242
R2 Overall	0.1376	0.1966	0.1806
Observations	1,995	2,100	1,646
Groups	105	105	105

* *p*<0.1; ** *p*<0.05; *** *p*<0.01; Parentheses contain clustered std. errors; *ρ*=0.790

TABLE C.4: Tests for Joint Significance in Combined Analysis, With Cost Lags

Baseline	Model (3)	Model (4)
F(31, 104) = 2.88	F(17, 104) = 1.43	F(17, 104) = 0.99
Prob > F = 0.0000	Prob > F = 0.1382	Prob > F = 0.4733

TABLE C.5: Baseline and Complete Fitted Models for EERS Analysis, Without Cost Lags

Variables	Baseline	(1)	(2)
eers_policy	7.14e-02	6.48e-02	5.13e-02
	(3.70e-02)*	(3.70e-02)*	(5.54e-02)
eers_policy_lag1	7.36e-02	7.40e-02	7.82e-02
	(2.25e-02)***	(2.24e-02)***	(2.31e-02)***
eers_policy_lag2	5.47e-02	5.73e-02	5.89e-02
	(1.97e-02)***	(1.99e-02)***	(2.30e-02)**
eers_policy_lag3	5.21e-02	5.42e-02	5.51e-02
	(2.49e-02)**	(2.47e-02)**	(2.79e-02)*
eers_policy_lag4	2.22e-03		
	(2.05e-02)		
eers_policy_lag5	2.54e-02		
	(1.97e-02)		
eers_policyXrps_policy	-1.36e-02	-6.61e-03	9.73e-05
	(4.60e-02)	(4.55e-02)	(6.73e-02)
eers_policyXderegulation	-3.40e-02	-3.39e-02	-1.08e-02
	(4.19e-02)	(4.21e-02)	(5.04e-02)
decoupling_policy	5.31e-02	5.48e-02	5.60e-02
	(3.71e-02)	(3.76e-02)	(5.66e-02)
eers_policyXdecoupling_policy	-1.27e-02	-1.05e-02	-8.03e-04
	(3.48e-02)	(3.45e-02)	(4.80e-02)
c&i_revenues	8.11e-05	8.06e-05	7.58e-05
	(3.30e-05)**	(3.30e-05)**	(3.18e-05)**
c&i_revenuesXdecoupling_policy	-2.02e-05	-2.16e-05	-2.20e-05
	(7.79e-06)**	(7.81e-06)***	(9.33e-06)**
power_expenditures	1.31e-05	1.34e-05	2.14e-05
	(9.10e-06)	(9.19e-06)	(1.75e-05)
t&d_expenditures	3.08e-04	3.13e-04	2.56e-04
	(9.71e-05)***	(9.66e-05)***	(8.78e-05)***
heating_degree_days	9.16e-05	9.19e-05	9.22e-05
	(9.37e-06)***	(9.34e-06)***	(1.04e-05)***
cooling_degree_days	3.35e-04	3.40e-04	3.24e-04
	(2.48e-05)***	(2.44e-05)***	(2.70e-05)***
median_income_lag1	3.38e-03	2.91e-03	2.85e-03
	(3.38e-03)	(3.33e-03)	(3.72e-03)

median_income_lag2	-9.70e-03	-1.12e-02	-1.27e-02
	(3.27e-03)***	(3.12e-03)***	(3.65e-03)***
median_income_lag3	-7.60e-03	-8.67e-03	-8.31e-03
	(3.23e-03)**	(3.23e-03)***	(3.86e-03)**
median_income_lag4	-3.88e-03		
	(2.32e-03)*		
employment_rate	-4.81e-03	-5.66e-03	-4.54e-03
	(3.75e-03)	(3.67e-03)	(3.87e-03)
employment_rate_lag1	-1.70e-02	-1.60e-02	-1.77e-02
	(5.46e-03)***	(5.42e-03)***	(6.22e-03)***
employment_rate_lag2	1.57e-02	1.62e-02	1.38e-02
	(4.53e-03)***	(4.54e-03)***	(4.55e-03)***
employment_rate_lag3	1.50e-02	1.60e-02	1.86e-02
	(5.73e-03)**	(5.68e-03)***	(6.16e-03)***
employment_rate_lag4	1.66e-02	1.44e-02	1.57e-02
	(5.22e-03)***	(5.14e-03)***	(5.67e-03)***
dsm_percust_annual_25	-6.48e-03	-8.52e-03	-1.71e-02
	(4.49e-02)	(4.53e-02)	(4.61e-02)
dsm_percust_annual_50	-1.59e-02	-1.73e-02	-3.05e-02
	(5.23e-02)	(5.27e-02)	(5.39e-02)
dsm_percust_annual_75	-6.68e-03	-8.44e-03	-1.67e-02
	(5.31e-02)	(5.34e-02)	(5.47e-02)
dsm_percust_annual_100	-3.02e-03	-3.74e-03	-1.23e-02
	(5.38e-02)	(5.42e-02)	(5.54e-02)
dsm_percust_annual_max	1.97e-02	1.95e-02	1.39e-02
	(6.14e-02)	(6.13e-02)	(6.36e-02)
dsm_percust_4yrs_50	1.20e-02	1.38e-02	1.58e-03
	(7.05e-02)	(6.93e-02)	(6.90e-02)
dsm_percust_4yrs_100	2.37e-02	2.49e-02	2.02e-02
	(7.16e-02)	(7.06e-02)	(6.99e-02)
dsm_percust_4yrs_150	6.30e-03	8.77e-03	1.19e-03
	(7.39e-02)	(7.30e-02)	(7.27e-02)
dsm_percust_4yrs_200	2.52e-02	2.97e-02	2.24e-02
	(7.36e-02)	(7.26e-02)	(7.20e-02)
dsm_percust_4yrs_max	4.08e-03	1.05e-02	5.21e-03
	(7.44e-02)	(7.31e-02)	(7.27e-02)
_constant	-3.99e-02	-4.05e-02	-3.92e-02
	(1.28e-02)***	(1.30e-02)***	(1.35e-02)***
R2 Within	0.6181	0.6176	0.6495
R2 Between	0.1081	0.1012	0.1753
R2 Overall	0.5306	0.5290	0.5580
Observations	2,310	2,310	1,852
Groups	105	105	105

* p<0.1; ** p<0.05; *** p<0.01; Parentheses contain clustered std. errors; ρ=0.793

TABLE C.6: Tests for Joint Significance in EERS Analysis, Without Cost Lags

Baseline	Model (1)	Model (2)
F(19, 104) = 0.88	F(17, 104) = 0.92	F(18, 104) = 1.02
Prob > F = 0.6120	Prob > F = 0.5537	Prob > F = 0.4446

TABLE C.7: Baseline and Complete Fitted Models for EERS Analysis, With Cost Lags

Variables	Baseline	(3)	(4)
eers_policy	-3.97e-02	-2.94e-02	-3.98e-02
	(3.61e-02)	(3.56e-02)	(5.06e-02)
eers_policy_lag1	2.92e-02	3.87e-02	4.49e-02
	(2.16e-02)	(2.13e-02)*	(2.22e-02)**
eers_policy_lag2	1.68e-02		
	(2.04e-02)		
eers_policy_lag3	7.75e-03		
	(2.56e-02)		
eers_policy_lag4	-1.09e-02		
	(1.96e-02)		
eers_policy_lag5	-1.99e-03		
	(1.96e-02)		
eers_policyXrps_policy	5.08e-02	4.21e-02	5.03e-02
	(4.77e-02)	(4.57e-02)	(6.38e-02)
eers_policyXderegulation	-2.74e-02	-1.78e-02	7.07e-03
	(4.14e-02)	(4.11e-02)	(4.86e-02)
decoupling_policy	1.48e-02	2.24e-02	1.05e-02
	(3.47e-02)	(3.50e-02)	(4.96e-02)
eers_policyXdecoupling_policy	2.88e-02	2.53e-02	3.91e-02
	(3.21e-02)	(3.27e-02)	(4.22e-02)
c&i_revenues	1.19e-04	1.19e-04	1.15e-04
	(4.54e-05)***	(4.32e-05)***	(4.63e-05)**
c&i_revenues_lag1	3.33e-05	3.14e-05	4.21e-05
	(2.09e-05)	(2.13e-05)	(1.99e-05)**
c&i_revenues_lag2	3.21e-05	2.67e-05	
	(1.54e-05)**	(1.54e-05)*	
c&i_revenuesXdecoupling_policy	-1.02e-05	-1.05e-05	-1.12e-05
	(7.29e-06)	(7.52e-06)	(8.55e-06)
power_expenditures	1.76e-05	1.70e-05	2.90e-05
	(1.11e-05)	(1.11e-05)	(1.96e-05)
exppower_lag1	4.34e-06		
	(7.38e-06)		
exppower_lag2	2.94e-06		
	(3.72e-06)		
t&d_expenditures	2.15e-04	2.61e-04	2.08e-04
	(8.89e-05)**	(8.70e-05)***	(7.99e-05)**
t&d_expenditures_lag1	1.53e-04	1.89e-04	2.24e-04
	(8.98e-05)*	(8.87e-05)**	(9.74e-05)**
t&d_expenditures_lag2	2.93e-05		
	(7.53e-05)		
heating_degree_days	8.89e-05	8.88e-05	9.07e-05
	(8.99e-06)***	(7.83e-06)***	(9.42e-06)***
cooling_degree_days	3.20e-04	3.19e-04	3.07e-04
	(2.66e-05)***	(2.49e-05)***	(3.12e-05)***
median_income_lag1	1.49e-02	1.18e-02	1.32e-02
	(3.61e-03)***	(3.25e-03)***	(3.79e-03)***
median_income_lag2	-1.46e-03	-5.40e-03	-7.52e-03
	(3.35e-03)	(3.07e-03)*	(3.57e-03)**
median_income_lag3	-1.05e-02	-1.20e-02	-1.11e-02

	(3.26e-03)***	(3.01e-03)***	(3.50e-03)***
median_income_lag4	-1.06e-02	-1.19e-02	-9.63e-03
	(2.37e-03)***	(2.49e-03)***	(2.90e-03)***
employment_rate	-2.82e-02	-2.68e-02	-2.47e-02
	(4.65e-03)***	(4.28e-03)***	(4.45e-03)***
employment_rate_lag1	-3.98e-02	-3.91e-02	-4.21e-02
	(6.03e-03)***	(5.23e-03)***	(5.89e-03)***
employment_rate_lag2	-6.71e-03		
	(5.07e-03)		
employment_rate_lag3	-1.63e-03		
	(6.36e-03)		
employment_rate_lag4	-1.26e-02		
	(7.39e-03)*		
dsm_percust_annual_25	-3.33e-02	-3.33e-02	-4.84e-02
	(5.45e-02)	(5.32e-02)	(5.54e-02)
dsm_percust_annual_50	-4.58e-02	-4.29e-02	-6.30e-02
	(6.25e-02)	(6.09e-02)	(6.34e-02)
dsm_percust_annual_75	-2.58e-02	-2.24e-02	-3.82e-02
	(6.36e-02)	(6.22e-02)	(6.48e-02)
dsm_percust_annual_100	-1.48e-02	-1.59e-02	-3.09e-02
	(6.54e-02)	(6.34e-02)	(6.59e-02)
dsm_percust_annual_max	1.03e-02	1.65e-02	3.04e-03
	(7.49e-02)	(7.35e-02)	(7.72e-02)
dsm_percust_4yrs_50	-2.84e-02	-3.28e-02	-3.90e-02
	(5.08e-02)	(5.20e-02)	(5.32e-02)
dsm_percust_4yrs_100	-2.59e-02	-2.79e-02	-2.18e-02
	(5.23e-02)	(5.30e-02)	(5.40e-02)
dsm_percust_4yrs_150	-4.80e-02	-4.21e-02	-3.81e-02
	(5.63e-02)	(5.62e-02)	(5.76e-02)
dsm_percust_4yrs_200	-2.00e-02	-1.56e-02	-4.02e-03
	(5.66e-02)	(5.61e-02)	(5.73e-02)
dsm_percust_4yrs_max	-4.07e-02	-3.60e-02	-2.17e-02
	(5.77e-02)	(5.67e-02)	(5.81e-02)
_constant	2.09e+00	1.75e+00	1.74e+00
	(1.91e-01)***	(1.20e-01)***	(1.23e-01)***
R2 Within	0.2378	0.2318	0.2270
R2 Between	0.0197	0.0857	0.0822
R2 Overall	0.1359	0.1681	0.1540
Observations	1,995	2,100	1,646
Groups	105	105	105

* *p*<0.1; ** *p*<0.05; *** *p*<0.01; Parentheses contain clustered std. errors; *ρ*=0.793

TABLE C.8: Tests for Joint Significance in EERS Analysis, With Cost Lags

Baseline	Model (3)	Model (4)
F(29, 104) = 1.33	F(18, 104) = 0.97	F(16,104) = 1.14
Prob > F = 0.1482	Prob > F = 0.5013	Prob > F = 0.3278

TABLE C.9: Baseline and Complete Fitted Models for RPS Analysis, Without Cost Lags

Variables	Baseline	(1)	(2)
rps_policy	5.93e-02	5.82e-02	4.94e-02
	(2.44e-02)**	(2.45e-02)**	(2.71e-02)*
rps_policy_lag1	3.95e-02	4.25e-02	3.79e-02
	(1.92e-02)**	(1.93e-02)**	(1.88e-02)**
rps_policy_lag2	5.72e-02	5.77e-02	4.34e-02
	(3.10e-02)*	(3.10e-02)*	(3.89e-02)
rps_policy_lag3	5.11e-02	5.21e-02	3.15e-02
	(2.53e-02)**	(2.54e-02)**	(2.77e-02)
rps_policy_lag4	6.55e-02	6.57e-02	7.15e-02
	(2.20e-02)***	(2.20e-02)***	(2.47e-02)***
rps_policy_lag5	4.14e-02	3.99e-02	4.37e-02
	(2.07e-02)**	(2.08e-02)*	(2.23e-02)*
eers_policyXrps_policy	-5.06e-03	-4.52e-03	1.71e-02
	(2.53e-02)	(2.53e-02)	(2.97e-02)
rps_policyXderegulation	-4.87e-02	-4.98e-02	-2.83e-02
	(3.10e-02)	(3.08e-02)	(3.66e-02)
decoupling_policy	-2.39e-02	-2.36e-02	2.08e-02
	(6.37e-02)	(6.42e-02)	(9.28e-02)
rps_policyXdecoupling_policy	6.44e-02	6.44e-02	2.88e-02
	(7.27e-02)	(7.31e-02)	(9.98e-02)
c&i_revenues	1.13e-04	1.14e-04	1.09e-04
	(3.90e-05)***	(3.92e-05)***	(4.20e-05)**
c&i_revenuesXdecoupling_policy	-2.14e-05	-2.19e-05	-2.47e-05
	(8.46e-06)**	(8.51e-06)**	(1.02e-05)**
power_expenditures	1.53e-05	1.59e-05	2.51e-05
	(9.29e-06)	(9.38e-06)*	(1.79e-05)
t&d_expenditures	2.45e-04	2.44e-04	2.02e-04
	(1.01e-04)**	(1.00e-04)**	(9.14e-05)**
heating_degree_days	9.72e-05	9.73e-05	9.86e-05
	(9.35e-06)***	(9.33e-06)***	(1.07e-05)***
cooling_degree_days	3.43e-04	3.46e-04	3.31e-04
	(2.40e-05)***	(2.38e-05)***	(2.75e-05)***
median_income_lag1	3.04e-03	2.65e-03	3.04e-03
	(3.15e-03)	(3.15e-03)	(3.49e-03)
median_income_lag2	-1.06e-02	-1.16e-02	-1.30e-02
	(3.10e-03)***	(3.01e-03)***	(3.48e-03)***
median_income_lag3	-8.51e-03	-9.34e-03	-9.23e-03
	(3.28e-03)**	(3.28e-03)***	(3.88e-03)**
median_income_lag4	-3.32e-03		
	(2.30e-03)		
residential_revenues_lag1	7.77e-05	8.18e-05	7.19e-05
	(5.33e-05)	(5.37e-05)	(5.58e-05)
residential_revenues_lag2	1.28e-04	1.27e-04	1.38e-04
	(5.65e-05)**	(5.62e-05)**	(6.31e-05)**
residential_revenues_lag3	2.31e-04	2.28e-04	2.22e-04
	(6.00e-05)***	(5.94e-05)***	(6.31e-05)***
residential_revenues_lag4	1.09e-04	1.05e-04	9.81e-05
	(4.43e-05)**	(4.38e-05)**	(4.57e-05)**
residential_customers_lag1	1.38e-04	1.35e-04	1.64e-04

	(1.24e-04)	(1.24e-04)	(1.29e-04)
residential_customers_lag2	-3.04e-04	-3.07e-04	-3.56e-04
	(1.13e-04)***	(1.13e-04)***	(1.49e-04)**
residential_customers_lag3	-2.58e-04	-2.61e-04	-2.67e-04
	(1.16e-04)**	(1.16e-04)**	(1.77e-04)
residential_customers_lag4	-4.14e-04	-4.11e-04	-3.71e-04
	(8.96e-05)***	(9.09e-05)***	(1.01e-04)***
employment_rate	-5.85e-04	-1.36e-03	-6.16e-04
	(3.89e-03)	(3.85e-03)	(4.08e-03)
employment_rate_lag1	-1.88e-02	-1.80e-02	-1.91e-02
	(5.33e-03)***	(5.32e-03)***	(6.17e-03)***
employment_rate_lag2	1.63e-02	1.67e-02	1.35e-02
	(4.24e-03)***	(4.28e-03)***	(4.20e-03)***
employment_rate_lag3	1.43e-02	1.50e-02	1.81e-02
	(5.52e-03)**	(5.49e-03)***	(5.98e-03)***
employment_rate_lag4	1.49e-02	1.32e-02	1.42e-02
	(5.09e-03)***	(4.96e-03)***	(5.44e-03)**
dsm_percust_annual_25	-5.76e-03	-7.67e-03	-1.33e-02
	(4.62e-02)	(4.66e-02)	(4.69e-02)
dsm_percust_annual_50	-7.31e-03	-8.94e-03	-1.84e-02
	(5.33e-02)	(5.37e-02)	(5.45e-02)
dsm_percust_annual_75	8.49e-03	6.77e-03	2.38e-03
	(5.44e-02)	(5.47e-02)	(5.55e-02)
dsm_percust_annual_100	1.52e-02	1.35e-02	8.72e-03
	(5.54e-02)	(5.57e-02)	(5.68e-02)
dsm_percust_annual_max	3.74e-02	3.55e-02	3.10e-02
	(6.18e-02)	(6.20e-02)	(6.42e-02)
dsm_percust_4yrs_50	1.79e-02	1.95e-02	9.55e-03
	(6.93e-02)	(6.83e-02)	(6.79e-02)
dsm_percust_4yrs_100	3.14e-02	3.23e-02	2.76e-02
	(7.03e-02)	(6.94e-02)	(6.88e-02)
dsm_percust_4yrs_150	1.73e-02	1.79e-02	1.22e-02
	(7.25e-02)	(7.17e-02)	(7.15e-02)
dsm_percust_4yrs_200	3.82e-02	3.95e-02	3.65e-02
	(7.25e-02)	(7.15e-02)	(7.14e-02)
dsm_percust_4yrs_max	1.64e-02	1.77e-02	1.44e-02
	(7.31e-02)	(7.22e-02)	(7.20e-02)
_constant	-3.56e-02	-3.71e-02	-3.30e-02
	(1.36e-02)**	(1.36e-02)***	(1.43e-02)**
R2 Within	0.6282	0.6279	0.6574
R2 Between	0.2774	0.2691	0.3484
R2 Overall	0.5708	0.5692	0.5981
Observations	2,310	2,310	1,852
Groups	105	105	105

* p<0.1; ** p<0.05; *** p<0.01; Parentheses contain clustered std. errors; ρ=0.794

TABLE C.10: Tests for Joint Significance in RPS Analysis, Without Cost Lags

Baseline	Model (1)	Model (2)
F(20, 104) = 1.43	F(18, 104) = 0.95	F(22, 104) = 2.02
Prob > F = 0.1268	Prob > F = 0.5184	Prob > F = 0.0099

TABLE C.11: Baseline and Complete Fitted Models for Deregulation Analysis, Without Cost Lags

Variables	Baseline	(1)	(2)
Deregulation	-1.01e-01	-1.00e-01	-1.23e-01
	(2.18e-02)***	(2.11e-02)***	(2.80e-02)***
deregulation_lag1	-6.33e-02	-6.49e-02	-8.20e-02
	(3.41e-02)*	(3.39e-02)*	(5.41e-02)
deregulation_lag2	-3.45e-02	-3.39e-02	-2.32e-02
	(2.44e-02)	(2.46e-02)	(3.11e-02)
deregulation_lag3	8.00e-02	8.07e-02	8.76e-02
	(3.16e-02)**	(3.10e-02)**	(4.29e-02)**
deregulation_lag4	-1.41e-02		
	(1.88e-02)		
deregulation_lag5	2.82e-02		
	(2.49e-02)		
eers_policyXderegulation	6.11e-03	5.78e-03	3.23e-02
	(2.85e-02)	(2.85e-02)	(3.87e-02)
rps_policyXderegulation	2.76e-02	3.22e-02	4.98e-02
	(2.37e-02)	(2.12e-02)	(2.69e-02)*
decoupling_policy	1.14e-03	1.16e-03	5.56e-03
	(4.11e-02)	(4.10e-02)	(5.55e-02)
deregulationXdecoupling_policy	6.61e-02	6.71e-02	7.75e-02
	(2.69e-02)**	(2.69e-02)**	(2.76e-02)***
c&i_revenues	6.31e-05	6.34e-05	5.94e-05
	(3.24e-05)*	(3.26e-05)*	(3.15e-05)*
c&i_revenuesXdecoupling_policy	-1.01e-05	-9.95e-06	-1.25e-05
	(7.84e-06)	(7.84e-06)	(9.62e-06)
power_expenditures	1.40e-05	1.39e-05	2.39e-05
	(8.66e-06)	(8.86e-06)	(1.72e-05)
t&d_expenditures	3.65e-04	3.75e-04	3.18e-04
	(9.52e-05)***	(9.53e-05)***	(8.59e-05)***
heating_degree_days	9.46e-05	9.48e-05	9.49e-05
	(9.47e-06)***	(9.39e-06)***	(1.04e-05)***
cooling_degree_days	3.33e-04	3.34e-04	3.19e-04
	(2.46e-05)***	(2.45e-05)***	(2.73e-05)***
median_income_lag1	2.68e-03	2.76e-03	2.21e-03
	(3.29e-03)	(3.30e-03)	(3.59e-03)
median_income_lag2	-1.00e-02	-1.03e-02	-1.36e-02
	(3.19e-03)***	(3.17e-03)***	(3.57e-03)***
median_income_lag3	-8.39e-03	-8.24e-03	-9.29e-03
	(3.29e-03)**	(3.28e-03)**	(3.86e-03)**
median_income_lag4	-4.92e-03	-4.97e-03	
	(2.39e-03)**	(2.41e-03)**	
employment_rate	-3.67e-03	-3.57e-03	-3.58e-03

	(3.79e-03)	(3.79e-03)	(3.89e-03)
employment_rate_lag1	-1.90e-02	-1.89e-02	-1.95e-02
	(5.38e-03)***	(5.38e-03)***	(6.12e-03)***
employment_rate_lag2	1.52e-02	1.50e-02	1.31e-02
	(4.18e-03)***	(4.17e-03)***	(4.29e-03)***
employment_rate_lag3	1.56e-02	1.55e-02	1.91e-02
	(5.42e-03)***	(5.43e-03)***	(5.82e-03)***
employment_rate_lag4	1.80e-02	1.82e-02	1.73e-02
	(5.11e-03)***	(5.06e-03)***	(5.31e-03)***
dsm_percust_annual_25	2.40e-04	8.29e-05	-1.09e-02
	(4.46e-02)	(4.46e-02)	(4.55e-02)
dsm_percust_annual_50	1.16e-03	1.11e-03	-1.46e-02
	(5.20e-02)	(5.20e-02)	(5.34e-02)
dsm_percust_annual_75	2.15e-02	2.09e-02	1.07e-02
	(5.28e-02)	(5.28e-02)	(5.40e-02)
dsm_percust_annual_100	3.25e-02	3.15e-02	1.96e-02
	(5.38e-02)	(5.37e-02)	(5.54e-02)
dsm_percust_annual_max	5.79e-02	5.68e-02	4.39e-02
	(6.03e-02)	(6.03e-02)	(6.31e-02)
dsm_percust_4yrs_50	2.41e-02	2.40e-02	1.27e-02
	(7.18e-02)	(7.17e-02)	(6.96e-02)
dsm_percust_4yrs_100	4.00e-02	3.96e-02	3.42e-02
	(7.27e-02)	(7.27e-02)	(7.04e-02)
dsm_percust_4yrs_150	3.27e-02	3.22e-02	2.66e-02
	(7.46e-02)	(7.46e-02)	(7.26e-02)
dsm_percust_4yrs_200	5.49e-02	5.50e-02	5.15e-02
	(7.44e-02)	(7.43e-02)	(7.21e-02)
dsm_percust_4yrs_max	3.88e-02	3.83e-02	3.50e-02
	(7.51e-02)	(7.50e-02)	(7.30e-02)
_constant	-9.48e-03	-8.86e-03	-8.92e-03
	(1.44e-02)	(1.40e-02)	(1.43e-02)
R2 Within	0.6191	0.6189	0.6502
R2 Between	0.1564	0.1565	0.2148
R2 Overall	0.5410	0.5406	0.5673
Observations	2,310	2,310	1,852
Groups	105	105	105

* p<0.1; ** p<0.05; *** p<0.01; Parentheses contain clustered std. errors; ρ=0.793

TABLE C.12: Tests for Joint Significance in Deregulation Analysis, Without Cost Lags

Baseline	Model (1)	Model (2)
F(20, 104) = 1.25	F(18, 104) = 1.12	F(18, 104) = 1.16
Prob > F = 0.2326	Prob > F = 0.3452	Prob > F = 0.3105