Essays in Energy Economics

Inauguraldissertation

zur

Erlangung des Doktorgrades

der

Wirtschafts- und Sozialwissenschaftlichen Fakultät

der

Universität zu Köln

2017

vorgelegt

von

Diplom-Volkswirt Simon Paulus

aus

Lennestadt

Referent	Prof. Van Anh Vuong, Ph.D.
Korreferent	Prof. Dr. Marc-Oliver Bettzüge
Tag der Promotion	12.12.2017

Acknowledgements

For supervising my dissertation, I firstly would like to thank my supervisor Prof. Van Anh Vuong, Ph.D. for her support. She provided fruitful and constructive comments helping me to improve each of my articles. I also would like to thank Prof. Dr. Marc-Oliver Bettzüge for offering me the chance to theoretically learn and grow in the academic field of energy-economic research and his helpful advice and suggestions on the articles that have been embedded in this thesis.

Furthermore, I am grateful for the inspiring collaboration with Dr. habil. Christian Growitsch, Dr. Andreas Knaut, Martin Paschmann and Prof. Dr. Heike Wetzel on the joint research articles that individually but also taken together widened my horizon.

In addition, I am thankful to my colleagues at ewi Energy Research & Scenarios for the many fruitful discussions and ideas in the broad field of energy markets. In particular, my thanks go to Joachim Bertsch, Broghan Helgeson, Jakob Peter and Johannes Wagner and finally yet importantly to Zorica Marijanović, Maria Novikova and Lena Pickert who provided excellent research assistance.

Finally, I would like to thank my family.

Simon Paulus Cologne, October 2017

Contents

Acknowledgements v

List of Figures ix

List of Tables xi

1 Introduction 1

1.1 Introducing the Essays . . . 2

1.2 Future Research and Possible Improvements to Methodologies . . . 4

2 When Are Consumers Responding to Electricity Prices? An Hourly Pattern of Demand Elasticity 7

2.1 Introduction . . . 7

2.2 Measuring Market Demand Reactions Based on Wholesale Prices . . . 10

2.2.1 The Retail Market for Electricity . . . 10

2.2.2 The Wholesale Market for Electricity . . . 11

2.2.3 The Interaction of Wholesale and Retail Markets . . . 13

2.3 Empirical Framework . . . 15

2.3.1 Data . . . 15

2.3.2 Econometric Approach . . . 18

2.4 Empirical Application . . . 20

2.5 Conclusion . . . 23

2.6 Appendix . . . 25

3 Competition and Regulation as a Means of Reducing CO_2-Emissions - Experience from U.S. Fossil Fuel Power Plants 27

3.1 Introduction . . . 27

3.2 U.S. electricity generation from fossil fuels 2000 - 2013 . . . 29

3.3 Empirical approach . . . 32

3.3.1 Benchmarking model . . . 32

3.3.2 Benchmarking data . . . 37

3.3.3 Second-stage regression 38
3.4 Results 42
3.4.1 Benchmarking results 42
3.4.2 Second-stage regression results 47
3.5 Conclusions 50

4 The Impact of Advanced Metering Infrastructure on Residential Electricity Consumption - Evidence from California 53
4.1 Introduction 53
4.2 Literature Background 55
4.3 Identification Strategy 57
4.4 The Californian Case 59
4.5 Data 63
4.5.1 Dependent Variable: Residential Electricity Consumption . . . 63
4.5.2 Explanatory Variables 65
4.6 Empirical Analysis 67
4.6.1 Derivation of the Control Group Using Synthetic Controls . . . 67
4.6.2 Difference-in-Differences Estimation Results 71
4.7 Conclusion 77
4.8 Appendix 79

5 Electricity Reduction in the Residential Sector - The Example of the Californian Energy Crisis 85
5.1 Introduction 85
5.2 Literature 87
5.3 The Energy Crisis and its containment through conservation programs 90
5.4 Data 92
5.4.1 Dependent Variable: Residential electricity consumption . . . 93
5.4.2 Explanatory Variables 93
5.5 Empirical Application 96
5.5.1 Synthetic control group derivation and results 96
5.5.2 Two-stage least-squared treatment regression and results . . . 99
5.6 Conclusion 104
5.7 Appendix 107

Bibliography 117

Curriculum Vitae 127

List of Figures

2.1 Electricity price formation on the wholesale market 12
2.2 Supply and demand curves for one exemplary hour 14
2.3 Hourly data for load, electricity price, wind and solar generation for 2015 16
2.4 Correlations with load and prices in 2015 19
2.5 Hourly dummies and price elasticity of electricity demand in 2015 . . 21
2.6 Prices for coal, gas and co2 certificates from January to December 2015 25

3.1 Cost of fossil fuel receipts at electricity generating plants in USD per million Btu 30
3.2 Shares of total U.S. net electricity generation from fossil fuels in % . 31
3.3 Global Malmquist CO_2 emission performance index (GMCPI) 34
3.4 Cumulative GMCPI trends for the top and bottom performers for the period 2000-2013 48

4.1 Smart-metering legislation across the US states (Energy Information Administration 2011) 58
4.2 Investor-Owned Utilities (IOUs) and the respective share of Californian customer accounts (2015, Dec.) 60
4.3 Share of Californian (three major IOUs) households with AMI (smart meters) over time 62
4.4 Candidate states with low AMI penetration 70
4.5 Descriptive comparison and differences between the development of residential electricity consumption in California and ‘Synthetic California’ 72
4.6 Simplified illustration of Advanced Meter Infrastructure (AMI) and its informational feedback 79
4.7 Development of energy-efficiency savings in California over time . . . 80
4.8 Simplified schedules for tier and time-of-use in the residential sector 84

5.1 Californian residential electricity consumption and conservation programs . . . 92
5.2 Descriptive Comparison for the 'Synthetic Control Group'-State (SECC) and California . . . 99
5.3 Sample bill including '20/20' rebate for residential customers. [Source: Southern California Edison, 2017] . . . 107
5.4 Un- or scheduled capacity revisions by IOUs in MW. [Source: Blumstein et al., 2002] . . . 107
5.5 Synthetic Control Results - Difference Plot . . . 109
5.6 Residential consumption in pre-selected states over 48-month period 113

List of Tables

2.1 Literature review of estimated short-run elasticity 9
2.2 Descriptive statistics (for weekdays, without public holidays and Christmas time) 15
2.3 Regression results 22

3.1 Descriptive statistics: state-level data 2000 to 2013 38
3.2 Determinants of CO_2 emission performance: summary statistics . . . 40
3.3 State-specific regulatory policies 41
3.4 CO_2 emission efficiency scores per state 43
3.5 Cumulative GMCPI per state over the period 2000-2013 (2000 = 1) . 45
3.6 Cumulative GMCPI decomposition per state over the period 2000-2013 (2000 = 1) 46
3.7 Determinants of CO_2 emission performance: estimation results 49

4.1 Energy efficiency savings data 65
4.2 List of variables and references 68
4.3 Descriptive statistics 69
4.4 IV Estimates for DiD estimation 75
4.5 Descriptive statistics: Differences in levels (California minus Synthetic California) 80
4.6 Weights of the exogenous variables 81
4.7 IV Estimates for DiD estimation when controlling for yearly time dummies 83

5.1 List of variables and references 95
5.2 Determinants of monthly residential electricity consumption: IV estimation results 103
5.3 Descriptive Statistics 108
5.4 Weights of the exogenous variables 108
5.5 IV Estimates when controlling for pre- and post crisis treatment time dummies 115

1 Introduction

Energy economic research contributes to a better understanding of energy markets, such as resource and electricity markets. Within this broad field, research on markets, policy interventions and environmental issues is, among others, conducted.

One unique characteristic of energy markets, serving as 'common ground' for academic studies in the field of energy economics, is the condition of a reliable power supply that satisfies power consumption over time and even more importantly in real time. Given that supply and demand levels could change (rapidly) on a temporal scale, based on for instance forced generation unit, transmission line outages, sudden load changes or regulations, this seemingly unremarkable condition has far-reaching implications for generators, consumers and policy makers alike. Whereas both, the demand and supply side can individually contribute to a secure system, policy makers may be willing to set the right framework for energy markets and correct market failures or even implement policy instruments for a desired outcome.

In this thesis, the following four essays on energy economics, covering the listed topics, are presented. Each chapter is based on a single article to which the authors contributed equally:

Chapter 2: When are Consumers Responding to Electricity Prices? An Hourly Pattern of Demand Elasticity (based on Knaut & Paulus (2016))

Chapter 3: Competition and Regulation as a Means of Reducing CO_2-Emissions - Experience from U.S. Fossil Fuel Power Plants (based on Growitsch et al. (2017))

Chapter 4: The Impact of Advanced Metering Infrastructure on Residential Electricity Consumption - Evidence from California (based on Paschmann & Paulus (2017))

Chapter 5: Electricity Reduction in the Residential Sector - The Example of the Californian Energy Crisis (based on Paulus (2017))

The four essays are stand-alone and may be read in any order; however, with the analysis of the demand side in Chapter 2, I intend to shed some light on the commonly assumed inelastic demand assumption in electricity markets by studying the German market. Chapter 3, 4 and 5 study policy interventions affecting both, the generation and demand side in electricity markets. Whereas Chapter 3 addresses policy intervention directed towards environmental protection, Chapter 4 and 5 rather investigate the impact on residential demand reduction through policy interventions specifically targeting a change in electricity usage.

The presented methodologies to tackle the issues discussed and the topic selection itself are guided by the author's interest. The following introduction provides a brief summary of the four essays, including the research question and a brief discussion of the results. Furthermore, the author sets out how each of the four essays adds to existing literature and serve for a better understanding of the investigated topics. The introduction concludes with possible extensions for future research, critical reflections and some improvements to methodologies for the essays.

1.1 Introducing the Essays

Chapter 2 focuses on the demand elasticity in the German wholesale market by applying a two stage least-squared estimation technique. Complementary to already conducted research, the estimated demand elasticity is not sub-market specific. The estimation is based on hourly time intervals. It is motivated by the thought that utility resulting from electricity consumption for all end consumers differs in every hour. Thus, the higher temporal resolution reveals hourly patterns for demand elasticities ranging from -0.02 to -0.13 for the analyzed market area. The article adds to attempts for measuring demand elasticities of higher temporal order in electricity market by building on some initial thoughts of Bönte et al. (2015). However, an analysis for Germany is so far lacking in the literature. Our analysis makes use of the stochastic character of renewable generation that primarily affects the supply side but not the demand side thereby serving as a suitable instrument in order to solve simultaneity issues occurring in electricity markets. The found hourly elasticity results for the German market may be used for further academic studies attempting to model electricity markets with simulation methods where commonly demand developments for sectors are a prior defined as perfectly 'inelastic', a restriction that from the author's point of view is implicitly questioned.

Chapter 3 investigates the influences of regulation and gas prices on the emission levels of fossil power plants for all states in the U.S. Research has been motivated by the rising influence of shale gas in the past decade influencing gas prices and consumption. It furthermore investigates the switch from a heavily coal-based generation portfolio to a less carbon-intense gas-fired generation portfolio over a thirteen years period by taking gas price effects and a tightened CO_2-regulation for emission in the generation portfolio into account. The essay is based on Growitsch et al. (2017) and uses nonparametric benchmarking techniques to first identify best practice states between 2000 and 2013. Example states and their generation portfolios are used to back up results obtained by the approach and provide an intuitive understanding for some states, where initial interpretation of benchmarking results may not be straightforward (i.e. for North Dakota). Secondly, a regression on the CO_2 emission performance over time is conducted by controlling among others for gas prices and all CO_2-related regulation, occurring in the form of emission standards and cap and trade systems. The empirical analysis presented in Chapter 3 adds to the literature on benchmarking within the power generation field, where good and bad outputs need to be simultaneously modeled. We make use of the standard assumptions of Färe & Primont (1995) and extend the standard model of Shephard (1953) by using an input distance function allowing for a multi-input and output simulation that is indispensable when analyzing emissions of fossil power generation. Besides best practice states, our results show lower gas prices and stringent CO_2 regulations are suitable means to reduce CO_2 emissions.

Chapter 4 analyzes the policy-induced Advanced Metering Infrastructure deployment in California and the related impact of additional information on residential electricity consumption. Contrary to the other chapters, Chapter 4 is positioned in the literature on behavioral economics linking informational feedback, the nature of consumers being rationally bounded with residential electricity consumption (as for instance also done by Allcott & Rogers (2014)). A rather systemic perspective is framing this chapter by analyzing the respective impact of Advanced Metering Infrastructure deployment on electricity savings. With the help of synthetic control techniques (Abadie et al., 2010), the obstacle of not having a direct control group within a large-scale framework is overcome. A Difference-in-Differences estimation accounts for causality and persistency matters over a 13-year period. As such, the chosen approach differs with respect to test pilots analyzing shorter time spans and the fact that a subsample of the population may cause severe estimation bias. The results show a significant negative impact of Advanced Metering Infrastructure on monthly residential electricity consumption that ranges from 6.1% to 6.4% over the respective period. Additionally, an impact of Advanced Metering Infrastructure on residential electricity consumption only occurs in non-heating periods and does not fade out over the analyzed time period.

Chapter 5 investigates supply shortages in the Californian electricity market and the role of policy measures to contain the Energy Crisis. The contribution of this paper lies not only in the assessment of policy measures and electricity price effects to curb residential electricity consumption, it furthermore reveals that consumption in the Californian residential sector may be reduced by up to 12% triggered partly by an adjustment within respect to secondary energy use in the residential sector. As my results show, this 'reduction potential' or 'residential comfort buffer' is more likely to be leveraged in summer periods which I relate to comfort issues that consumers are not willing to 'sacrifice' on in winter periods. Chapter 5 adds to the discussing of electricity price impacts in residential electricity markets (Albadi & El-Saadany, 2008) and the effectiveness of short term policy measures targeting residential electricity reduction rather than technical replacements of household appliances that commonly cover longer time periods. It is thus positioned in the context of policy measures not related to changing technical household appliances. Methodologically, Chapter 5 makes uses of a synthetic control group derivation. A nationwide analysis for the impact of conservation programs, in particular the '20/20' rebate program and the mass media campaign, emerging from the Californian Energy Crisis has not been conducted so far. The mutual impact of conservation impacts is estimated via a treatment regression.

1.2 Future Research and Possible Improvements to Methodologies

Expect for Chapter 4 and 5 mutually sharing the application of a synthetic control group derivation, all four chapters address different research questions, each of which requires a different methodology. Chapter 3 presents a non-parametric benchmarking approach to model emission improvements over time, followed by an applied econometric method. Even though the baseline model is extended by the features of multiple inputs and outputs, reflecting that emissions cannot be reduced without reducing electricity generation, some researchers tend to rather follow the material balance constraint programing (i.e. Førsund (2008)) essentially imposing the condition that residuals cannot be used when jointly modeling input and output on a multi-dimensional level. The critique applied to previous literature may therefore also apply to the analysis presented here. In addition, the model may fail to incorporate important features of the industry on a micro level. Firm specific data may thus grasps the fundamental industry structure of the fossil generation with more detail. However, it may also be noted that the aggregated data used by the authors stems from a detailed data survey conducted by the Energy Information Administration agency in the U.S. (i.e. EIA form-860) that builds upon data collection on the power plant unit level. Although numerous estimation specification have been tested, both with respect to appropriateness of the chosen instrument and variable selection, estimation bias through variables possessing certain additional explanatory power cannot be ruled out with complete certainty.

Chapter 2 estimates hourly demand elasticity in the German market. With respect to the applied instrument the authors are confident that chosen wind generation is well-defined and appropriate for estimating prices in the first stage. Other instruments may be considered for solving the endogeneity issue in order to support or neglect our findings. Furthermore, extending the analysis over a multi-year period would provide interesting insights into the degree of hourly demand elasticities over longer periods. As data on renewable infeed has started to be officially published in 2014, the authors consider an evaluation of other years as an interesting additional analysis. Lastly, the regional scope of the analysis lacks an important issue not completely addressed in this chapter. In particular, the regional connection to neighboring states where electricity may be bought at lower prices are only indirectly reflected by using realized consumed volumes and electricity prices that have been subject to trading prior to settlement.

As already stated, Chapter 4 and 5 methodologically share the application of a synthetic control group derivation. The empirical analysis in Chapter 5 ends with the year 2002 whereas the empirical analysis of Chapter 4 commences in 2003. In both chapters, the methodological approach builds on Abadie et al. (2010) and mimics the residential electricity consumption that would have occurred without the treatment. The gathered data represent a wide range of socio-economic variables accounting on a monthly basis for both fluctuations of residential electricity consumption over time and the respective differences between the states. The assumption of parallel trends prior the policy treatment is valid in both chapters and both chapters add to literature on policy-induced residential consumption changes. Whereas Chapter 4 analyzes longer periods, Chapter 5 sheds light on whether or not short term consumption changes may be realized. Methodologically, Chapter 4 specifically accounts for Advanced Metering Infrastructure penetration in the estimation and Chapter 5 captures residential electricity consumption with a treatment regression by using time dummies and controlling for all other explanatory variables. An empirical analysis for the conservation measures in Chapter 5 specifically accounting for explanatory variables may provide a promising further research avenue.

2 When Are Consumers Responding to Electricity Prices? An Hourly Pattern of Demand Elasticity

System security in electricity markets relies crucially on the interaction between demand and supply over time. However, research on electricity markets has been mainly focusing on the supply side arguing that demand is rather inelastic. Assuming perfectly inelastic demand might lead to delusive statements regarding the price formation in electricity markets. In this article, we quantify the short-run price elasticity of electricity demand in the German day-ahead market and show that demand is adjusting to price movements in the short-run. We are able to solve the simultaneity problem of demand and supply for the German market by incorporating variable renewable electricity generation for the estimation of electricity prices in our econometric approach. We find a daily pattern for demand elasticity on the German day-ahead market where price-induced demand response occurs in early morning and late afternoon hours. Consequently, price elasticity is lowest at night times and during the day. Our measured price elasticity peaks at a value of approximately -0.13 implying that a one percent increase in price reduces demand by 0.13 percent.

2.1 Introduction

Understanding the price elasticity of demand is important since demand adjustments based on price movements contribute to the functioning of electricity markets. In electricity markets it is worth stressing that balancing demand and supply occurs on a high temporal frequency which, not only in Germany, results in debates on whether or not it is possible to match demand and supply at all times. An inelastic price elasticity of demand assumption, as often argued for the short-run, would imply that the burden of balancing electricity consumption and generation at all times rests with the supply side.

The empirical literature estimating long-run and short-run price elastictiy of demand in electricity markets is extensive. For the short-run, peer-reviewed studies have estimated the elasticity for different sectors and time intervals. Table 2.1 shows that estimates of price elasticity vary from -0.02 to -0.3 depending on the chosen approach, the country-specific data and the sector. Taylor et al. (2005), for instance, find that short-run elasticity ranges from -0.05 to -0.26 for the industrial sector in North Carolina by using annual data. He et al. (2011) confirm this finding whereas Bardazzi et al. (2015) measure a slightly higher elasticity in terms of magnitude for the Italian industry sector. For the residential sector, numerous studies have been performed as well (i.e. Ziramba (2008), Dergiades & Tsoulfidis (2008) and Hosoe & Akiyama (2009)). However, little attention has been devoted to the price response of the whole market with respect to wholesale prices. So far, this market has only been investigated by Genc (2014) and Lijesen (2007). Whereas Genc (2014) applies a bottom-up Cournot modeling framework, Lijesen (2007) uses a regression approach in order to quantify the price elasticity during peak hours. Genc and Lijesen conclude from their chosen approaches that the hourly price elasticity is rather small. They furthermore argue that in peak hours demand switching behavior of consumers barely occurs in practice.

In this article we extend the existing literature on short-run elasticity with respect to the wholesale price in two ways. First, we use wind generation as an instrument variable to solve the simultaneity problem of demand and supply.[1] Second, we account for the variation in utility from electricity consumption during the day. Using hourly data on load, temperature, prices and wind generation for the German day-ahead market in 2015, we quantify the level of price elasticity and its variation throughout the day.

Our results show that the short-run price elasticity of demand in the German electricity market is not perfectly inelastic. Even though our obtained short-run price elasticity of demand is generally low, consumers still react to price movements. Measuring the price elasticity of demand can give a more meaningful understanding of the contribution of demand reactions to system security. However, we stress that a price elasticity of demand with respect to the day-ahead price is not explicitly showing the contribution of each consumer group. The daily pattern of our estimate of price elasticity reveals some prominent peaks in the morning and evening, where the price elasticity of demand is highest. As expected, these hours show overall high price levels providing incentives to consumers for a reduction of their consumption. In the morning and evening hours, price elasticity varies between -0.08 and -0.13. Thus, we infer that demand adjustments in these hours are to some extent beneficial for consumers. On the contrary, we measure a lower price elasticity of demand at

[1] The approach is similar to Bönte et al. (2015).

Table 2.1: Literature review of estimated short-run elasticity

Source	Type of model	Type of data	Elasticity	Sector	Region
Garcia-Cerrutti (2000)	Dynamic random variables model	Annual	-0.79 to 0.01, mean -0.17	Residential	California
Al-Faris (2002)	Dynamic cointegration and Error Correction Model	Annual, 1970-1997	-0.04 / -0.18		Oman
Bjørner & Jensen (2002)	Log-linear fixed effects	Panel, 1983-1996	-0.44		
Boisvert et al. (2004)	Generalized Leontief		Peak: -0.05	TOU	
Holtedahl & Joutz (2004)	Cointegration and Error Correction Model	Annual, 1955-1996	-0.15	Residential	Taiwan
Reiss & White (2005)	Reduced form approach	Annual , 1993 and 1997	0 to -0.4	Residential	California
Taylor et al. (2005)	Generalized McFadden with nonlinear OLS and Seemingly Unrelated Regression	1994-2001	-0.26 to -0.05	Industry	Duke Energy, North Carolina
Bushnell & Mansur (2005)	lagged residential prices		-0.1	Residential	San Diego
	Error Correction Model	Annual, 1969-2000	-0.263	Residential	Australia
Bernstein et al. (2006)	dynamic demand model with lagged variables and fixed effects	Panel, 1977-2004 1977-1999	-0.24 to -0.21	Residential, Commercial	US
Rapanos & Polemis (2006)		1965-1999	-0.31		Greece
Halicioglu (2007)	Bounds testing approach to cointegration within ARDL model	1968-2005	-0.33		Turkey
Lijesen (2007)	reduced form regression linear, loglinear		-0.0014 -0.0043	Wholesale	Netherlands
Dergiades & Tsoulfidis (2008)	Bounds testing approach to cointegration within ARDL model	1965-2006	-1.06	Residential	US
Ziramba (2008)	Bounds testing approach to cointegration within ARDL model	1978-2005	-0.02	Residential	South Africa
Hosoe & Akiyama (2009)	OLS/Translog cost function	1976-2006	0.09 to 0.3	Residential	Japan
He et al. (2011)	General equilibrium analysis	2007	-0.017 to -0.019, -0.293 to -0.311, -0.0624 to -0.0634	Industry, residential, agriculture	China
Bardazzi et al. (2015)	Two-stage translog model	Panel, 2000-2005	–0.561 to -0.299	Industry	Italy
Genc (2014)	Cournot competition model	Hourly 2007, 2008	-0.144 to -0.013 -0.019 to -0.083	Wholesale	Ontario

night times and during the day. A lower elasticity indicates less willingness of consumers to adjust the consumption due to high or low electricity prices. This can be due to the fact that economic activity in general is higher during daytime.

The remainder of the paper is organized as follows. Section 2.2 deepens the understanding of supply and demand in electricity markets. Section 2.3 describes the data and presents the applied econometric approach. Section 2.4 discusses the estimation results. Section 2.5 concludes.

2.2 Measuring Market Demand Reactions Based on Wholesale Prices

In order to specify our econometric model capturing demand reactions due to electricity wholesale price movements, knowledge about the supply and demand functions in electricity markets is pivotal. In this section, we therefore describe the functioning of the retail and wholesale electricity market before arguing that demand elasticity can be estimated based on market demand being defined as aggregated demand of all end consumer groups and wholesale electricity prices. We further specify the drivers of demand and supply by setting up the respective functions.

2.2.1 The Retail Market for Electricity

Consumers commonly sign contracts with retailers to take charge of their electricity demand. These contracts are subject to different possible tariff schemes ranging from time-invariant pricing to real-time pricing. Tariff structures vary depending on the consumer group and metering facilities.[2] Small end consumers (e.g. households, businesses, or small industries) in Germany are mostly on time-invariant tariffs. This means that the price of electricity for these consumer groups is at the same level for every hour over the entire year. These consumers therefore have little incentive to adjust their demand in the short-run. For larger consumers, such as big industrial companies, contracts are differently designed allowing them to benefit from adjusting consumption in the short run.[3]

In Germany, the retail price that consumers pay for electricity consists of several components. The most important component is the price for electricity generation, which is the price that generators charge for the generation of electricity. Besides paying for the generation of electricity, end consumers also pay for the transmission and distribution of electricity, as well as for additional taxes and levies. In Germany, for instance the retail price consists of network charges, the renewable support levy, and taxes which are added to the wholesale price. Some of these additional price

[2]The electricity consumption of many end consumers is not observable over time because the metering facilities only display the amount of electricity consumed but not during which period measurement is performed.

[3]According to Bundesnetzagentur (2016), consumers can be grouped by their metering profile into customers with and without interval metering. Only consumers with interval metering have the technical capability to be billed depending on the time of usage. For Germany in 2014, 268 TWh were supplied to interval metered customers and 160 TWh to customers without interval metering.

components vary substantially depending on the consumer group.[4] The differing retail prices for each consumer group lead to a total electricity demand of all consumers that varies over the year. This aggregated demand of all end consumers is equal to the observed load in the total electricity system.

2.2.2 The Wholesale Market for Electricity

The price for electricity generation is determined in the wholesale market. In principal, the wholesale market allows different players to place bids that eventually either result in produced quantities or demanded quantities for a specific point in time. Participants in these markets are for example utilities, retailers, power plant operators and large industrial consumers.

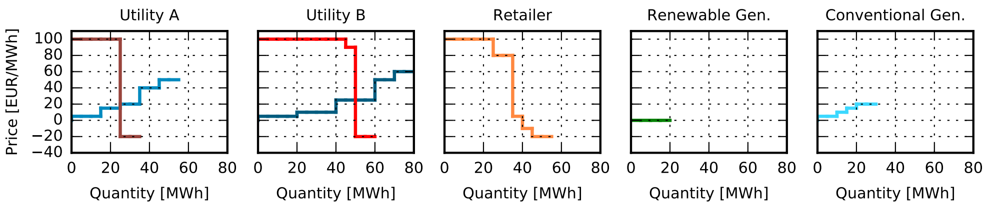
Figure 2.1(i) gives an exemplary overview of the five different players and their corresponding electricity demand and supply on the wholesale market. The first two players are two different utilities, A and B. As such, utility A and B illustrate cases for players with different generation assets while at the same time each of them possesses different customer bases. However, for both utilities, we would expect that generation for their own customer base depends on the marginal cost of generation. In other words, if the wholesale price is above the marginal cost of the utility's marginal cost of generation, the utility chooses to supply their customer base instead of demanding quantities from the wholesale market.

The next player in the market we refer to is the retailer. As a retailer, supplying electricity is by default not an option and therefore we expect them to demand electricity quantities only. The opposite is true for renewable and conventional generation players. With marginal costs of zero, renewable generation players offer their production at very low cost compared to conventional generation players where marginal costs are greater than zero and vary depending on the generation technology.

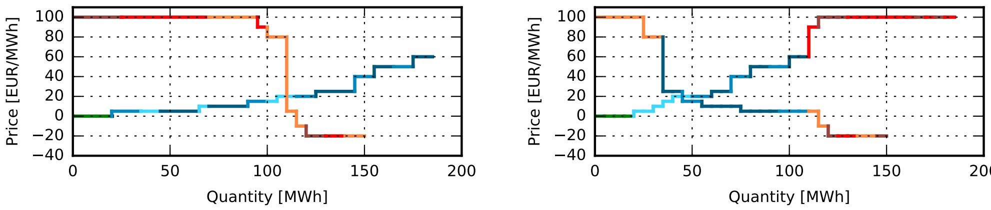
Figure 2.1(ii) horizontally aggregates all demand and supply curves from each player we identified. It thus shows the aggregated demand and supply, as well as the realized equilibrium electricity price of 20 EUR/MWh.

Figure 2.1(iii) shows the resulting supply and demand bids by the individual players in the wholesale market. First, players that can only supply electricity, such as renewable or conventional generators, appear in ascending order on the supply side

[4] In Germany, for example, electricity intensive industries are exempted from paying the renewable support levy.



(i) Wholesale market players



(ii) Supply and demand aggregation (iii) Supply and demand in the wholesale market

Figure 2.1: Electricity price formation on the wholesale market

only. Second, retailers demand quantities and generally more, if prices are low. Third, players that own generation assets and also have customers, net their supply and demand positions internally before submitting bids. This is the case for utility A and B. The bids for the demand and supply side depend on the internal netting of supply and demand. In total this results in four possible outcomes for placing bids which can be describes as follows

- sell bid on the supply side for generation units that have not been internally matched and could satisfy the demand of other participants
- purchase bid on the demand side for demand that has not been internally matched
- sell bid on the supply side, resulting from demand that has been matched internally but would be able to reduce consumption if the price rises above a given threshold (see e.g. demand of utility B with 90 EUR/MWh)
- purchase bid on the demand side for generation units that have internally be matched but that would substitute their production if the price falls below their marginal costs of generation.

Whereas the first two outcomes are intuitively straightforward, outcomes three and four may seem counter intuitive at first. Due to the internal matching of supply and demand, parts of the demand and supply curve that have been internally matched result in bids on the opposite side. By placing these bids, utilities can optimize their position and choose to substitute formally demanded quantities to supplied quantities or vice versa, above or below a certain wholesale price.

The supply and demand curves in Figure 2.1(ii) and 2.1(iii) look very different from a first glance, but both result in the same price for electricity and lead to the same allocation of resources. Nevertheless, both provide a very different impression of the price responsiveness of the demand side. Based on Figure 2.1(ii) the demand side can be characterized as rather price inelastic. In the example, the level of demand would not change if prices stay within a range of 5 to 80 EUR/MWh. Figure 2.1(iii) may however lead to the misleading conclusion that the demand side in electricity markets is rather price elastic. Within the submitted supply and demand bids at the wholesale market it is not possible to identify separate bids that actually stem from generators or actual consumers of electricity. It is therefore not possible to estimate the demand elasticity of actual electricity consumers based on the curves observed in the wholesale market. In order to estimate the demand elasticity of the actual electricity consumers it is, however, possible to combine the wholesale equilibrium price with the total load observed.

2.2.3 The Interaction of Wholesale and Retail Markets

Within this article we are interested in the reaction of electricity demand to electricity prices. Because disaggregated load data for each consumer group with the respective retail prices are not available, we focus our attention on the interaction of total hourly demand and hourly wholesale electricity prices. Figure 2.2 shows the relation we are interested in for an exemplary hour. The blue line depicts the supply curve for electricity generation. The red line is the aggregated demand curve of all consumers for electricity consumption. Consumers pay an average retail price of p^r, which is made up of the wholesale price for electricity (p^w) and additional price components (c).[5] When we account for the effect of the additional price components, we obtain the demand function that is observable in the wholesale market ($wholesale\ demand$, red dashed line). The intersection of wholesale demand and wholesale supply leads to point A and determines the wholesale price p^w, as well as the quantity consumed and produced q^{el}. By inferring the relationship illustrated in Figure 2.2 and using the wholesale price and total electricity demand, we are able to estimate the point elasticity of the red dashed demand curve.

[5]In Germany, most additional price components are added to the wholesale price independent on the price level or quantity consumed.

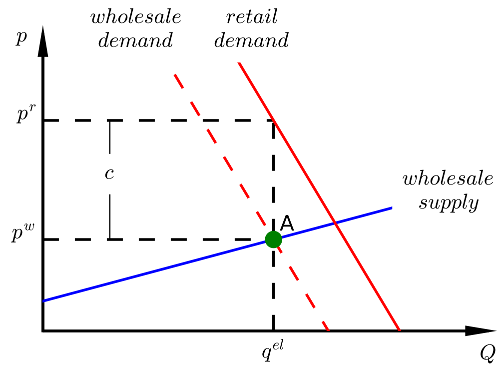


Figure 2.2: Supply and demand curves for one exemplary hour

The relations of the demand and supply curve in electricity markets are only vaguely sketched in Figure 2.2. In reality, demand is fluctuating over time due to varying utility levels throughout the day. The demand for electricity can be regarded as a function of various inputs and the relation can be written as

$$d^{el} = f(p^w, HDD, \textit{time-of-the-day}), \tag{2.1}$$

where d_{el} is the quantity consumed, p^w is the wholesale price for electricity, HDD are heating degree days capturing the seasonality within the data. HDD measure the temperature difference to a reference temperature. The variable therefore captures the seasonal variation of electricity demand. For example, if outside temperature is low, heating processes consume more electricity compared to warmer weather conditions.[6] In addition, electricity consumption depends on the time of usage. This is mainly driven by the variation of the consumer's utility function over the day. Additional variables determining the level of demand, such as economic activity, may also alter demand but are assumed to be time-invariant on an hourly basis and within the considered time span. Therefore, we abstract from including additional variables for the demand side in the short run.

Like the demand function, the supply of electricity can also be regarded as a function of multiple inputs with the wholesale price p^w being one of them. We define the supply function as:

[6]The data in Section 2.4 reveals that this relation is true for Germany, however it may not be applicable to other countries. In warmer climates also cooling degree days (CDD) determine the demand for electricity.

$$s^{el} = g(p^w, p^{fuel}, r), \tag{2.2}$$

where s^{el} is the quantity produced, p^{fuel} is a vector of fuel prices and r is the production of variable renewable energy.

In electricity markets, the structure of the supply side is commonly represented by the merit order curve. It represents the marginal generation costs of all conventional (fossil) power plants. The shape of the curve mainly depends on the technologies being used for power generation and their respective fuel prices p^{fuel}.[7] However, variable renewable electricity generation is becoming increasingly important within the generation portfolio. This is particularly true for the German market region. Since renewable technologies do not rely on fossil fuel inputs to generate electricity, their fuel costs are close to zero. Additionally, its stochastic nature that is driven by wind speeds and solar radiation makes generation vary throughout time. We will later make use of the stochastic nature and by using wind generation as an instrument variable within our econometric model.

2.3 Empirical Framework

2.3.1 Data

Our data set consists of hourly data for 2015. We include hourly data for load, day-ahead-prices and the forecast of production from variable renewables for Germany. In addition, HDD are calculated based on hourly temperatures that we obtain from the NASA Goddard Institute for Space Studies (GISS). Summary statistics for all variables are provided in Table 2.2.

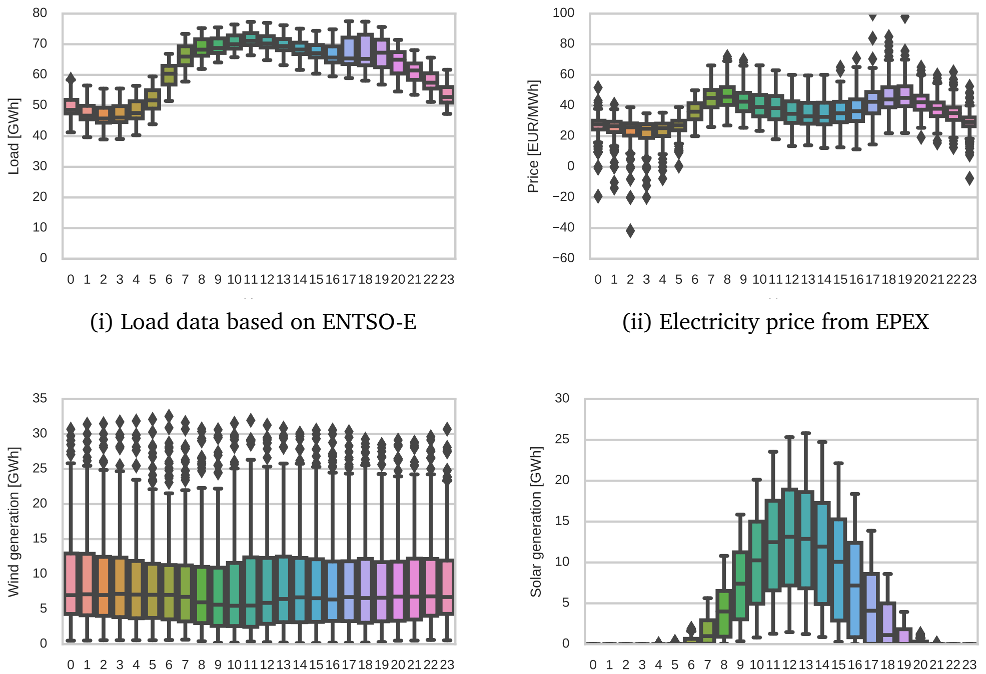
Table 2.2: Descriptive statistics (for weekdays, without public holidays and Christmas time)

Variable	Mean	Std. Dev.	Min.	Max.	Source
Load [GWh]	61.688	9.428	38.926	77.496	ENTSO-E
Wind Generation [GWh]	8.574	6.864	0.153	32.529	EEX Transparency
Day-ahead price [EUR/MWh]	35.6	11.5	-41.74	99.77	EPEX Spot
Temperature [°C]	10.4	7.9	-6.3	34.6	NASA MERRA
Heating degree days [K]	10.1	6.9	0	26.3	NASA MERRA

The hourly load profile for Germany was taken from ENTSO-E. According to ENTSO-E, load is the power consumed by the network including network losses but ex-

[7] Common power plant types and fuels are hydro power, nuclear, lignite, coal, gas and oil.

cluding consumption of pumped storage and generating auxiliaries.[8] The load data includes all energy that is sold by German power plants to consumers.[9] Load therefore is the best indicator on the level of demand in the German market area since almost all energy sold has to be transferred through the grid to consumers. Figure 2.3(i) shows average hourly values for weekdays in the German market area in a box plot. The plot shows significant differences in the level for night hours (00:00-6:00, 19:00-00:00) compared to daytime. Also load peaks in the morning (9:00-12:00) and evening hours (16:00-18:00). Especially in the evening, variation in load levels is higher than at other times. The average load level is 62 GW and the maximum peak load is 77 GW in the early evening hours.



(i) Load data based on ENTSO-E

(ii) Electricity price from EPEX

(iii) Wind generation from EEX Transparency

(iv) Solar generation from EEX Transparency

Figure 2.3: Hourly data for load, electricity price, wind and solar generation for 2015

We obtain the hourly day-ahead price for electricity from the European Power Exchange (EPEX) which is the major trading platform for Germany. Historically the day-ahead price has evolved as the most important reference price on an hourly level

[8] ENTSO-E collects the information from the four German transmission system operators (TSO) and claims that the data covers at least 91% of the total supply. These quantities may also be reflected in the day-ahead price which we can not account for.

[9] To a small amount load may also include energy that is sold from neighboring countries to the German market. These trade flows impact the domestic electricity price and load. However, we expect this impact to be rather small.

in the wholesale electricity market. The day-ahead market run by EPEX Spot is by far the most liquid trading possibility close to the point of physical delivery.[10] The price is determined in a uniform price auction at noon one day before electricity is physically delivered. We follow this perspective and use the day-ahead price as our reference price for electricity generation. Although not all electricity is sold through the day-ahead-auction, the price reflects the value of electricity in the respective hours and contains all available information on demand and supply at that specific point in time. Figure 2.3(ii) shows a box plot for the hourly day-ahead electricity price for each hour of the day. The average hourly day-ahead electricity price is at 36 EUR/MWh over the 24 hours time interval and for weekdays (without public holidays and Christmas time). The electricity price pattern is similar to the load pattern emphasizing the fact that higher demand levels tend to increase prices in the day-ahead market. Especially during peak times in the morning and evening one can observe higher standard deviations and peaking prices. Standard deviation over all hours is around 12 EUR/MWh.

Electricity generation from wind and solar power is taken from forecasts published on the transparency platform by the European Energy Exchange (EEX). These forecasts result from multiple TSO data submissions to the EEX. Since they are submitted one day before physical delivery, they contain all information that is relevant for participants in the day-ahead market.[11] Figure 2.3(iii) and 2.3(iv) show box plots for electricity generation from wind and solar power. Due to weather dependent generation volatility, we observe a larger amount of volatility in the hourly data. Wind generation varies steadily throughout the day with a small increase during the day. Solar generation shows its typical daily pattern with no generation at night and peak generation values for midday.

The level of demand does not only depend on the electricity price which in return is partially influenced by generation from wind. We add temperature as an additional parameter to our investigation of electricity demand since the level of temperature is a main driver for the seasonal variation of demand. We compute a Germany wide average temperature based on the reanalysis MERRA data set provided by NASA (NASA, 2016). The hourly values are based on different grid points within Germany that are spatially averaged in order to obtain a consistent hourly value for Germany. Based on the hourly temperature we derive HDD that are relevant for the seasonal

[10]In 2015 264 TWh have been traded in the day-ahead market, compared to 37 TWh traded in the continuous intraday market (EPEX Spot, 2016).

[11]We also considered taking the actual generation from renewables but reckon that the ex-ante forecasts are reflecting the causal relationship in a better way since decisions made on the day-ahead market are based on forecast values.

variation of demand in electricity markets.[12]

2.3.2 Econometric Approach

Due to the fact that the electricity price is endogenously determined by the interaction of demand and supply, we choose a two-stage approach to solve the simultaneity problem.[13] As we are interested in estimating the demand function (2.1), possible instruments affecting the price but not the level of demand have to be determined. Possible instruments can be found on the supply side in (2.2), where fuel prices (p^{fuel}) and the production of variable renewable energy (r) are considered. Although fuel prices are one of the major drivers for generation decisions, a closer look reveals that they show little variation over the year 2015 (see Figure 2.6 in the Appendix). Therefore, we exclude them from a further analysis within our framework.

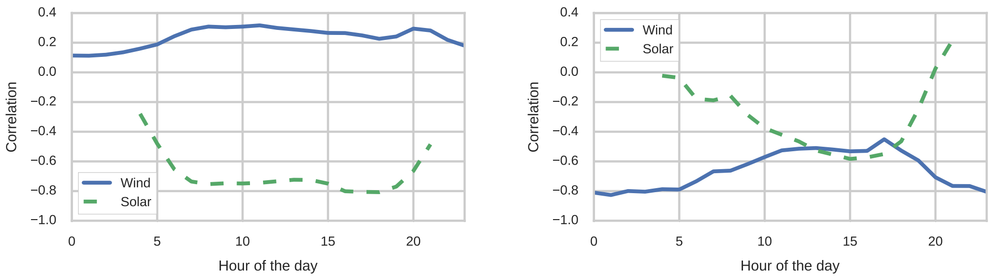
The production of variable renewable energy (r) can further be split into wind (w) and solar (s) generation. Figure 2.4 depicts the respective correlations of renewable generation with prices and load for each hour interval of the day. In Figure 2.4i, we observe that the correlation between solar generation and load is higher in absolute values than the correlation between wind generation and load. However, wind and solar generation are correlated opposite in sign with load being positively correlated with wind generation and solar generation negatively correlated with load.

Figure 2.4ii shows the correlation between renewable generation and electricity price. Both, wind and solar generation are negatively correlated with the electricity price, however their patterns are different throughout the day. The correlation between wind generation and electricity price weakens over the day until 17:00 where the correlation is lowest with an absolute value of -0.45. From 17:00 on the correlation between wind generation and price increases again. The pattern for the correlation between solar generation and electricity price is reversed whereas the increasing correlation until 17:00 is mainly driven by an increasing solar radiation. Based on the generally high correlation of wind and prices and at the same time low correlation of wind and load, we choose wind generation as an instrument for the price.[14]

[12] We calculate HDDs based on a reference temperature of 20 °C.

[13] Durbin and Wu–Hausman test statistics show highly significant p-values. The null hypothesis tests for all variables in scope being exogenous. With p-values for both test of both equal to 0,000 we reject the null of exogeneity implying that prices and demand are endogenous.

[14] Statistically speaking, weak instruments may cause estimation bias if the correlation with the endogenous explanatory variable (in our case $p^{w}_{h,t}$) is very low.



(i) Correlations with load

(ii) Correlations with price

Figure 2.4: Correlations with load and prices in 2015

More formally, wind generation as a variable fulfills the two conditions (1) $cov[w, p^w] \neq 0$ and (2) $cov[w, \mu] = 0$, where w is wind generation, p^w the wholesale electricity price and μ the error term of the general demand equation not to be confused with the error term $\mu_{h,t}$ of equation (2.4). The first condition is needed in order to provide unbiased electricity price estimates. In our context the chosen instrument w correlates with the electricity price (see Figure 2.4(ii)). From the second condition it follows that w and μ are not correlated.[15] Because wind can be regarded as a stochastic variable especially throughout the day and load inhibits strong daily patterns, both can be regarded as independent (see Figure 2.4(i)). With these two conditions fulfilled we are now able to postulate the first and second stage equations. The first stage can be written as

$$p^w_{h,t} = \gamma_{0,h} + \gamma_{1,h} \cdot w_{h,t} + \epsilon_{h,t} \tag{2.3}$$

and the second stage as

$$q^{el}_{h,t} = \beta_{0,h} + \beta_{1,h} \cdot \widehat{p^w_{h,t}} + \beta_2 \cdot HDD_t + \beta_3 \cdot MON_t + \beta_4 \cdot FRI_t + \mu_{h,t}. \tag{2.4}$$

We estimate price coefficients $\beta_{1,h}$ and dummy coefficients $\beta_{0,h}$ on an hourly basis h. We do this, because we expect the utility of electricity consumption to be different in each hour of the day. Here, $\beta_{0,h}$ captures the price independent change of utility from electricity consumption throughout the day. Since we observe a different

[15] Testing for validity expressed by $cov[w, \mu] = 0$ within our framework is not feasible since our model is exactly identified.

demand pattern for working days and week-ends, we eliminate week-ends and holidays from the data. Furthermore, we add dummies for Monday (MON) and Friday (FRI)[16] to capture differing demand levels at the beginning and end of the working week. Based on our estimates, we can calculate the average hourly price elasticity of electricity demand according to

$$\epsilon_h = \frac{\overline{p}_h^w}{\overline{q}_h} \frac{\partial q_h}{\partial p_h} = \frac{\overline{p}_h^w}{\overline{q}_h} \beta_{1,h}, \tag{2.5}$$

where ϵ_h is the hourly elasticity using the average price $\overline{p}_h^w$ and average demand $\overline{q}_h$ in the respective hour of the day (h).

2.4 Empirical Application

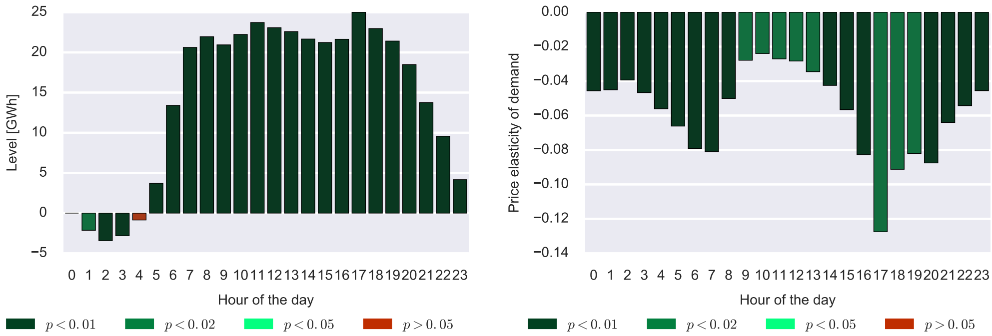
By applying the econometric framework, we are able to estimate the level of price elasticity of demand for the German day-ahead market on an hourly basis. The regression is based on levels and elasticity is calculated with respect to the average prices and quantities in each hour.[17]

The results of the estimation can be found in Table 2.3. When taking a look at the price coefficients in Table 2.3(a), we can see that all price coefficients are negative in sign and are significant at least at the 1% level. We note that coefficients during morning hours (9:00-12:00) are lower in absolute values. The highest value can be found at 17:00. In this particular hour, a wholesale price increase of 1 EUR/MWh leads to a demand reduction of 201.8 MWh. The hourly dummy coefficients in Table 2.3(a) capture the varying level of utility throughout the day. During the day, hourly coefficients are higher than at other times. In the evening, we can observe a peak in the level of utility, especially between 16:00 - 20:00 (see Figure 2.5(i)). Beside the hourly coefficients, we also account for the influence of temperature and weekdays on electricity demand. All coefficients are significant at the 0.1% level and can be explained in their sign. HDD have a positive sign and thus increase electricity demand. Mondays and Fridays are negative in sign, indicating that demand is generally lower at the start of the week and at the end compared to other working

[16]For Mondays the dummy is positive for the time between 0:00 and 9:00. For Fridays the time frame is from 17:00 to 23:00.

[17]In a previous version of the paper, we normalized our data to the median, which is why previous estimates differ from this version. Furthermore, elasticity was calculated with respect to the average price and quantity level including values of zero. As we are running a pooled regression many observations of zero were included which resulted in low estimates of the elasticity.

days.



(i) Hourly dummies (ii) Hourly price elasticity

Figure 2.5: Hourly dummies and price elasticity of electricity demand in 2015

Since the focus of our work is on the hourly price elasticity of demand, we estimate the elasticity based on the results from the basic regression. The results are displayed in Figure 2.5(ii) and the numerical values can be found in Table 2.3(c).[18]

As observed before, all coefficients are negative in sign and significant at a strict 1% level. With the elasticity estimates at hand, we are able to plot a distinctive pattern for the hourly price elasticity of demand for the German day-ahead market. The unique shape of the hourly price elasticity of demand pattern is depicted above in Figure 2.5(ii). Our results show that demand reactions are rather small. However, a perfect inelastic demand assumption can also be neglected. More precisely, the elasticity is the lowest during night times (22:00 - 6:00). During these hours electricity demand and utility from electricity consumption is generally lower (as we can also observe from Table 2.3(a)). The graph shows two prominent peaks of price elasticity of demand in the morning and in the evening. At these times working hours start and end. Possible reasons for a high elasticity of demand at those times is the shifting or delaying of consumption. When prices are low in the morning, some processes may be able to start the operation earlier and thereby circumventing a time with a higher electricity price level. The same might be true for the evening, when the workday ends. Here working hours may be extended to lower price levels at other times. Throughout the day, the price elasticity of demand remains relatively

[18] It is important to note that elasticity is calculated with respect to the wholesale price level and not the retail price level, as represented by the dashed red demand curve in Figure 2.2. The elasticity with respect to retail prices would be higher. For example if we consider the sum of additional price components (c) to be 150 EUR/MWh, which is an average value based on Eurostat (2016) for Germany, the highest elasticity measured would be -0.58 at hour 17:00-18:00. Without the sum of additional price components, we obtain an elasticity of -0.13 as indicated in Table 2.3(c).

Table 2.3: Regression results

Hour	Price	Dummy
0	-0.0847*** (-3.98)	.
1	-0.0853*** (-4.18)	-2.135** (-2.91)
2	-0.0781*** (-4.23)	-3.429*** (-4.94)
3	-0.0960*** (-4.89)	-2.816*** (-4.01)
4	-0.1150*** (-5.60)	-0.8526 (-1.18)
5	-0.1298*** (-6.01)	3.714*** (4.70)
6	-0.1322*** (-4.96)	13.410*** (11.95)
7	-0.1192*** (-4.37)	20.620*** (15.14)
8	-0.0743*** (-3.55)	21.960*** (19.48)
9	-0.0452** (-2.95)	20.940*** (24.20)
10	-0.0421** (-2.69)	22.230*** (26.42)
11	-0.0496** (-2.92)	23.720*** (27.34)
12	-0.0557** (-3.01)	23.080*** (26.61)
13	-0.0688*** (-3.30)	22.590*** (24.57)
14	-0.0844*** (-3.58)	21.660*** (22.02)
15	-0.1069*** (-4.02)	21.240*** (19.26)
16	-0.1486*** (-3.66)	21.630*** (13.19)
17	-0.2018** (-2.90)	24.990*** (8.15)
18	-0.1349** (-2.65)	22.970*** (9.41)
19	-0.1175** (-3.19)	21.410*** (11.81)
20	-0.1327*** (-5.14)	18.490*** (15.26)
21	-0.1034*** (-5.68)	13.760*** (15.81)
22	-0.0890*** (-4.66)	9.565 (11.29)
23	-0.0836*** (-4.05)	4.164 (5.25)

(a) Dummy and price coefficients

	Coefficient
Heating degree days	0.4679*** (81.99)
Monday dummy	-3.340*** (-28.08)
Friday dummy	-1.997*** (-12.07)
Constant	46.57*** (84.62)
Observations	5760
R^2	0.940
Adjusted R^2	0.939

t statistics in parentheses

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

(b) Regression coefficients

Hour	Elasticity
0	-0.0456*** (-3.96)
1	-0.0451*** (-4.15)
2	-0.0394*** (-4.20)
3	-0.0467*** (-4.85)
4	-0.0561*** (-5.57)
5	-0.0661*** (-5.99)
6	-0.0792*** (-4.95)
7	-0.0810*** (-4.36)
8	-0.0501*** (-3.54)
9	-0.0279** (-2.95)
10	-0.0240** (-2.68)
11	-0.0271** (-2.91)
12	-0.0283** (-3.00)
13	-0.0345*** (-3.29)
14	-0.0425*** (-3.57)
15	-0.0566*** (-4.01)
16	-0.0828*** (-3.64)
17	-0.1275** (-2.88)
18	-0.0912** (-2.64)
19	-0.0821** (-3.18)
20	-0.0875*** (-5.12)
21	-0.0640*** (-5.65)
22	-0.0543*** (-4.63)
23	-0.0456*** (-4.03)

t statistics in parentheses

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

(c) Elasticity

low and is less significant. At those hours, economic activity is high and the option to shift or delay electricity consumption might not be feasible for consumers. In other words, consumers are bound to consume electricity which results in high electricity consumption regardless of the price level.

2.5 Conclusion

We estimate the hourly pattern of price elasticity of demand for the German day-ahead market, using hourly data on load, price, generation of wind and temperature. By doing this, we are able to determine the degree of short-run demand response within this market. To the best of our knowledge, a market-wide hourly analysis of the price elasticity of demand has not been conducted so far.

Based on our two-stage regression approach which uses wind generation as an instrument to proxy the electricity price, we find that hourly price elasticity of demand is not completely price inelastic. Especially during the morning and evening demand is responding to price signals. Values for price elasticity range from approximately -0.02 to -0.13 depending on the investigated hour. The hourly price elasticity pattern reveals that elasticity is lowest in the night hours and around mid day. Low values for price elasticity during night time (22:00 - 06:00) indicate that consumers are less likely to react. Around middle day economic activity is high which may explain the low elasticity values. Price elasticity of demand is the highest in the early morning (04:00 - 07:00) and late afternoon (16:00 - 20:00) hours, with levels between -0.08 and -0.13.

The empirical results indicate a high level of variation in the price elasticity of demand throughout the day in the German day-ahead market. Although the hourly elasticity is low from a first glance, load shifting accumulates over the year. The found elasticity pattern helps to understand when demand shifting occurs and when demand may be able to contribute to system security in situations of low supply. We find that especially during critical situations, such as peak times in the morning and evening, price elasticity of demand is high and may contribute to a secure electricity system.

Our research sheds some light on how flexible the German electricity market has already been in 2015, given the underlying renewable generation of the German day-ahead market. It may also give policy makers a starting point for evaluating the interaction of supply and demand in electricity markets. In addition to the analysis of the day-ahead market, we reckon that further research on demand response could focus on short-term markets, such as the intraday market. These markets are essential to the integration of large amounts of renewable electricity because they are able to balance forecast errors of wind and solar electricity. Whereas this additional research would gain further insights onto the short-term demand response, we argue that currently the day-ahead market remains the most important market where demand and supply are balanced.

2.6 Appendix

2.6.1 Price Development of Potential Other Instrument Variables

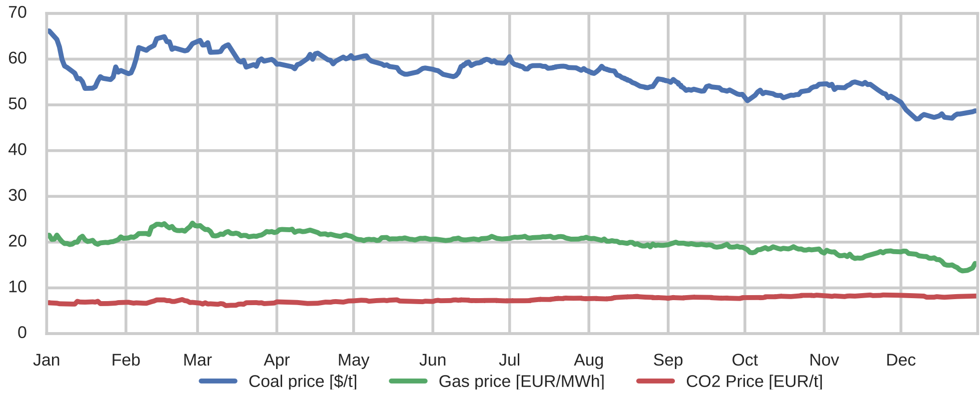


Figure 2.6: Prices for coal, gas and co2 certificates from January to December 2015

3 Competition and Regulation as a Means of Reducing CO_2-Emissions - Experience from U.S. Fossil Fuel Power Plants

Levels of CO_2 emissions from electricity generation in the U.S. have changed considerably in the last decade. This development can be attributed to two factors. First, the shale gas revolution has reduced gas prices significantly, leading to a crowding out of the more CO_2-intensive coal for electricity generation. Secondly, environmental regulations have been tightened at both the federal and the state level. In this article, we analyze the relative CO_2 emission performance across 48 states in the U.S. using a two-stage empirical approach. In the first stage, we identify the states that followed best practice between 2000 and 2013, by applying nonparametric benchmarking techniques. In the second stage, we regress our CO_2 emission performance indicators on the state-specific national gas prices, the states' CO_2 regulatory policies and a number of other state-specific factors in order to identify the main drivers of the developments. We find that the CO_2 emission performance improved on average by 15% across all states from 2000 to 2013. Furthermore, our second-stage results support the argument that decreasing natural gas prices and stringent regulatory measures, such as cap-and-trade programs, have a positive impact on the state-specific CO_2 emission performance.

3.1 Introduction

During the last decade, the electricity sector in the U.S. has undergone considerable change. On the supply side, the plummeting of gas prices induced by the so-called shale gas revolution has created incentives for power producers to increase gas usage and even to switch investment decisions in new capacity from coal to gas. As natural gas emits less than 50% of the CO_2 per kwh that coal does, emissions might have dropped as a result of fuel competition. Policy-wise, greenhouse gas emissions from the generating fleet have become a nationwide concern: in 2013, U.S. electricity generation accounted for more than 2,000 million tons of carbon dioxide (CO_2)

emissions, or about 38% of the total U.S. energy-related emissions. About 70% of the electricity generated in 2013 was produced from fossil fuels (U.S. Energy Information Administration (EIA), 2016b).

Recently, the U.S. government has announced that it will pursue CO_2 reduction strategies to cut CO_2 emissions by 26-28% by 2025 compared to 2005 levels.[19] One important measure for achieving this aim is the so-called Clean Power Plan. As part of this, the U.S. Environmental Protection Agency (EPA) has suggested regulations to require existing power plants to reduce power sector emissions by 32% from their 2005 levels by 2030 (U.S. Environmental Protection Agency (EPA), 2015). Prior to these new guidelines, the rules were also tightened to permit fewer carbon emissions from electricity generation. States have introduced different means of regulation, from CO_2 performance standards (e.g. in Washington) to regional cap-and-trade programs (e.g. the Regional Greenhouse Gas Initiative (RGGI)). Both trends, interfuel competition and regulation, seem to have significantly decreased electricity-related CO_2 emissions. From their peak in 2007, CO_2 emissions from electricity generation dropped by about 16% between 2007 and 2013 (U.S. Energy Information Administration (EIA), 2016b). Whether the main reason for CO_2 reduction was competition or regulation remains an empirical question.

In this article, we analyze the success of the U.S. states in reducing CO_2 emissions from fossil fuel power plants. We identify CO_2 emission performance at the state level over time, and drivers that may have contributed to changing CO_2 developments. Faced with these developments, we argue that an overall fuel switching from high emitters like coal-fired power plants to cleaner technologies like natural gas combustion has occurred. To examine whether or not state-specific fuel price developments and/or CO_2 regulations also drove down emissions, we follow a two-step approach. First, we employ nonparametric data envelopment analysis techniques that allow us to measure the relative CO_2 emission performance across states considering the multiple-input and multiple-output production structure of electricity generation. As inputs, we use fuel consumption and nameplate capacity, and, as outputs, the electricity produced and CO_2 emissions. In doing so, we are able to provide a more comprehensive picture of each state's fossil fuel electricity generation process and its relative CO_2 emission performance, compared to a simple output-oriented CO_2 intensity measure, such as CO_2 emissions per unit of electricity produced. Comprehensive reviews of data envelopment analysis applications in

[19]Press statement released by the Office of the Press Secretary, The White House, accessible at www.whitehouse.gov/the-press-office/2015/03/31/fact-sheet-us-reports-its-2025-emissions-target-unfccc.

energy and environmental studies can be found in Zhou et al. (2008) and Zhang & Choi (2014). Furthermore, a number of studies have addressed the measurement of the environmental efficiency of U.S. power plants (e.g., Färe et al., 2013, Hampf & Rødseth, 2015, Sueyoshi & Goto, 2013, Sueyoshi et al., 2010, Welch & Barnum, 2009).

In a second stage, we regress the performance indicators we have obtained on the state-specific natural gas prices, the states' CO_2 regulatory policies and a number of other state-specific factors in order to identify the main drivers of the development. This approach allows us not only to answer the question of whether fuel price competition and/or emissions regulation have proven to be successful in comprehensively reducing greenhouse gases but also to evaluate the impact of regulatory reforms at the state level.

The remainder of this article is organized as follows. Section 3.2 provides a short overview of U.S. electricity generation from fossil fuels, and its trends. Section 3.3 describes the empirical approach. Section 3.4 presents and discusses the results and Section 3.5 concludes.

3.2 U.S. electricity generation from fossil fuels 2000 - 2013

U.S. electricity generation has undergone substantial changes since the early 2000s. Electricity generation from fossil fuels does not rely today on the same power generation technology mix that used to prevail within the U.S. fossil fuel market. The reasons for this can be found on the regulatory as well as on the market side. On the market side, one of the most prominent drivers has been the development of U.S. shale gas production. In less than a decade, the production of shale gas in the U.S. has managed to make U.S. gas imports irrelevant and has made the national gas industry self-sufficient (Wang et al., 2014). As a consequence, the price structure of fossil fuel inputs for electricity generation has changed significantly.

Figure 3.1 shows the cost of fossil fuel receipts at electricity generating plants in dollars per million British thermal units (MMBtu) (U.S. Energy Information Administration (EIA), 2016a).[20] We observe that, until 2008, fuel prices increased for all fuel types shown. Interestingly, coal and petroleum prices started to increase again after 2009, while the natural gas price declined. We partly link this gas price devel-

[20]The annual cost for fossil fuel receipts is calculated from the averages of monthly values, weighted by quantities, in Btu across all U.S. states.

opment to the additional shale gas production volumes that submerged the supply side of the gas market. This development not only affected the U.S. natural gas prices but, as a consequence, also boosted the role of natural gas-fired plants in electricity generation (Krupnick et al., 2013).

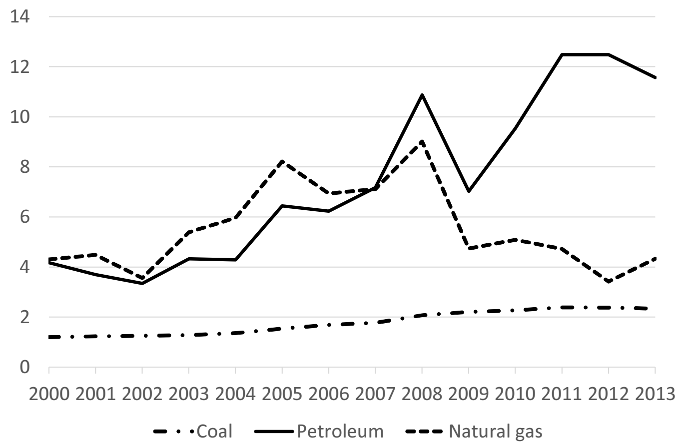


Figure 3.1: Cost of fossil fuel receipts at electricity generating plants in USD per million Btu

In this context, Figure 3.2 shows the shares of net electricity generation from fossil fuels including coal, natural gas, petroleum and other gases over the same time horizon (U.S. Energy Information Administration (EIA), 2015a). Here, we observe that the share of net electricity generation from coal was 73% in 2000 and more than three times higher than the share (22%) of net generation from natural gas in that year. However, net generation from natural gas steadily increased over time while net generation from coal significantly decreased supporting our argument that decreasing gas prices made gas-fired generation more attractive. In 2013, 58% of total U.S. net electricity generated from fossil fuels was generated from coal, and 41% from natural gas.

Taken together, these observations may lead to the conclusion that low gas prices have triggered alterations in the use of fuels and the investment in coal or gas-fired plants. However, such a conclusion is strongly dependent on the time horizon of the study: as power plant capacity is assumed to be quasi-fixed in the short run, an instantaneous fuel switch from coal to natural gas that alters the technology mix can only be achieved if capacity is idle and favorable fuel prices trigger a quick response of gas-fired generation. Contrary to this short-run response, the portfolio of power generation technologies is subject to change in the long run. The addition of capacity depends on the current and expected technology-specific investment cost and fuel prices.

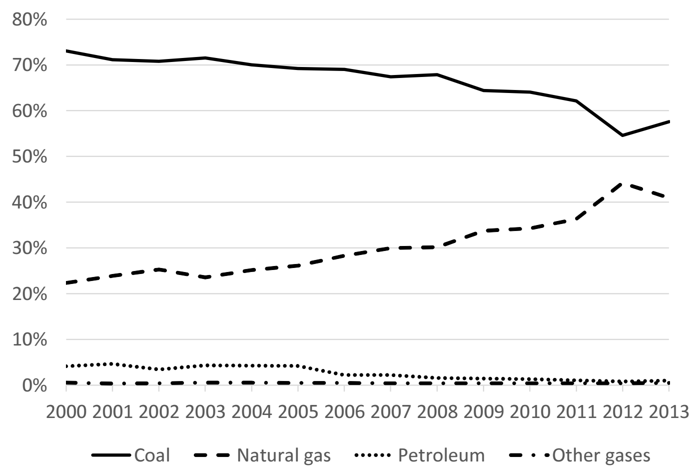


Figure 3.2: Shares of total U.S. net electricity generation from fossil fuels in %

Besides the influence of shale gas on the market side, past and future regulations also affect the portfolio of power generation technologies. As an example, stricter regulation of CO_2 provides incentives for an increased usage of gas-fired power plants. Since generating electricity from natural gas produces nearly half as much CO_2 per kilowatt-hour as coal, such a stricter regulation of CO_2 may decrease emissions. However, to date there have been no nation-wide standards that require power plants to reduce their CO_2 emissions. State-specific regulatory policies include overall greenhouse gas (GHG) reduction targets and, CO_2 performance standards related to power plants, as well as regional CO_2-cap-and-trade systems related to power plants. Some states adopted one or all of these measures in the early years of this century, while others have not yet adopted any measures.[21]

Hence, given the developments in fuel prices and the various state-specific CO_2 regulations, the CO_2 emission performance in a state may be influenced by a fuel switch from coal to gas in the short run. Such a switch is, however, constrained by the availability of capacity. In the long run, however, a state can influence its CO_2 emission performance by re-designing regulations and making certain power generation technologies more favorable than others. In this way, a state's portfolio of power generation technologies is, for instance, altered by building new gas-fired power plants and retiring old coal-fired power plants, and thus the capacity share of gas-fired power plants increases, and more natural gas can be used for electricity production.

[21] A detailed overview on state-specific CO_2 regulations is given in Section 3.3.3.

3.3 Empirical approach

3.3.1 Benchmarking model

In order to analyze the state-specific CO_2 emission performance of U.S. fossil fuel power plants we model a production technology that includes both desirable and undesirable outputs. If we assume that $x = (x_1, \ldots, x_N) \in \Re^N_+$ denotes a vector of inputs, $y = (y_1, \ldots, y_M) \in \Re^M_+$ denotes a vector of desirable or good outputs, and $b = (b_1, \ldots, b_I) \in \Re^I_+$ denotes a vector of undesirable or bad outputs, the production technology set can be modeled as:

$$P(x) = \{(y, b) : x \text{ can produce } (y, b)\}, \tag{3.1}$$

where $P(x)$ represents all the combinations of desirable and undesirable outputs (y, b) that can be produced using the input vector x. $P(x)$ is a convex and compact set and satisfies the standard properties of "no free lunch", the possibility of inaction, and strong or free disposability of inputs and good outputs (e.g. Färe & Primont, 1995).

Furthermore, in order to account for the joint production of desirable and undesirable outputs we follow Zhou et al. (2010) and impose two additional assumptions. First, we assume the desirable and the undesirable outputs to be together weakly disposable:

$$\text{if } (y, b) \in P(x) \text{ and } 0 \leq \lambda \leq 1, \text{ then } (\lambda y, \lambda b) \in P(x). \tag{3.2}$$

This assumption reflects the opportunity cost of abatement activities. In other words, a reduction of undesirable outputs is not costless, and negatively influences the production level of the desirable outputs.[22]

Second, the desirable and the undesirable outputs are considered as being null-joint:

$$\text{if } (y, b) \in P(x) \text{ and } b = 0, \text{ then } y = 0. \tag{3.3}$$

This means that no desirable outputs can be produced without producing some undesirable outputs.[23]

A production technology that seeks the maximal decrease of undesirable outputs

[22] The concept of weak disposability was introduced by Shephard (1970).
[23] The null-jointness assumption was introduced by Shephard & Färe (1974).

and satisfies the above assumptions can be represented by an input distance function. Introduced by Shephard (1953), such a function can be formally defined as:

$$D(x, y, b) = \sup \{\theta : (y, b/\theta) \in P(x)\} \geq 1, \tag{3.4}$$

where θ represents the proportion by which the undesirable output b is scaled to reach the boundary or frontier of the production technology set $P(x)$. The distance function value θ is bounded below by one. A value of one identifies the observed output vector as located on the frontier, whereas values greater than one belong to output vectors below the frontier. When CO_2 emissions are the only undesirable output, Zhou et al. (2010) label this function as the Shephard carbon distance function. Furthermore, the inverse of the function is closely related to Farrell's 1957 measure of input-oriented technical efficiency (TE), that is:

$$TE(x, y, b) = [D(x, y, b)]^{-1} \leq 1. \tag{3.5}$$

This measure is a pure technical measure of efficiency, focusing on how much good and bad output is produced from a given quantity of inputs. In our case, efficiency among the states can differ, in the sense that the same amount of fossil fuel and the same amount of capacity can produce the same amount of electricity but fewer CO_2 emissions. This can be the result of using a better input quality, that is, by a higher share of the state's electricity output being produced from natural gas-fired power plants that are less carbon-intensive. This share, in turn, is influenced by the capacity share of natural gas-fired power plants in the state's electricity generating portfolio, and its utilization rate.

In order to measure efficiency changes over time, we combine the concepts of the Malmquist CO_2 emission performance index (MCPI) of Zhou et al. (2010) and the global Malmquist productivity index (GPI) of Pastor & Lovell (2005). The derived index represents the state-specific CO_2 emission performance over time and is termed the global Malmquist CO_2 emission performance index (GMCPI).

Compared to a conventional contemporaneous Malmquist productivity index that constructs the reference technology in period t from the observations in that period only, the GMCPI incorporates information from all observations in all periods. By doing this, the GMCPI provides a single measure of productivity change, is circular, and does not suffer from any infeasibility problems, thus avoiding the three well-known problems of conventional contemporaneous Malmquist productivity indices

(Pastor & Lovell, 2005).

First, in order to define the GMCPI, we consider two benchmark technologies: a contemporaneous benchmark technology and a global benchmark technology. Following Pastor & Lovell (2005), the contemporaneous benchmark technology is defined as:

$$P^t(x) = \{(y^t, b^t) : x^t \text{ can produce } (y^t, b^t)\}, \text{with } t = 1 \ldots, T, \tag{3.6}$$

and the global benchmark technology as:

$$P_T^G(x) = conv\{P^1(x) \cup \ldots \cup P^T(x)\}. \tag{3.7}$$

The two technologies are graphically illustrated in Figure 3.3. The vertical axis shows the desirable output y and the horizontal axis shows the undesirable output b, i.e., CO_2 emissions. P^t and P^{t+1} represent the areas of all feasible combinations of the desirable and the undesirable output that can be produced by the input vector x in periods t and $t+1$, respectively. These technologies are enveloped by the global technology P_T^G that represents the area of all feasible input-output combinations in all periods.

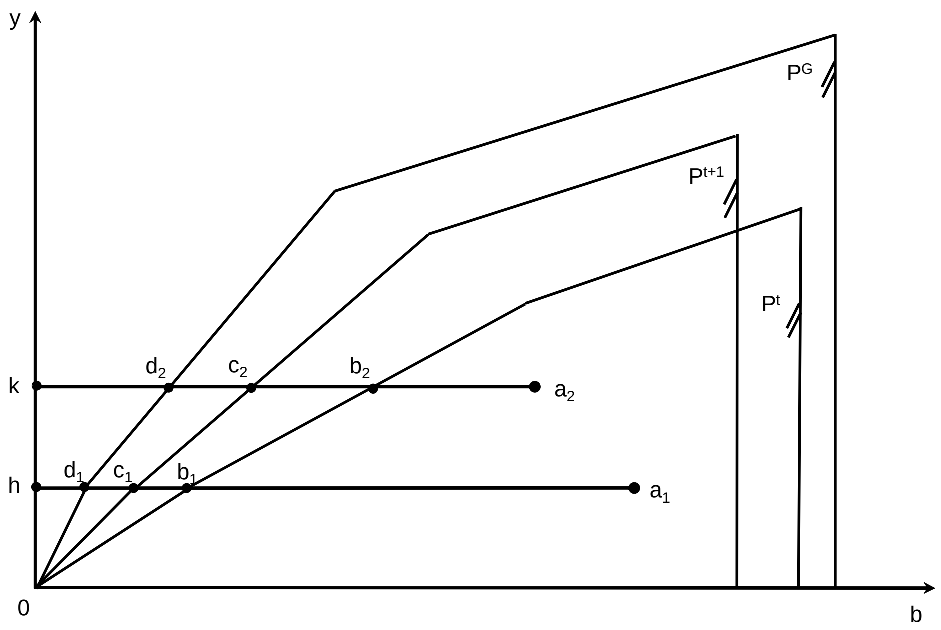


Figure 3.3: Global Malmquist CO_2 emission performance index (GMCPI)

Given Equation 3.4, and with $D^G(t) = D^G(x^t, y^t, b^t)$ and $D^G(t+1) = D^G(x^{t+1}, y^{t+1}, b^{t+1})$, the GMCPI between period t and period $t+1$ can now be defined as:[24]

$$GMCPI = \frac{D^G(t)}{D^G(t+1)}, \tag{3.8}$$

A value equal to one indicates no change in the CO_2 performance between period t and period $t+1$. If the value is less than one, the CO_2 performance decreased, while a value greater than one represents an increase.

Furthermore, the GMCPI can be decomposed into two components: efficiency change EC and best practice change BPC. That is,

$$GMCPI = EC \times BPC, \tag{3.9}$$

where

$$EC = \frac{D(t)}{D(t+1)}, \tag{3.10}$$

and

$$BPC = \frac{D^G(t)/D^t(t)}{D^G(t+1)/D^{t+1}(t+1)}. \tag{3.11}$$

EC captures the change in the distance of an observation to its respective frontier in periods t and $t+1$. Considering points a_1 and a_2 in Figure 3.3 as the production points of a decision making unit (DMU) in periods t and $t+1$, EC is equal to $(\overline{ha_1}/\overline{hb_1})/(\overline{ka_2}/\overline{kc_2})$. $EC > 1$ indicates a decrease in the distance and hence efficiency progress, whereas $EC < 1$ represents an increase in the distance and hence efficiency regress. Similarly, a shift of the contemporaneous frontier away from or towards the global frontier between period t and period $t+1$ is captured by BPC. In Figure 3.3 BPC is calculated as $BPC = ((\overline{ha_1}/\overline{hd_1})/(\overline{ha_1}/\overline{hb_1}))/((\overline{ka_2}/\overline{kd_2})/(\overline{ka_2}/\overline{kc_2}))$. $BPC > 1$ indicates technical progress, while $BPC < 1$ shows technical regress.

In order to determine the required global and contemporaneous distance functions, we employ data envelopment analysis techniques. With $s = t, t+1$ and $k = 1, \ldots, K$ observations, the contemporaneous distance function for each observation k' in each period s can be obtained by solving the following linear program:

[24]For notational convenience, we abbreviate the distance functions $D^G(x^t, y^t, b^t)$, $D^G(x^{t+1}, y^{t+1}, b^{t+1})$, $D^t(x^t, y^t, b^t)$ and $D^t(x^{t+1}, y^{t+1}, b^{t+1})$, respectively, to $D^G(t)$, $D^G(t+1)$, $D(t)$ and $D(t+1)$ in the following equations.

$$
\begin{aligned}
\left[D^s\left(x^s, y^s, b^s\right)\right]^{-1} &= \min_z \frac{1}{\theta} \\
s.t. \sum_{k=1}^{K} z_k^s y_{km}^s &\geq y_{k'm}^s, \qquad m = 1, \ldots, M, \qquad (i) \\
\sum_{k=1}^{K} z_k^s x_{kn}^s &\leq x_{k'n}^s, \qquad n = 1, \ldots, N, \qquad (ii) \\
\sum_{k=1}^{K} z_k^s b_{ki}^s &= \theta b_{k'i}^s, \qquad i = 1, \ldots, I, \qquad (iii) \\
z_k^s &\geq 0, \qquad k = 1, \ldots, K, \qquad (iv)
\end{aligned}
\tag{3.12}
$$

where z_k^s are intensity variables assigning a weight to each observation k when constructing the best-practice frontier. The inequality constraints in (i) and (ii) guarantee that observation k' does not produce more desirable outputs or use fewer inputs than the efficient benchmark on the frontier. The equality constraints in (iii) impose weak disposability, and the non-negativity constraints in (iv) indicate that the reference technology exhibits constant returns to scale.

Note that, with only one undesirable output, the optimal solutions to the linear program under the assumption of weak disposability and the linear program under the assumption of strong disposability are identical. In other words, with $I = 1$ the equality constraint in (iii) can be replaced by the inequality constraint $\sum_{k=1}^{K} z_k^s b_{ki}^s \leq \theta b_{k'i}^s$ (Oggioni et al., 2011).

Finally, with $t = 1, \ldots, T$, the global distance function for each observation k' in each period s can be obtained by solving the following linear program:

$$
\begin{aligned}
\left[D^G\left(x^s, y^s, b^s\right)\right]^{-1} &= \min_z \frac{1}{\theta} \\
s.t. \sum_{t=1}^{T} \sum_{k=1}^{K} z_k^t y_{km}^t &\geq y_{k'm}^s, \qquad m = 1, \ldots, M, \qquad (i) \\
\sum_{t=1}^{T} \sum_{k=1}^{K} z_k^t x_{kn}^t &\leq x_{k'n}^s, \qquad n = 1, \ldots, N, \qquad (ii) \\
\sum_{t=1}^{T} \sum_{k=1}^{K} z_k^t b_{ki}^t &= \theta b_{k'i}^s, \qquad i = 1, \ldots, I, \qquad (iii) \\
z_k^t &\geq 0, \qquad k = 1, \ldots, K, \qquad (iv)
\end{aligned}
\tag{3.13}
$$

As before, in the case of a single undesirable output, the equality constraint in (iii) can be replaced by the respective inequality constraint.

3.3.2 Benchmarking data

We conduct our analysis using state-level panel data for 48 out of the 50 federal states in the U.S. for a 13-year period starting in 2000 and ending in 2013.[25] The data come from the survey forms EIA-860 and EIA-923 of the U.S. Energy Information Administration (EIA), which provide detailed information on the inputs and outputs of U.S. power plants (U.S. Energy Information Administration (EIA), 2015a,b).

As inputs we include aggregated fuel consumption measured in billion British thermal units (Bn Btu)[26] and aggregated nameplate capacity measured in gigawatts (GW) for all coal- and natural gas-fired power plants in each state.[27] Fuel consumption directly influences power plant usage and therefore the desirable and undesirable output (net generation and CO_2 emissions, respectively). Nameplate capacity serves as a proxy for the capital input. In the short run, too much capacity is inefficient, since idle capacity will not be used for generation. However, in the medium and long run a higher capacity offers more flexibility for switching fuels. Hence, the capacity variable in our model reflects the trade-off between optimal capacity in the short run and optimal flexibility in the medium and long run. Besides this interpretation focusing on the electricity generation side of gas and coal, one may relate inefficiencies to the fact that demand profiles trigger distances to the respective efficient frontier of each state. This may for instance be the case when two states with different demand profiles possess the same fossil fuel capacity mix, the same gas price and additionally face identical CO_2 regulatory constraints. Depending on the respective demand structure, both with respect to season and day, gas-fired plants may only be used as back-up capacity in one state, whereas in the other state gas-fired generation covers demand at a certain level throughout the day. In both states this would result in different generation and therewith emission output although the production technology is identical in both states.

Table 3.1 provides descriptive statistics based on state-level data for the two input variables, fuel consumption and generation capacity, and the two output variables, CO_2 emissions measured in million tons and net generation measured in gigawatt-

[25]Vermont is excluded because it has zero electricity production from coal or gas over this time period, and so is Hawaii because of its geographic isolation from the mainland.

[26]We account for the state-specific heat values of coal by using the EIA's State Energy Data System (SEDS). The coal consumed by the electrical power sector in each state is calculated by dividing the total heat content of coal received at the electrical power plants by the total quantity consumed in physical units, which is collected on Form EIA-923 for each year.

[27]As the amount of electricity generated from petroleum is very small in the U.S. (see Figure 3.2) we do not include petroleum-fired power plants in our analysis.

hours (GWh), for the 48 U.S. states from 2000 to 2013.[28] Emissions and net generation from coal and gas are used as outputs in order to reflect the link and trade-offs between production and pollution.

The descriptive statistics shown in Table 3.1 reflect a wide range of values, since power generation sizes and technologies differ across the states. Therefore, the table primarily shows the size of the U.S. fossil fuel power generation sector. The depicted minimum and maximum values can be directly linked to certain U.S. states.

Table 3.1: Descriptive statistics: state-level data 2000 to 2013

	Unit	Mean	SD	Min value	Max value
Net generation from coal and gas	GWh	57,254.3	56,237.2	1,194.2	358,396.7
CO_2 emissions	million t	48.6	44.5	0.8	266.4
Fuel consumption	Bn Btu	546,921.7	512,824.3	8,392.0	3,159,475.0
Nameplate capacity	GW	15.9	16.1	0.7	101.5

Over the whole period, Texas is by far the largest CO_2 emitter across all U.S. states in the electrical power sector. With a peak value of 266 million tons of emitted CO_2 in 2011, "Texan" CO_2 emissions are more than twice the CO_2 emissions of Ohio, which rank in second place. At the same time, Texas also ranks highest in terms of overall electricity generated and fuel consumed. Peak annual electricity generation was equal to 358,397 GWhs and peak annual fossil fuel amounted to 3,159,475 billion Btu, both values occurring in the year 2011. In 2011 Texas had an installed gas and coal-fired capacity of 101.5 GW. The minimum values shown in Table 3.1 all belong to Idaho in 2000 and 2011.

3.3.3 Second-stage regression

In order to test which factors determine the differences in the CO_2 emission performances of the states over time, we regress their cumulative GMCPI obtained in the first step of our analysis on several state-specific factors, in a second step. The cumulative GMCPI until period t, rather than the GMCPI for each two-year period, is used in order to account for all CO_2 emission performance changes until that period. As such the cumulative GMCPI is an aggregated measure capturing GMCPI changes over time intervals up to a certain point in time (i.e. year) and is thus different from

[28] Because of some suspicious changes in one or more of the in- and outputs from one year to the other (changes higher than 100%) we exclude the observations for Idaho and New Hampshire in the years 2000 to 2002, as well as the observation for Maine in the year 2000, from our data set.

a two-year comparison[29]:

$$\begin{aligned} CumGMCPI_{it} = {} & \alpha_0 + \alpha_1 GasPrice_{it} + \alpha_2 Target_{it} + \alpha_3 Standards_{it} + \alpha_4 Cap_{it} \\ & + \alpha_5 \ln GDPPC_{it} + \alpha_6 NucShare_{it} + \alpha_7 HydroShare_{it} \\ & + \alpha_8 WindShare_{it} + \alpha_t Dum_t + \alpha_i Dum_i + \epsilon_{it+1}, \end{aligned} \tag{3.14}$$

where $GasPrice_{it}$ is the annual state-specific natural gas electrical power price that reflects the price of gas used by electricity generators. $Target_{it}$, $Standards_{it}$ and Cap_{it} are dummy variables equal to one if in state i and year t greenhouse gas emissions targets, CO_2 performance standards or a cap-and-trade program, respectively, are in place and equal to zero otherwise. $GDPPC_{it}$ is the annual real gross domestic product (GDP) per capita by state. $NucShare_{it}$, $HydroShare_{it}$ and $WindShare_{it}$ are state i's share of nuclear, hydroelectric and wind energy in state i's total nameplate capacity in year t. Dum_t and Dum_i denote year and state fixed effects, the α's are parameters to be estimated and the ϵ reflects the error term.

Data for the annual state-specific natural gas electrical power price are drawn from the EIA Natural Gas Summary. The data originally come from the Federal Energy Regulatory Commission (FERC), Form-423, and are in nominal dollars per thousand cubic feet. The price index for GDP from the US Bureau of Economic Affairs (BEA) is used to transform the nominal prices into constant prices based on the year 2009. Data on the real GDP per capita are also taken from the BEA and are in 2009-dollars.

The summary statistics on the second-stage variables depicted in Table 3.2 reflect the high heterogeneity among the states. The maximum real gas price of \$11.56 per thousand cubic feet is observed for Georgia in 2005. In the same year, the price in Alaska was only \$3.72 per thousand cubic feet. As for real GDP per capita, the maximum value of \$70,918 is found for Alaska in 2009. This value is more than twice the minimum value, which is found for Mississippi in 2001.

Similar differences can be seen for the shares of the three most common CO_2-free

[29] An illustrative example is given in Table 3.5, where we use the full time span starting with the change in emission performance between 2000 and 2001 and then multiply this GMCPI, which relates measures of t and $t+1$, with growth or de-growth rates resulting from all following years.

Table 3.2: Determinants of CO_2 emission performance: summary statistics

	Unit	Mean	SD	Min value	Max value
Gas price	2009 $	6.14	2.12	2.16	11.55
Real GDP per capita	2009 $	45 648	8 519	28 957	70 918
Nuclear share in nameplate capacity	%	8.45	8.78	0	41.30
Hydroelectric share in nameplate capacity	%	10.33	17.85	0	87.12
Wind share in nameplate capacity	%	2.40	4.77	0	30.02
GHG emissions targets	0/1	0.24	0.43	0	1
CO_2 performance standards	0/1	0.07	0.25	0	1
Cap and trade	0/1	0.07	0.25	0	1

electricity generation technologies in the states' total nameplate capacity.[30] The low mean and standard deviation values for the share of wind show that the generation of electricity from wind is of low relevance in many states in the time period of the observations. In fact, in 37 of the 48 states the wind share in the nameplate capacity is below 10% in all years. Noteworthy exceptions are Iowa, with a share of about 30%, and North Dakota, with a share of about 27% in 2013. The nuclear and hydroelectric share in nameplate capacity is about 10% on average. Exceptions here are Idaho, with a hydroelectric share of about 87% in 2000, and New Hampshire with a nuclear share of about 41% in 2000 and 2001.

Information on state-specific regulatory policies is taken from the website of the Center for Climate and Energy Solutions (C2ES).[31] The C2ES collects a variety of data on state and regional climate actions within the U.S. Table 3.3 lists the states that have adopted the state-specific regulatory policies to be tested and the dates when these policies were put in place in each state. The most common policy is the definition of GHG emissions targets. By 2013, 18 of the 48 states included in the study had set emission reduction targets, to be achieved by a certain date. The baseline and target years, as well as the reduction levels, vary among the states. The most common short-term targets, to be met by 2020, are the reduction of emissions to 1990 levels (four states) and to 10% below 1990 levels (eight states). In the long-term, the targets vary between 50% and 85% below the 1990 and 2005 levels. Most states have a long-term target year of 2050.

[30] As the share of solar thermal and photovoltaic in total nameplate capacity is far below 1% for almost all states in the time period of the observations, it is not included in the analysis. Only Arizona, California, North Carolina, New Jersey, Nevada, and New Mexico show values above 1%. The maximum value is 4.3% in California in 2013. A similar argument applies to geothermal energy and pumped storage. While in a limited number of states these technologies play a minor role, they are not installed at all in the vast majority of states.

[31] http://www.c2es.org/us-states-regions, last accessed 29.02.2016.

Table 3.3: State-specific regulatory policies

Year	GHG emissions targets	CO_2 performance standards	Cap and trade
2000		OR	
2001	CT, MA, ME, NH, RI	OR	
2002	CT, MA, ME, NH, RI, NY	OR	
2003	CT, MA, ME, NH, RI, NY	OR	
2004	CT, MA, ME, NH, RI, NY	OR, WA	
2005	CT, MA, ME, NH, RI, NY, CA, NM	OR, WA	
2006	CT, MA, ME, NH, RI, NY, CA, NM, AZ	OR, WA, CA	
2007	CT, MA, ME, NH, RI, NY, CA, NM, AZ, FL, IL, MN, NJ, OR, WA	OR, WA, CA, MT	
2008	CT, MA, ME, NH, RI, NY, CA, NM, AZ, FL, IL, MN, NJ, OR, WA, CO	OR, WA, CA, MT	
2009	CT, MA, ME, NH, RI, NY, CA, NM, AZ, FL, IL, MN, NJ, OR, WA, CO, MD, MI	OR, WA, CA, MT, IL	CT, DE, MA, MD, ME, NH, NJ, NY, RI
2010	CT, MA, ME, NH, RI, NY, CA, NM, AZ, FL, IL, MN, NJ, OR, WA, CO, MD, MI	OR, WA, CA, MT, IL	CT, DE, MA, MD, ME, NH, NJ, NY, RI
2011	CT, MA, ME, NH, RI, NY, CA, NM, AZ, FL, IL, MN, NJ, OR, WA, CO, MD, MI	OR, WA, CA, MT, IL	CT, DE, MA, MD, ME, NH, NJ, NY, RI
2012	CT, MA, ME, NH, RI, NY, CA, NM, AZ, FL, IL, MN, NJ, OR, WA, CO, MD, MI	OR, WA, CA, MT, IL, NY	CT, DE, MA, MD, ME, NH, NY, RI
2013	CT, MA, ME, NH, RI, NY, CA, NM, AZ, FL, IL, MN, NJ, OR, WA, CO, MD, MI	OR, WA, CA, MT, IL, NY	CT, DE, MA, MD, ME, NH, NY, RI, CA

Note: Arizona (AZ), California (CA), Colorado (CO), Connecticut (CT), Delaware (DE), Florida (FL), Illinois (IL), Maine (ME), Maryland (MD), Massachusetts (MA), Michigan (MI), Minnesota (MN), Montana (MT), New Hampshire (NH), New Jersey (NJ), New Mexico (NM), New York (NY), Oregon (OR), Rhode Island (RI), Washington (WA).

In addition to GHG emissions targets, six states have adopted CO_2 performance standards. The standards and their area of application differ considerably among the states. While in some states the standards only apply to specific (e.g. baseload) or new power plants, in others they apply to all power plants. Furthermore, standards might require generators to reduce emissions from power plants directly to a given emissions rate per output unit, or they might also allow indirect measures such as, payments to third-party mitigation projects. Overall, no consistent pattern in the design of state-level CO_2 performance standards is observable.

The last regulatory policy included in our analysis is the implementation of a cap-and-trade program. Cap-and-trade is a system that sets a decreasing limit on emissions from one or multiple economic sectors. Below the cap there is a market in which the entities convered by the program can trade carbon allowances. An entity that emits less than its allocated limit can sell its allowances to an entity that emits more, and vice versa. The less an individual entity emits, the less it pays. Hence, there is an economic incentive to reduce emissions.

Within the observed period a cap-and-trade system was only implemented in the north and Mideast of the U.S. and in California. In its first control period from 2009-2011 the Regional Greenhouse Gas Initiative (RGGI) included fossil fuel electricity generation in ten northern and mid-eastern states (see Table 3.3: Vermont is one of the ten but is not included in our data set.). All fossil fuel power plants with 25 megawatts or greater capacity had to comply with the cap, with the aim of stabilizing emissions between 2009 and 2014 and achieving a 10% reduction by 2019. New Jersey withdrew from the system before the start of the second control period in 2012. Furthermore, in 2013 California implemented an overall emission cap that applies to all major industrial sources and electric utilities. By 2015 the system was enlarged to distributors of transportation fuels, natural gas, and other fuels. Each year the total amount of allowances is reduced by 3% in order to reduce emissions.

3.4 Results

3.4.1 Benchmarking results

Table 3.4 reports the CO_2 emission efficiency scores for each state for the years 2000, 2006 and 2013, obtained from the linear program given in Equation 3.13. In 2013 the best results are achieved by the New England states Maine (1.00), Rhode Island (0.95) and Connecticut (0.94), as well as California (0.87) and Oregon (0.80). Considering the other years, this ranking is stable only for Maine and Rhode Island. In all years, Maine and Rhode Island are ranked either first or second, reflecting their exceptionally high shares of electricity generated from natural gas (more than 95% and 100% in all years, for Maine and Rhode Island respectively).

Table 3.4: CO_2 emission efficiency scores per state

State	2000	2006	2013	Rank 2013	State	2000	2006	2013	Rank 2013
Alabama	0.44	0.47	0.57	18	Nebraska	0.41	0.41	0.40	44
Alaska	0.47	0.50	0.51	27	Nevada	0.57	0.69	0.78	8
Arizona	0.48	0.55	0.54	22	New Hampshire		0.64	0.70	13
Arkansas	0.40	0.47	0.48	29	New Jersey	0.54	0.57	0.80	6
California	0.68	0.78	0.87	4	New Mexico	0.47	0.46	0.49	28
Colorado	0.49	0.48	0.46	32	New York	0.56	0.59	0.77	9
Connecticut	0.53	0.73	0.94	3	North Carolina	0.44	0.44	0.54	21
Delaware	0.42	0.43	0.64	14	North Dakota	0.46	0.47	0.45	33
Florida	0.53	0.64	0.73	11	Ohio	0.44	0.44	0.47	30
Georgia	0.44	0.46	0.58	17	Oklahoma	0.47	0.53	0.53	24
Idaho		0.64	0.73	10	Oregon	0.76	0.79	0.80	5
Illinois	0.38	0.39	0.39	46	Pennsylvania	0.44	0.46	0.55	20
Indiana	0.43	0.43	0.43	35	Rhode Island	0.90	0.97	0.95	2
Iowa	0.36	0.37	0.37	48	South Carolina	0.46	0.46	0.51	26
Kansas	0.40	0.40	0.39	47	South Dakota	0.42	0.40	0.42	38
Kentucky	0.45	0.42	0.42	41	Tennessee	0.42	0.41	0.40	45
Louisiana	0.51	0.53	0.59	16	Texas	0.52	0.55	0.57	19
Maine		0.88	1.00	1	Utah	0.56	0.52	0.51	25
Maryland	0.48	0.44	0.41	42	Virginia	0.40	0.41	0.53	23
Massachusetts	0.55	0.70	0.78	7	Washington	0.50	0.55	0.60	15
Michigan	0.44	0.43	0.42	37	West Virginia	0.51	0.47	0.44	34
Minnesota	0.41	0.39	0.42	39	Wisconsin	0.37	0.39	0.42	40
Mississippi	0.45	0.53	0.72	12	Wyoming	0.51	0.49	0.47	31
Missouri	0.41	0.42	0.43	36	Mean	0.48	0.52	0.57	
Montana	0.48	0.44	0.41	43	Median	0.46	0.47	0.52	

Note: To conserve space, only the values for the first, the middle and the last year of sample are presented. The values for all years are available from the authors upon request.

The other top performer states show a rather heterogeneous development. For example, in 2000, Connecticut only reached an efficiency score of 0.53. In the years to 2013 Connecticut almost doubled this score, reaching a value of 0.94 in 2013. Interestingly, from 2000 to 2013, Connecticut increased the share of natural gas in the total electricity generated from coal and natural gas from 56% to 96%. In contrast, the natural gas shares in California and Oregon increased only slightly, from, respectively, 98% and 71% in 2000 to 99% and 79% in 2013. The rankings of California and Oregon vary between second and fifth place within these years.

The low performer states in 2013 are the Midwest states of Iowa (0.37), Kansas (0.39), Illinois (0.39), and Nebraska (0.40), as well as Tennessee (0.40). Interestingly, while the low performance states all show a high share for coal generation, other states with even higher shares perform better. For example, Wyoming, with a coal share of almost 100%, is ranked at place 31. These results show that, in addition to the coal and gas capacity mix, the CO_2 content of the burned coal and the overall capacity utilization also influence the efficiency rankings.

As the efficiency scores in Table 3.4 are obtained from a within-year comparison, they only present a static view of the CO_2 emission performance of the states. In order to evaluate the CO_2 emission performance over time, we calculate the GMCPI defined in Equation 3.8 for each two-year period and each state. The cumulative GMCPIs over the period 2000-2013 are reported in Table 3.5.

The results show that, on average, the states improved their CO_2 emission performance from 2000 to 2013 by about 15%. Furthermore, for 34 of the 48 states a positive development in the CO_2 emission performance is shown. The top five performers are Connecticut (1.76), Mississippi (1.62), Delaware (1.54), New Jersey (1.47), and Massachusetts (1.53). The low performers are Montana (0.86), Maryland (0.86), West Virginia (0.88), Utah (0.92), and Kentucky (0.92). On average, the CO_2 emission performance of the low performers decreased by about 11% from 2000 to 2013.

As shown in Equations 3.9-3.11, the GMCPI can be decomposed into two components. Table 3.6 depicts the cumulative efficiency change and the cumulative best practice change. First, referring to the cumulative best practice change, the results indicate a positive rate of technological change over time, on average and for 44 of the 48 states. The average rate of cumulative best practice change is 13%. While this result suggests technological improvements for almost all input mixes and levels, it does not indicate whether all states have implemented these improvements. A state's positive rate of cumulative best practice change simply indicates a shift of the state's relevant portion of the contemporaneous frontier towards the global frontier, between the first period and the last period. However, it does not indicate whether the state actually operates on that frontier or causes its own outward shift (Färe et al., 1994). For example, the highest rate of cumulative best practice change is shown for Louisiana, and is about 79%. However, we also observe a cumulative efficiency decrease for Louisiana of about 36%. This means that, for Louisiana's production technology, CO_2 reducing innovations occurred over time, but Louisiana was not able to follow these innovations. Graphically speaking, over the observed period Louisiana was not able to catch-up to the outwardly shifting contemporaneous frontier towards the global frontier. Overall, Louisiana's cumulative GMCPI indicates an

Table 3.5: Cumulative GMCPI per state over the period 2000-2013 (2000 = 1)

State	CumGMCPI	Rank	State	CumGMCPI	Rank
Alabama	1.31	12	Nebraska	0.99	36
Alaska	1.09	25	Nevada	1.37	8
Arizona	1.13	22	New Hampshire	1.20	16
Arkansas	1.19	18	New Jersey	1.47	4
California	1.28	13	New Mexico	1.02	33
Colorado	0.95	42	New York	1.38	7
Connecticut	1.76	1	North Carolina	1.21	15
Delaware	1.54	3	North Dakota	0.97	39
Florida	1.40	6	Ohio	1.07	27
Georgia	1.32	10	Oklahoma	1.12	24
Idaho	1.33	9	Oregon	1.06	28
Illinois	1.04	30	Pennsylvania	1.26	14
Indiana	0.98	37	Rhode Island	1.06	29
Iowa	1.01	34	South Carolina	1.13	23
Kansas	0.98	38	South Dakota	0.99	35
Kentucky	0.92	44	Tennessee	0.96	41
Louisiana	1.15	20	Texas	1.08	26
Maine	1.16	19	Utah	0.92	45
Maryland	0.86	47	Virginia	1.31	11
Massachusetts	1.53	5	Washington	1.20	17
Michigan	0.97	40	West Virginia	0.88	46
Minnesota	1.03	32	Wisconsin	1.15	21
Mississippi	1.62	2	Wyoming	0.93	43
Missouri	1.03	31	Mean	1.15	
Montana	0.86	48	Median	1.11	

increase in its CO_2 emission performance of about 15%.

Table 3.6: Cumulative GMCPI decomposition per state over the period 2000-2013 (2000 = 1)

State	CumEC	CumBPC	State	CumEC	CumBPC
Alabama	1.10	1.19	Nebraska	0.87	1.14
Alaska	1.02	1.07	Nevada	1.08	1.27
Arizona	0.90	1.25	New Hampshire	1.13	1.06
Arkansas	1.14	1.05	New Jersey	1.35	1.09
California	1.24	1.04	New Mexico	0.88	1.17
Colorado	0.76	1.25	New York	1.28	1.08
Connecticut	1.67	1.05	North Carolina	1.13	1.07
Delaware	1.43	1.08	North Dakota	1.16	0.84
Florida	1.31	1.07	Ohio	0.93	1.16
Georgia	1.25	1.06	Oklahoma	1.05	1.07
Idaho	0.78	1.66	Oregon	0.86	1.23
Illinois	0.96	1.08	Pennsylvania	1.34	0.94
Indiana	0.84	1.17	Rhode Island	1.00	1.06
Iowa	0.88	1.15	South Carolina	0.96	1.17
Kansas	0.92	1.07	South Dakota	0.89	1.12
Kentucky	0.76	1.21	Tennessee	0.83	1.16
Louisiana	0.64	1.79	Texas	1.03	1.05
Maine	1.10	1.06	Utah	0.99	0.94
Maryland	0.68	1.27	Virginia	1.23	1.06
Massachusetts	1.31	1.08	Washington	0.95	1.26
Michigan	0.91	1.06	West Virginia	0.83	1.05
Minnesota	0.85	1.21	Wisconsin	1.08	1.06
Mississippi	1.49	1.09	Wyoming	1.00	0.93
Missouri	0.98	1.06	Mean	1.03	1.13
Montana	0.85	1.02	Median	0.99	1.08

An opposing picture is shown for, for example, Rhode Island. The cumulative efficiency change value of 1 and the equal cumulative best practice change and GMCPI values of 1.06 suggest that Rhode Island in all years operated on the best practice frontier and pushed it's relevant portion outwards towards the global frontier by technological innovations. Overall, Rhode Island realized an increase in its CO_2 emission performance of about 6% as a result of technological innovations.

A third example is given by North Dakota. North Dakota is one of the four states for which we observe a negative rate of technological change over time, namely −16%. This result indicates an inward shift of North Dakota's relevant portion of the contemporaneous frontier away from the global frontier. Such a result occurs if the states that determine this portion of the frontier experience a deterioration of their technological performance over time. In fact, Wyoming's cumulative efficiency change value of 1 and its cumulative best practice change value of 0.93 suggest that Wyoming is one of these states. Other states may have also belonged to this group in some years, but have been able to compensate for this in other years by input adjustments.

Altogether, our results on cumulative efficiency change and cumulative best practice change suggest that some innovative states shifted the contemporaneous frontier towards the global frontier by implementing technological innovations. However, the decline in cumulative efficiency change for 24 of the 48 states shows that half of the states were not able to follow these innovations and to catch-up to the new best practice frontier.

A better view of the CO_2 emission performance over time is shown in Figure 3.4, which depicts the cumulative GMCPI trends for the top and bottom performers for the period 2000-2013. While the lower part of the figure shows a relatively steady decline in the CO_2 emission performance of the bottom performers over time, the upper part indicates a relatively strong increase in the CO_2 emission performance of the top performers, particularly after 2008. This may be a first indication that the significant decrease in the natural gas price after 2008 is a major driver of CO_2-reduced electricity generation from fossil fuel power plants, although this is yet to be proven.

3.4.2 Second-stage regression results

Table 3.7 present the estimation results for Equation 3.14. As reverse causality, that is, not only regulation has an impact on the CO_2 emission performance but the CO_2 emission performance also has an impact on the regulation, might be a problem, we first conduct a test of endogeneity. The test provides moderate evidence against the null hypothesis that the regulatory variables are exogenous ($p=0.031$). Therefore, we estimate two model specifications: one treating the regulatory variables as exogenous, and one treating the regulatory variables as endogenous. In the latter we apply the two-stage least squares (2SLS) estimator and instrument the regulatory variables with their first lags as well as with a dummy variable equal to one in the case of a governor from the democrat party, and zero otherwise. Both specifications include state and year fixed effects.

The results of the two specifications are very similar. The regression diagnostics for the 2SLS specification suggest that the instrumental variables used for the regulatory variables are sufficient. The under-identification test rejects the null hypothesis that the model is not identified ($p<0.01$), the over-identification test fails to reject the null hypothesis that the instruments are not valid ($p>0.50$), and the Kleinbergen-

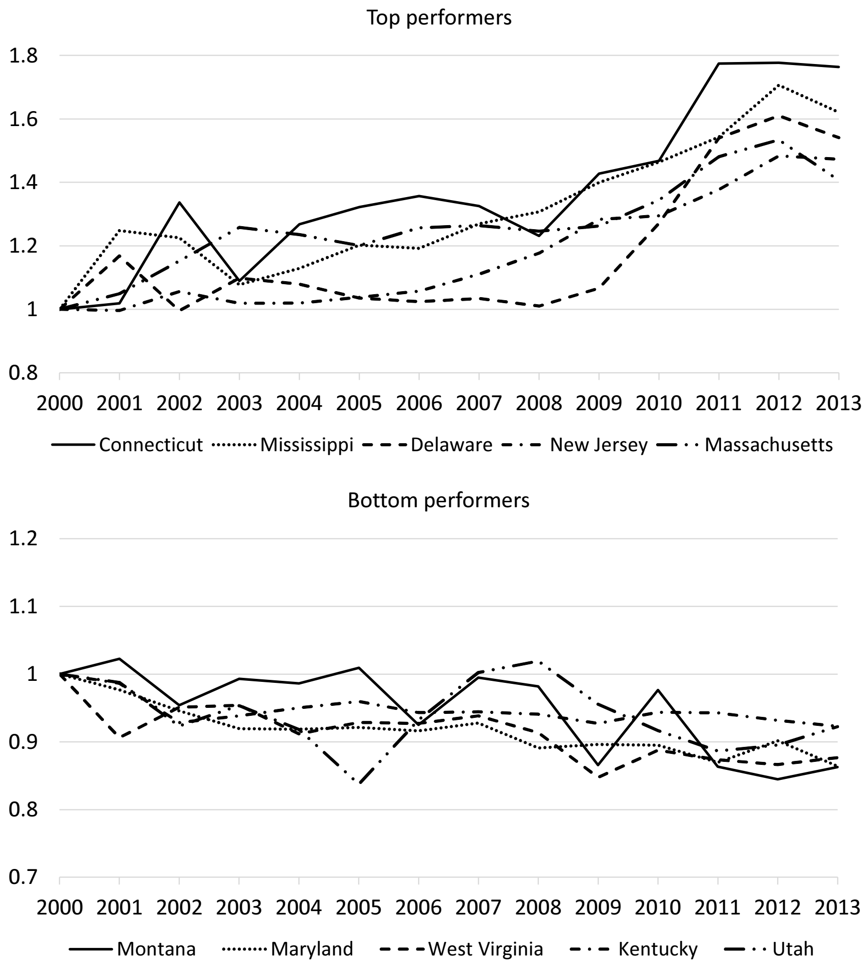


Figure 3.4: Cumulative GMCPI trends for the top and bottom performers for the period 2000-2013

Table 3.7: Determinants of CO_2 emission performance: estimation results

		Fixed effects		2SLS	
Variable	Parameter	Coef.	Std. err.	Coef.	Std. err.
Constant	α_0	2.356**	(1.191)	–	
Gas price	α_1	−0.011**	(0.004)	−0.011***	(0.004)
GHG emissions targets	α_2	0.003	(0.018)	0.040	(0.029)
CO_2 performance standards	α_3	0.043	(0.029)	0.022	(0.038)
Cap-and-trade system	α_4	0.077***	(0.026)	0.137***	(0.042)
Real GDP per capita (log)	α_5	−0.097	(0.110)	−0.126	(0.119)
Nuclear share in nameplate capacity	α_6	−0.014**	(0.006)	−0.014**	(0.006)
Hydroelectric share in nameplate capacity	α_7	−0.010**	(0.004)	−0.009**	(0.004)
Wind share in nameplate capacity	α_8	−0.008***	(0.001)	−0.007***	(0.001)
State fixed effects	α_i	yes		yes	
Year fixed effects	α_t	yes		yes	
R-squared	R_2	0.802		0.490	
Adjusted R-quared	R_2(adj.)	0.767		0.400	
Endogeneity test	P-value	–		0.071	
Underidentification test	P-value	–		0.000	
Overidentification test	P-value	–		0.500	
Kleinbergen-Paap	F-statistic	–		15.258	
Observations	N	437		436	

Notes: Robust standard errors in parentheses. Instruments for 2SLS: First lags of regulatory variables and dummy variable for party of the governor. ***, ** and *: significant at the 1%-, 5%-, and 10%-level. All estimations were performed in Stata 13.1 using the official areg command and the user-written xtivreg2 command developed by Schaffer (2012).

Paap F-statistic is greater than the rule of thumb of 10 (15.258), indicating that weak instruments are no problem.

The results in Table 3.7 indicate a statistically significant impact of the natural gas price, and a regional cap-and-trade-system, as well as the state's shares of nuclear, hydroelectric and wind energy in total nameplate capacity, on the state's CO_2 emission performance of fossil fuel power plants. As expected, an increase in the natural gas price has a negative impact on the cumulative GMCPI. In both specifications the estimated coefficient of −0.011 suggests that a $1 increase in the price decreases the cumulative GMCPI by one percentage point. Similar results are shown for the shares of the most common CO_2-free electricity generation technologies in the state's total nameplate capacity. The estimated coefficients of between −0.007 and −0.014 suggest that an additional percentage point in the shares decreases the cumulative GMCPI by between 0.7 and 1.4 percentage points. This result can be explained by a lower incentive for states with a high share of CO_2-free electricity generation capacity to reduce the $C0_2$ emissions from their fossil fuel generation capacity.

Finally, among the regulatory variables we only find a statistically significant impact for a regional cap-and-trade system. The estimated coefficients indicate that the implementation of such a system increases the cumulative GMCPI by 7.7 and 13.7 percentage points, respectively, for the two specifications. This result emphasizes that stringent regulation is the most important driver of the states' CO_2 emission performance.

3.5 Conclusions

CO_2 emissions from fossil-fueled electricity generation in the U.S. have dropped considerably in the last decade. As U.S. states seem to show varying success in reducing these CO_2 emissions, the objective of this article was to compare the relative CO_2 emission performance of fossil fuel power plants across the states for the period 2000-2013. In particular, we analyzed whether or not the inter-fuel competition induced by the shale gas revolution and/or state-specific CO_2 regulations have contributed to the developments over time.

For a better understanding of the state-specific CO_2 emission performance over time we first applied a nonparametric benchmarking approach. In doing this, we did not just consider a simple measure of CO_2 intensity, such as CO_2 emissions per unit of electricity produced, but we also took other factors, such as fuel consumption and nameplate capacity, into account. This approach allowed us to measure the relative CO_2 emission performance across states, considering both the input and the output dimension of the states' fossil fuel electricity generation profiles, and hence provided a more comprehensive picture of the states' relative CO_2 emission performance than a simple output-oriented CO_2 intensity measure.

In particular, we used a 'global' Malmquist CO_2 performance index (GMCPI) to measure each state's performance against a global benchmarking technology. The cumulative GMCPI obtained can be interpreted as a total factor CO_2 emission performance index between 2000 and 2013. Overall, we find that the CO_2 emission performance across all states improved, on average, by 15% from 2000 to 2013. Decomposing the performance index into its elements, efficiency change and technological change, revealed that this development was mainly due to technological progress. However, the observed efficiency decline in 24 of the 48 states shows that half of the states were not fully able to implement the technological improvements introduced in some innovative states.

To test whether fuel competition and/or emissions regulations led to an improvement in the CO_2 emission performance over time, we regressed the cumulative GMCPI on natural gas prices, regulatory policies and a number of other state-specific factors. Altogether, the results support the argument of increased inter-fuel competition induced by the shale gas revolution and the positive impact of this on electricity-related CO_2 emissions. That is, lower natural gas prices come with a higher state-specific CO_2 emission performance over time. Furthermore, considering state-level regulatory policies, the results suggest a positive impact of regional cap-and-trade programs on the state-specific CO_2 emission performance over time.

As for the other two regulatory policies considered, there may be several reasons why we do not find them to have a statistically significant impact on the states' CO_2 emission performance. First, the setting of a GHG emissions target does not necessarily come with a set of concrete actions. In most states there is a long period between the announcement of a target and the implementation of mandatory regulations within the individual sectors. Hence, GHG emissions targets can be seen as a soft type of regulatory policy rather than a stringent set of actions. Second, the design of CO_2 performance standards varies enormously among the states. While some standards may have an impact, others may not. In all likelihood, this heterogeneity prevents us from finding a statistically significant impact of state-specific CO_2 performance standards in general.

Altogether, we conclude that lower gas prices and stringent CO_2 regulations are suitable means to reduce electricity-related CO_2 emissions. However, although the effect of lower natural gas prices is statistically significant, it should be carefully interpreted. Taken literally, a \$5 drop in the natural gas price, as observed on the national level between 2008 and 2013, is estimated to increase a state's CO_2 emission performance by about 5 percentage points. Whether or not this effect is small or large in environmental terms cannot be clearly answered within our framework. A more comprehensive evaluation should include all the economic and environmental costs (and benefits): in the case of natural gas, this also incorporates the environmental costs resulting from shale gas exploitation. A similar argument applies to our estimated effect of cap-and-trade regulation. While regional cap-and-trade programs seem to be very effective in reducing CO_2 emissions, policy makers should carefully weigh the costs and benefits of such programs before considering a regional and sectoral expansion.

4 The Impact of Advanced Metering Infrastructure on Residential Electricity Consumption - Evidence from California

One important pillar in the debate about energy-saving measures addresses energy conservation. In this paper, we focus on the deployment of advanced metering infrastructure to reduce the impact of limited information and bounded rationality of consumers. For California, we empirically analyze the influence of a statewide and policy-driven installation of advanced metering infrastructure. We apply synthetic control methods to derive a suitable control group. We then conduct a Difference-in-Differences estimation and find a significant negative impact of smart meters on monthly residential electricity consumption that ranges from 6.1 to 6.4%. Second, such an impact only occurs in non-heating periods and does not fade out over the analyzed time period.

4.1 Introduction

In the light of exacerbated discussions on climate targets and emission reduction goals, energy-saving measures have become increasingly important. In the residential sector, such measures have to account for specific characteristics such as limited information and bounded rationality. Although there should be a natural interest in reducing electricity consumption, it is common knowledge that the savings potential is yet to be leveraged. In this paper, we analyze the impact of advanced metering infrastructure (AMI) on residential electricity consumption. The AMI feeds back real-time information on electricity consumption and enables bidirectional communication between the consumer and the respective service utility.

Since, from a consumer‘s perspective, cost recovery after installing AMI is at least questionable, pilot tests and policy-induced measures are the prevalent ways of evaluating smart-meter deployment. The respective impact of smart meters on electricity consumption may differ in both frameworks. In pilot tests, a loss of generality resulting from small samples and the Hawthorne effect, whereby individuals alter their behavior in response to their awareness of being observed, may be relevant. Therefore, we focus on a statewide policy measure and identify a lack of empirical evidence in the existing literature. On the basis of our analyses, decision makers may assess the effectiveness of a policy-driven deployment of smart meters.

We analyze the impact of AMI based on empirical evidence from California. Following the Californian Energy Crisis in 2001, the government issued a decision regarding statewide deployment of smart meters in the Energy Action Plan II of 2005. As a consequence, the three major service utilities committed themselves to installing AMI right across their service areas beginning in 2008. As such, smart meters provide consumers and utilities with more detailed consumption information.[32] We compare the Californian development of residential electricity consumption over time with the respective one in a synthetic control group named 'Synthetic California'. We construct this control group using synthetic control methods in order to resemble Californian characteristics (Abadie et al., 2010). Furthermore, we isolate the effect of advanced metering infrastructure by filtering out distorting effects such as energy savings related to energy-efficiency measures.

We find a significant reduction of the average monthly residential electricity consumption in California that effectively ranges between 6.1 and 6.4% during our period of observation. However, we identify a clear seasonal pattern of electricity savings, showing significant reductions of electricity consumption only in non-heating periods. We suggest that this may be due to the fact that some household appliances are more likely to be substitutable in non-heating periods and thus provide higher saving potentials. On the contrary, heating represents a more basic need and therefore electricity consumption patterns may be less likely to change during heating periods.[33] Finally, our results suggest that the impact of additional informational feedback on electricity consumption is continuous during our period of observation.

We reckon that, at least within the seven years under analysis, smart-meter deployment is a suitable way to achieve overall electricity savings in the residential sector. However, for service utilities, an ongoing assessment of the respective impact on electricity consumption may be beneficial to foster persistent effects. Finally, seasonal fluctuations with respect to the impact of AMI suggest that energy-conservation measures should be complemented by other energy-saving measures in order to achieve a general and continuous reduction in electricity consumption.

[32]The smart meters may provide data with higher temporal resolution and device-specific information.
[33]In the US, up to 65% of households have electric space heating and thus a significant impact on electricity consumption is expected.

The remainder of the paper is organized as follows. Section 4.2 provides the main literature background. In Section 4.3, we depict the identification strategy for measuring the impact of smart meters on residential electricity consumption. We then present the most relevant characteristics of residential electricity consumption in Section 4.4 and furthermore provide a broad overview on energy-saving measures that are relevant for the analysis. Our applied empirical approach and the data are described in Section 4.5, and the respective results are discussed in Section 4.6. Finally, we draw conclusions in Section 4.7.

4.2 Literature Background

When analyzing the impact of AMI on residential electricity consumption, we essentially expect the respective influence to be triggered by additional informational feedback. The paper at hand in a broader context is hence positioned in behavioral economics. One important pillar for such literature deals with aspects surrounding bounded rationality, which may serve as an explanatory approach for the actual behavior of consumers. As the provision of informational feedback directly addresses the limited information of consumers, we first focus on some basic principles in the literature. According to Simon (1957), the term 'bounded rationality' refers to the rationality that is exhibited by the economic behavior of humans. More precisely, rationality is assumed to be bounded due to the limited information that individuals have at certain reference points in time. Naturally, how decisions are taken, assuming that individuals first face a lack of perfect information and second are not even capable of processing all the information they encounter, remains an open question. The joint answer given by behavioral economists and psychologists has directed researchers to the aspect of time itself. Over time, decisions of individuals are influenced by new information that, after being 'fed back' to the individuals, triggers adjustments in their decisions. Such an informational feedback (or 'learning') re-aligns initial thinking, punishes deviant behavior, and leads to the amelioration of decisions (Arthur, 1991, 1994, North, 1994). Arthur (1994) labels this behavioral 'process' as inductive reasoning, implying that the individual initially assumes a variety of working hypotheses, acts upon the most credible ones, and then replaces them by new ones if they fail to work. Thus, the interplay between economic and psychological research evidently can not be neglected (Rabin, 1998, Simon, 1986).

The essence of bounded rationality and informational feedback has inspired a vast body of prior research, not only in the field of energy (e.g., DiClemente et al., 2001). Above all, the impact of providing feedback on consumption is of particular interest. In the related literature, such an effect has most often been measured with the help of empirical work that is constrained by data and/or the experimental design itself. Therefore, the setting of experimental studies and the selection of variables are crucial.[34] This paper addresses the relevance of bounded rationality in the energy sector. In this context, informational feedback incorporates a measure that is supposed to effect an overall reduction of electricity consumption based on additional information. A summary of experimental energy-related studies has been published by Faruqui et al. (2010). The authors conducted their survey based on pilot programs in the United States, investigating the effect of in-home displays on consumer behavior, and found that reductions in consumption from such programs reached 7% on average. More recent research has been conducted by Gans et al. (2013) dealing with the effect of informational feedback on residential electricity consumption. In that study, the authors analyze the impact of smart meters in a large-scale natural experiment in Northern Ireland. They find that the decline in residential electricity consumption induced through smart meters ranges between 11 and 17%.

Targeting an overall reduction of electricity demand, the literature distinguishes between three different types of energy-saving measures. Despite the energy-conserving impact of informational feedback, electricity consumption can also be influenced by energy-efficiency programs and demand response. Whereas informational feedback induces a behavioral change so that 'using less electricity' results as the outcome, energy efficiency aims at a reduced energy usage while maintaining a comparable level of service (Boshell & Veloza, 2008, Davito et al., 2010, Gillingham et al., 2006). Efficiency is thus closely linked to the installation of energy-efficient technologies within households such as freezers, refrigerators, dishwashers, light bulbs, and other appliances. In contrast to these direct measures, demand response is related to the electricity market itself. Despite a reduction of peak demand that was observed in field experiments on dynamic pricing (Faruqui & Sergici, 2010), Joskow & Wolfram (2012) stress that the overall penetration of demand response measures in the US has been low so far. For California, the impact of demand response programs is still negligible today. In this paper, we focus on the isolated impact of deploying AMI and thus position this article in the literature analyzing energy-conservation measures.

Recently, behavioral literature has focused on the growing appreciation of how

[34] A review of such features from experimental studies can be found in Selten (1998).

non-price interventions can affect consumer behavior. As such, informational feedback provided to the consumer is pivotal in order to increase the household‘s responsiveness and likewise influence its electricity consumption. Among others, Allcott (2011) reports that providing social norm information induces consumers to conserve electricity. Allcott & Rogers (2014) expand the analysis on social norms by using data from the Opower program, in which home energy reports based on social comparison are repeatedly provided to residential electricity consumers.

Supplementing prior research, we focus on the impact of AMI in a large-scale framework rather than analyzing short-term pilot programs. Moreover, the literature so far gives a long list of issues related to the explanatory power of pilot tests. Such aspects cover, inter alia, the representative nature of the sample, the time horizon, additional and distorting monetary incentives, and measurement errors. Furthermore, a Hawthorne effect may be identified, reflecting the fact that people may alter their behavior when they know that they are participating in an experimental study (Adair, 1984). Thus, the transferability of results from pilot tests to a larger and more general context is at least questionable. We intend to fill this gap by deriving an empirical approach that will allow us to draw conclusions from an energy-conservation measure induced by statewide policy. Complementing prior research, we are thus able to assess the effectiveness of a policy-driven deployment of smart meters in the context of energy-conservation measures.

4.3 Identification Strategy

In the US, smart-meter[35] deployment in several states is fostered by legislation. While some states have not passed any smart-meter legislation yet, others have already fully adopted smart-meter plans. Figure 4.1 depicts the status of smart-metering legislation across the US states.

We use the dichotomy of states with significant impact of smart-metering legislation and states with negligible smart-meter penetration rates in order to derive an experimental setting. On the one hand, we identify the statewide and policy-induced smart-meter deployment in California as a treatment that allows us to analyze the impact of smart meters on consumption. On the other hand, states that do not yet have any smart-meter penetration may serve as a control group.

[35] Such smart meters are part of the Advanced Metering Infrastructure (AMI). For more details on AMI see Section 4.8.1 of the Appendix.

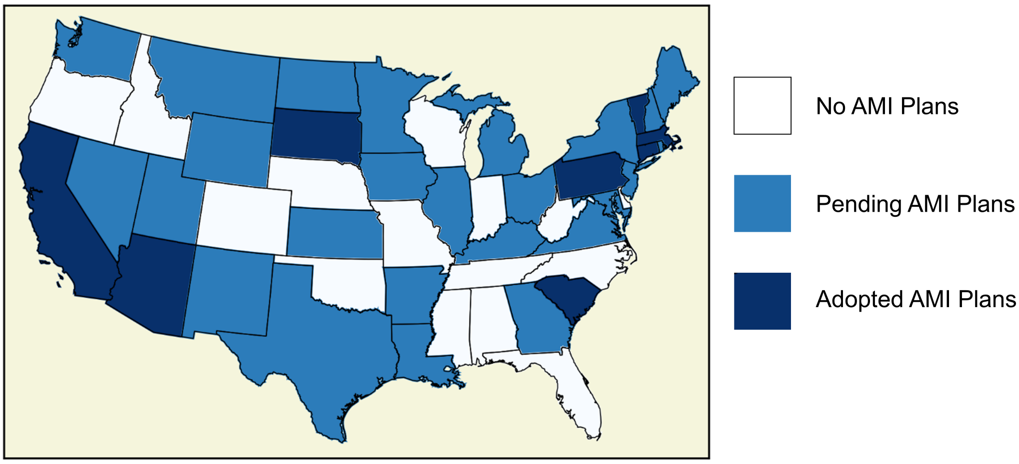


Figure 4.1: Smart-metering legislation across the US states (Energy Information Administration 2011)

The installation of smart meters refers to a short and precisely controllable period, essentially ranging from 2009 to 2011. Being a statewide measure, all residential customers are affected in the same manner. By analyzing the development of electricity consumption before, during, and after the deployment of smart meters, we are thus able to clearly relate back possible changes to the trigger event. We furthermore isolate the respective impact in question by controlling for the other electricity saving impacts (i.e. energy efficiency and self-consumption from renewable energies).

We would like to observe the development of residential electricity consumption in a population that faces the introduction of informational feedback over time (treatment group) and the respective control group. The control group should ideally reproduce the characteristics of the population that experiences the treatment. Since the characteristics influencing residential electricity consumption are heterogeneous across the US states, we do not expect a single state to resemble Californian consumption characteristics appropriately. In this paper, we therefore apply synthetic control methods in order to evaluate what might be a control group that meets the above outlined requirements. We thereby aim to guarantee quasi-randomness. In a next step, we then conduct a Difference-in-Differences estimation to test for causality as well as to quantify the reduction effect in scope.

4.4 The Californian Case

In order to evaluate the impact of deploying smart meters in California, it is first necessary to understand the most relevant drivers of residential electricity consumption and its development over time. This is crucial since, besides the deployment of smart-meter infrastructure, further political measures were adopted that tackle issues related to energy conservation, energy efficiency, and demand response. When it comes to energy savings, California is one of the most ambitious states, with various measures having been adopted to achieve an overall decrease of electricity consumption and thus greenhouse gas emissions. Beginning with the energy crisis in California in 2001, policy makers decided to foster an increase of energy efficiency with a particular focus on the residential sector.

In this regard, there were repeatedly updated energy action plans, all of which defined goals for energy consumption (California Energy Commission, 2003). These action plans mainly aimed at:

- meeting energy growth needs as well as optimizing resource efficiency and energy conservation;
- reducing electricity demand;
- ensuring security of gas and electricity supply including the provision of an appropriate infrastructure;
- achieving goals with respect to renewable energies and distributed electricity generation.

In order to tackle the above aims, the Energy Action Plan considered measures fostering voluntary dynamic pricing, explicit incentives for demand reduction, rewards for demand response, energy-efficiency investments, energy-conservation measures, energy-efficiency programs, and programs that support improvements of energy efficiency when it comes to buildings and devices. Furthermore, within the scope of the Energy Action Plan 2 in 2005, the government issued a decision for a large-scale deployment of smart meters (California Energy Commission, 2005). As a consequence, the three major investor-owned utilities (IOUs), namely Pacific Gas & Electric (PG&E), Southern California Edison (SCE), and San Diego Gas & Electric (SDG&E), started programs that deployed AMI within their service areas. As depicted in Figure 4.2, these IOUs cover more than 75% of all customer accounts[36] in

[36]These numbered 13,845,610 in December 2015 and the respective energy consumption is related to a share greater than 70%.

California (2015).

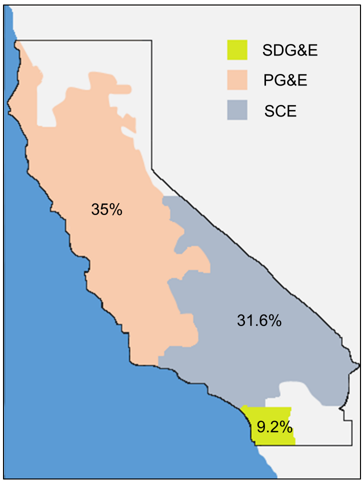


Figure 4.2: Investor-Owned Utilities (IOUs) and the respective share of Californian customer accounts (2015, Dec.)

Below, we explain the most relevant types of measures and their impact on residential electricity consumption in more detail. We distinguish between measures related to energy efficiency of buildings and devices, demand response triggered by electricity price schemes, and energy conservation including, among others, the deployment of AMI.

Demand Response Through Electricity Tariff Design

'Load shifting' is a typical demand response from electricity consumers. It occurs if consumers are able to react to price signals from the electricity market. Technically, a consumer reduces load in response to a signal from a service provider or grid operator. Today, electricity consumers in the residential sector in California face either a tiered tariff scheme or a time-of-use pricing scheme. In tiered tariff schemes, electricity prices are relative to a 'baseline' consumption of electricity within a defined territory. As such, the tariff scheme follows a typical quantity-dependent pricing that varies across predefined blocks of usage. The number of tiers offered and temporal definitions with respect to peak, semi-peak, and off-peak vary among IOUs, and peak prices can be more than twice the off-peak ones.[37] In general, consumers receive their electricity and gas bills at the end of each month, following a standardized 30-days billing cycle. Billing contains information on daily gas and electricity usage gathered by smart meters throughout the cycle. Consumers are thus able to identify

[37]We provide two simplified versions of residential tiered and time-of-use schedules in Section 4.8.7.

monthly variations of gas and electricity usage on daily and monthly levels.[38]

A two-tiered tariff had already been implemented in California prior to the energy crisis in 2000. However, with the energy crisis and the inconvenience caused by blackouts that were induced by supply shortages, regulators enhanced the tier structure by introducing five tiers. These were removed again in 2013 due to ongoing discussions on tier design and, as of today, Californian tariff design relies on time-of-use pricing that distinguishes between peak and off-peak times. Additionally, the implementation of real-time pricing has so far been ruled out as an option in California.

A change in tiered electricity tariff design could potentially provoke slight changes in overall consumption levels. This may, for example, be the case if load shifting causes a decrease in electricity consumption in peak periods which is even higher than the respective increase in off-peak periods. Within this paper, we assume that there is no significant impact of implementing more or less tiers on the absolute electricity consumption. To support this hypothesis, we test the assumption of parallel trends within our empirical analysis. We would expect potential distorting effects related to a change in the electricity tariff design, if any, to be uncovered within this procedure since the introduction of five tiers in California was in the pre-treatment periods.

Energy Efficiency

Besides regulatory efforts to ensure security of supply through tier design, numerous energy-efficiency policy measures which are directed towards a reduction of energy consumption exist for California (Office of Energy Efficiency and Renewable Energy, 2016). The majority of energy-efficiency measures are so-called rebate programs.[39] The three major IOUs, PG&E, SDG&E, and SCE, have all offered energy-efficiency rebate programs for energy-efficient technologies since 2006. Within these programs, consumers willing to replace equipment with energy star labelled devices receive a per unit rebate.[40] Such incentives are particularly designed to reduce load through state-of-the-art devices. While the utility level remains constant with the same service offered (i.e., for example, cooling in the fridge), less electricity is needed to ensure this service. Empirical evidence reveals a need to distinguish be-

[38] Sample bills from PG&E, SDG&E and SCE can be found under the service portal from each IOU.

[39] Additionally, appliance standards on a national level have been implemented in the Appliance Efficiency Regulations for California in 2006 as well as the Public Benefits Funds for Renewables and Efficiency launched in 1998.

[40] Further details on the applicable residential equipment are provided at the website 'http://programs.dsireusa.org/system/program/'.

tween different devices. Light bulbs, refrigerators, and freezers provide rather robust empirical evidence for electricity reduction if replaced within households. Thus, we expect a significant impact of energy-efficiency measures on electricity consumption (Gillingham et al., 2006). We therefore account for energy savings related to energy efficiency by adjusting electricity consumption data so that the impact of informational feedback can be studied independently.[41]

Energy Conservation

Finally, a change of consumption behavior is another way to achieve a reduction of electricity consumption. Through behavioral changes, 'consuming less electricity' with a given technology portfolio is feasible. However, information on the consumption must be revealed in such a way that consumers are able to make informed decisions. As bounded as these decisions may be, decisions change and, in most cases, may improve if such information is provided to consumers. In this paper, we focus on the three major IOUs in California, which are adopting plans to distribute smart meters to all households in their respective service areas. In fact, these plans were transformed into physical deployment of smart meters, as depicted in Figure 4.3. The deployment of AMI began in 2008, and first achieved a penetration rate above 10% in 2009.

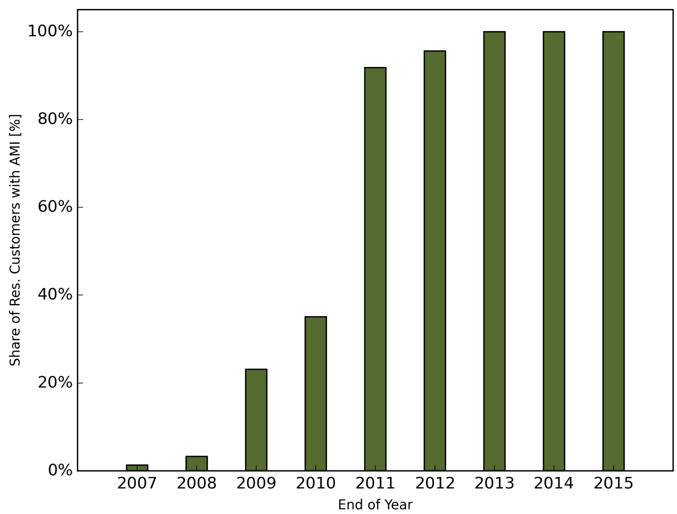


Figure 4.3: Share of Californian (three major IOUs) households with AMI (smart meters) over time

[41] For more details, see Section 4.5.

As of 2011 the share of Californian households with AMI corresponds to the share of customer accounts covered by the three major IOUs.[42]

Households having installed AMI with the respective smart meters are now able to track their daily electricity consumption via a meter on the device. Additionally, consumption data are processed by the utility and, as in the case of SDG&E, for instance, are provided to the customer via on online tool. With the help of the customer tool, households are able to check their gas and electric usage on a daily basis. By connecting a home area network to the smart meter, households are able to track energy consumption information and more details on their energy-usage profile. Most commonly, thermostats and in-home displays are state of the art in such technical setups (San Diego Gas and Electricity, 2016).

4.5 Data

We base our empirical analysis on variables that may have information on both fluctuations of residential electricity consumption over time and the respective differences between the states. We use monthly state-specific data, and in the following we briefly depict the variables we use as well as the respective sources.

4.5.1 Dependent Variable: Residential Electricity Consumption

We define the dependent variable in order to make it possible to isolate the impact of AMI on residential electricity consumption from other policy measures that coincide with the deployment of smart meters and that may also influence residential electricity consumption. We therefore correct data on residential electricity consumption provided by the IOUs for both own consumption related to residential photovoltaic (PV) electricity generation and electricity savings achieved through energy-efficiency programs. That is to say, we mimic the development of residential electricity consumption as if there was no treatment besides smart meters. The respective formula is depicted in Equation 4.1.

$$\begin{aligned} Demand_{m,s}^{res,adj} = & \; Demand_{m,s}^{res,billed} \\ & + Self\,Consumption_{m,s}^{res,PV} \\ & + Savings_{m,s}^{res,ee} \end{aligned} \tag{4.1}$$

[42]The share of Californian households in services areas that are covered by the three major IOUs may vary over time.

Our initial data on residential electricity consumption consists of monthly (m) state-specific (s) electricity sales in the residential sector, which we label $Sales^{res}_{m,s}$. As far as California is concerned, we only include data for the three major IOUs, PG&E, SCE, and SDG&E, in line with our identification strategy. Since the IOUs cover the major share (i.e. $> 75\%$) of residential customers in California, we assume that there is no loss of representative nature. In the next step, we divide $Sales^{res}_{m,s}$ by the respective number of customer accounts in order to get the average monthly electricity consumption per household for which consumers are billed ($Demand^{res,billed}_{m,s}$). We use this relative measure in order to compare residential electricity consumption in different states independently of the total level of consumption, which may differ. As outlined above, we now account for the average electricity generation from PV systems, which replaces electricity purchased from the grid. In general, California uses a billing system that is called net metering. The essence of this procedure refers to households being directly billed for their total electricity purchase minus the amount of energy that they feed back into the grid. Thus, there is a direct incentive for self-consumption of electricity generated from renewable energy sources. This self-consumed energy ($SelfConsumption^{PV,residential}_{m,s}$) has to be added to the basic electricity consumption data in order to get unbiased values.[43]

Second, we adjust our data for residential electricity savings that result from energy efficiency (ee) programs ($Savings^{res,ee}_{m,s}$). The respective data are collected from the individual service utilities in the US states and are listed in Table 4.1.[44] Such data are based on the technical savings potential, which is the number of residential devices that face a specific efficiency upgrade multiplied by the respective electricity consumption.[45] However, it is not clear whether or not the data are equal to the actual reduction in electricity consumption. First, rebound effects may not be ruled out. The existing literature, however, provides little support for such an increase in energy use, which is known as backfire (Gillingham et al., 2015). Second, Fowlie et al. (2015) found that projected savings from energy-efficiency programs may exceed actual reductions many times over. We therefore aim to control whether measurement errors with regard to energy efficiency savings may bias our empirical results. In the context of our identification strategy, we explicitly guarantee that smart meters are accessible at the time of the defined treatment period starting in

[43] For more details on the calculation methodology, see Section 4.8.5.

[44] We restrict our analysis to residential efficiency programs in California, New York, and New Mexico since those are the relevant states resulting from the synthetic control methods according to Section 4.6.1.

[45] In the example of New York, the data are furthermore corrected for free-rider and spillover effects (New York State Department of Public Service, 2016).

2009. As there is a time lag between significant energy-efficiency savings beginning in 2006[46] and the treatment, we are able to control for the accuracy of the methodology in filtering out the impact of energy-efficiency measures by testing for the assumption of parallel trends before the treatment.

As regards the data references for California, we rely on the California Energy Efficiency Statistics for the three major IOUs of interest (California Public Utilities Commission, 2016), for New York we take state-wide Energy Efficiency Portfolio Standard (EEPS) Program Electricity Savings Data (New York Office of Information Technology Services, 2016), and for New Mexico we review annual efficiency reports published by the major service utility[47] (Public Service Company New Mexico, 2016). An overview on the respective data is provided in Table 4.1. Whenever only a subset of utilities provides energy savings data, we restrict our empirical analysis to the average residential electricity consumption within the respective service area. However, the corresponding utilities that provide data cover the majority of households in their states and thus we assume their representative nature. By now adding $Savings_{m,s}^{res,ee}$, we finally get the average adjusted residential electricity consumption per household ($Demand_{m,s}^{res,adj}$), which we use as the dependent variable within our empirical framework.

Table 4.1: Energy efficiency savings data

State	Utilities	Period of time	Resolution
California	PG&E, SCE, SDG&E	2006-2015	Monthly
New York	Statewide	2008-2015	Monthly
New Mexico	PNM	2008-2015	Monthly

4.5.2 Explanatory Variables

By using panel data, we account for both cross-sectional and cross-temporal differences within the US states. Since we encounter varying temporal and spatial resolutions among our explanatory variables, we have to adjust some of our data in order to perform our estimation approach. For instance, household survey data are only available on census region level in most cases. Thus, we first address this spatial issue by assigning federal states to the census regions where necessary. As a

[46]The development of energy-efficiency savings in California is illustrated in Figure 4.7 in Section 4.8.2.

[47]This is the Public Service Company of New Mexico, which covers more than 50% of all customer accounts in New Mexico.

consequence, we face a minor loss of cross-sectional explanatory power. Second, for the chosen period between 2002 and 2015, we need to distinguish between continuously updated data with monthly observations, yearly available data, and household survey data based on observations in 2001, 2005, and 2009. For some survey data, we are able to add data for the years 2011 and 2013. In order to obtain an overall monthly and state-specific dataset, we use previous observations if no updated data are available.

Table 4.2 gives an overview of all variables that are used in our empirical analysis. Furthermore, it provides further details such as a brief explanation of each variable and depicts the respective sources. Key to our identification strategy is the deployment status of AMI (Energy Information Administration, 2016b). It reflects the treatment under analysis by measuring the progress of installation of smart meters by households over time. We furthermore include explanatory variables concerning the employment level, wages, residential electricity sales, customer accounts, and electricity prices that are published by the US Energy Information Administration (EIA) or the Bureau of Labor Statistics (BLS). It is worth mentioning that the electricity price is calculated as an average value across all tariff tiers. Furthermore, the EIA also provides data on residential electricity consumption, which are the basis for the derivation of the dependent variable. Data are provided on a monthly and state-specific level.

In addition, we include climate data. More precisely, heating degree days ($HDDs$) and cooling degree days ($CDDs$) are calculated based on per state temperature values that we obtain from the meteorological data forms of the National Oceanic and Atmospheric Administration (National Oceanic and Atmospheric Administration, 2016).[48]

Complementing these data, we add data reflecting household characteristics with a focus on electricity usage behavior and appliances. Such data are taken from the Residential Energy Consumption Survey (RECS) and the American Household Survey (AHS) for three and five reference points in time, respectively, namely 2001, 2005, 2009, 2011, and 2013. The survey data consist of different technologies and the percentage of households using specific electrical appliances. For instance, we include data on the average number of refrigerators per household, the share of households that use electric heating, and the usage intensity of heating by fuel type for census regions and states. Physical household characteristics such as the average

[48] To derive HDDs, for example, the difference between daily high and low temperatures is compared to the threshold of 65 °F and summed over all days of a month. The respective data are furthermore standardized to 1000.

number of rooms per household, the average number of electric ovens, and the average floor space available per household are additionally gathered on a state level. Data on the share of household members with a high-school diploma or higher as well as the average number of 'elderly' people living in each state are taken from RECS as well. Finally, as we expect macro-economic indicators to be relevant when explaining the development of electricity consumption over time, we include data on the unemployment level and adjusted gross domestic product. Hereby, we also control for the impact of the Great Recession. Both indicators are taken from the BLS. In addition, Table 4.3 shows descriptive statistics for all variables used for our empirical estimations under Section 4.6.2.

4.6 Empirical Analysis

Following the identification strategy from Section 4.3, we use a two-stage empirical approach. First, we derive a control group by applying synthetic control methods.[49] In a second step, we conduct a Difference-in-Differences estimation to quantify the effect under analysis.

4.6.1 Derivation of the Control Group Using Synthetic Controls

States are rather heterogeneous. This implies that characteristics driving residential electricity consumption exhibit significant regional variation. Above all, these characteristics include climatic conditions such as temperature and humidity, housing, and social characteristics as well as demographic aspects. Consequently, it is questionable whether a single US state adequately resembles Californian characteristics with respect to residential electricity consumption. In order to circumvent such hindrances, we apply synthetic control methods and derive a weighted combination of US states that we use as the control group, 'Synthetic California'. The application of synthetic control methods is positioned in the context of a vast body of existing literature that gives further insights into methodological details (e.g. Abadie & Gardeazabal (2003), Abadie et al. (2010), and Abadie et al. (2015)). The individual weights for the synthetic counterfactual are determined according to the objective function expressed by Formula 4.2.

$$\min_{w}(X_1 - X_0 \cdot w)' V (X_1 - X_0 \cdot w) \tag{4.2}$$

[49]The respective procedure is described in detail in Section 4.6.1.

Table 4.2: List of variables and references

Label	Explanation	Resolution	Region	Measure	Ref(2016)
$AMI_{m,s}$	Share of households with AMI	Yearly	State-specific	%	EIA
$CDD_{m,s}$, $HDD_{m,s}$	Cooling degree days, Heating degree days	Monthly	State-specific	1000°F	NOAA
$Clothesdryer_{m,s}$	Avg. share of electric clothesdryers	'01,'05,'09	Census regions	Relative share	RECS
$Customers_{m,s}^{res}$	Total residential customer counts	Monthly	State-specific	Total	EIA
$Demand_{m,s}^{res,billed}$	Avg. electricity sales per household	Monthly	State-specific	MWh	EIA
$Education_{m,s}$	Share of household members with a high school degree or higher	'01,'05,'09, '11,'13	Census regions	Relative share	RECS
$ElderlyPeople_{m,s}$	Avg. number of old people living in a household	'01,'05,'09, '11,'13	Census regions	Total	RECS
$Feedback_{m,s}^{PV}$	Total residential feed-back (grid) from PV	Monthly	State-specific	MWh	EIA
$Floorspace_{m,s}$	Avg. floorspace per household	'01,'05,09	Census regions	m^2	RECS
$GDP_{m,s}$	Total real GPD per employee	Yearly	State-specific	mil. USD	BLS
$Heating\ Equipment_{m,s}$	Share of households using electric heating	'01,'05,'09	Census regions	Percent	RECS
$Irradiation_{m,s}$	Avg. (1998-2009) solar irradiation	Monthly	State-specific	kWh/ m^2/day	NREL
$MainHeating_{m,s}$	Share of households with electricity as main heating fuel	'01,'05,'09	Census regions	Relative share	RECS
$Oven_{m,s}$	Avg. number of electric ovens per household	'01,'05,'09	Census regions	Total	RECS
$Price_{m,s}^{res}$	Avg. electricity price for residential customers	Monthly	State-specific	Euro/ kWh	EIA
$Refrigerators_{m,s}$	Avg. number of refrigerators per household	'01,'05,'09	Census regions	Total	RECS
$Rooms_{m,s}$	Avg. number of rooms per household	'01,'05,'09	Census regions	Total	RECS
$Unemployment_{m,s}$	Unemployment level	Yearly	State-specific	Relative share	RECS
$Wage_{m,s}$	Avg. weekly wage	Monthly	State-specific	1000 USD	BLS

Notes to Table 4.2: Census regions include 9 regions and 4 states (CA, NY, FL, TX) if not otherwise stated. The exact references are: NOAA (National Oceanic and Atmospheric Administration, 2016), RECS (Energy Information Administration, 2016a), EIA (Energy Information Administration, 2016b), BLS (Bureau of Labor Statistics, 2016), NREL (National Renewables Energy Laboratory, 2016).

Table 4.3: Descriptive statistics

Variable	N	Mean	SD	Min	25%	Median	75%	Max
$CDD_{m,s}$	2352	0.07	0.10	0.0	0.0	0.003	0.10	0.58
$Clothesdryer_{m,s}$	2352	0.77	0.14	0.47	0.54	0.84	0.90	0.97
$Demand^{res,adj}_{m,s}$	2352	0.81	0.27	0.41	0.60	0.73	0.95	1.97
$Education_{m,s}$	2352	0.59	0.03	0.54	0.56	0.59	0.62	0.64
$Elderlypeople_{m,s}$	2352	0.33	0.03	0.28	0.31	0.33	0.34	0.37
$Floorspace_{m,s}$	2352	2049	250	1568	1895	2080	2289	2405
$GDP_{m,s}$	2352	0.006	0.001	0.004	0.005	0.006	0.007	0.009
$HDD_{m,s}$	2352	0.47	0.42	0.00	0.06	0.38	0.80	1.92
$HeatingEquipment_{m,s}$	2352	0.25	0.17	.06	0.13	0.23	0.29	0.65
$MainHeating_{m,s}$	2352	0.22	0.16	0.06	0.09	0.18	0.24	0.62
$Oven_{m,s}$	2352	1.02	.02	1.00	1.01	1.01	1.03	1.09
$Price^{res}_{m,s}$	2352	0.111	0.038	0.048	0.082	0.100	0.141	0.241
$Refrigerators_{m,s}$	2352	1.24	0.05	1.14	1.20	1.23	1.28	1.30
$Rooms_{m,s}$	2352	5.81	.32	5.19	5.65	5.93	6.13	6.21
$Unemployment_{m,s}$	2352	0.06	0.02	0.02	0.05	0.06	0.08	0.12
$Wage_{m,s}$	2352	0.85	0.18	0.52	0.52	0.80	0.96	1.46
$AMI_{m,s}$	2352	0.03	0.16	0.00	0.00	0.00	0.00	0.99

Here w denotes a vector with weights for each state that has yet to be derived. The individual weights sum up to one. In order to optimize these weights, we rely on a procedure that minimizes the distance vector between Californian pre-treatment characteristics (X_1) and the respective characteristics of the resulting control group ($X_0 w$). These characteristics include all variables that are depicted in Section 4.5. We divide the pre-treatment period into two sub-periods. In more detail, we consider a first pre-treatment period (1) that starts in 2002 and ends in 2005. Based on this first period, we calculate the weights for the synthetic control group according to the above mentioned methodology. Additionally, we define a second pre-treatment period beginning when the Energy Action Plan in California was adopted (2006) and continuing until the beginning of the treatment period in 2009 (see Figure 4.5). The second pre-treatment period allows the assumption of parallel trends to be tested.

With regard to the data, the varying temporal resolution does not distort the derivation of a synthetic control group since the respective methodology is based on averages over time. More precisely, neglecting temporal variability, the chosen approach aims to determine weights such that average values of the explanatory variables during the first pre-treatment periods are resembled. We then account for the relative importance of the individual explanatory variables X by introducing a weight vector V. Following standard synthetic control methods (e.g., Abadie &

Gardeazabal, 2003), we rely on a regression-based technique in order to derive V.[50] Naturally, the set of time periods for determining V is also restricted to the first set of pre-treatment periods.

The set of states that are considered to be control group candidates is restricted. Suitable candidate states should exhibit no significant impact of AMI during the entire period of observation. Thus, we use a subset of states with a smart meter penetration lower than 10% as possible control group candidates. The respective threshold exactly matches the definition of our treatment as we consider the treatment period beginning in the first year with a Californian share of AMI higher than 10%. The remaining candidate states are depicted in Figure 4.4.

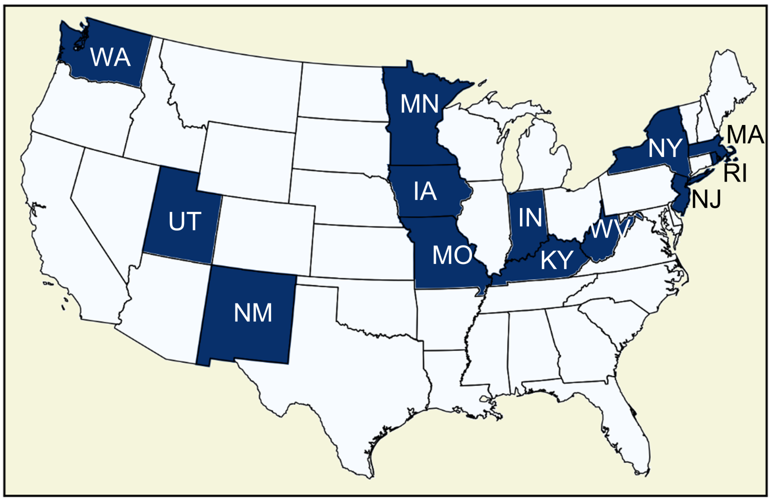


Figure 4.4: Candidate states with low AMI penetration

As a result, we obtain Synthetic California, which combines the states of New York and New Mexico, which are given weights of 62.5 and 37.5% respectively. A deeper analysis of the underlying causal relations reveals that New York adequately resembles Californian housing characteristics, whereas New Mexico is particularly characterized by similar climate conditions.

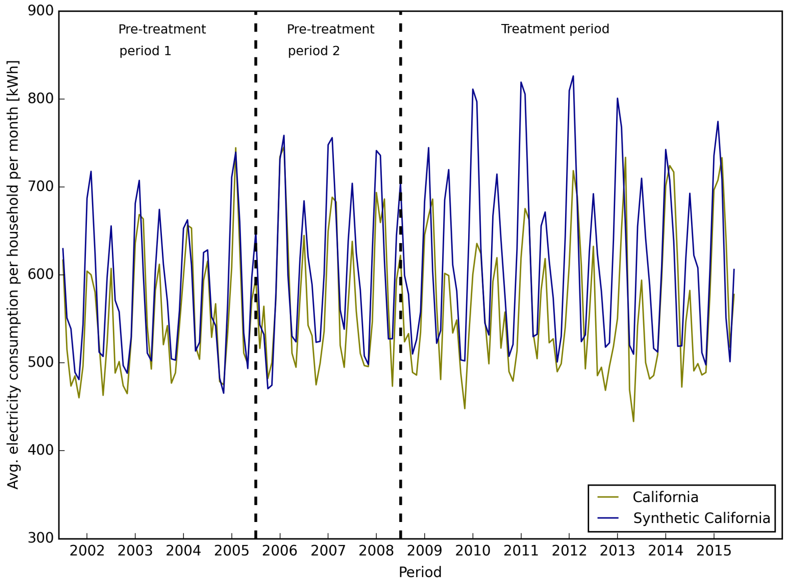
We now reduce our initial dataset by considering just the two sections, California and Synthetic California. The variables for Synthetic California are calculated as the weighted combination $X_0 w$. The resulting development of residential electricity consumption is depicted in Figure 4.5(i), where we highlight the three periods that we differentiate. For illustration purposes, Figure 4.5(ii) depicts the respective difference plot. In order to support the claim of a suitable control group, it is crucial

[50]Details on weights are listed in Section 4.8.4.

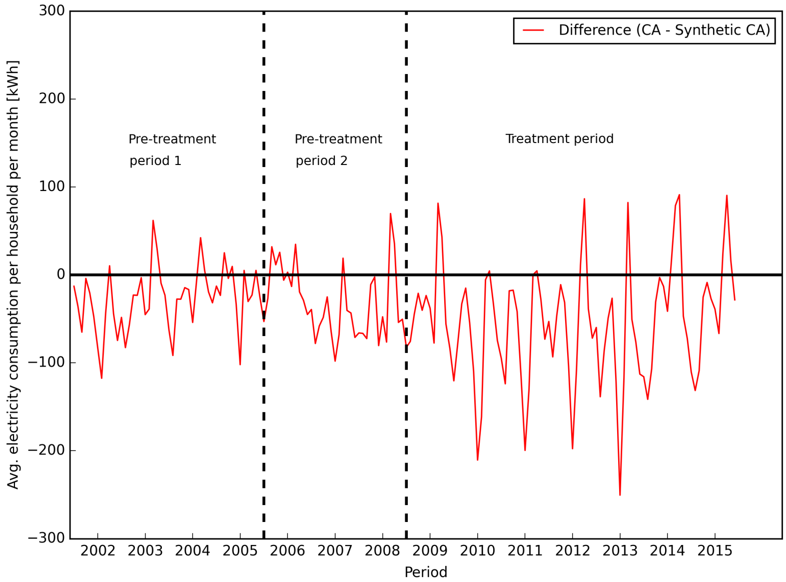
that the pattern of residential electricity consumption in Synthetic California before the treatment resembles the respective real Californian one. We therefore compare the differences in residential electricity consumption between the two sections in both pre-treatment periods. In general, the consumption pattern in the upper figure is characterized by seasonal trends. More precisely, the development of residential electricity consumption exhibits recurrent upwards and downwards movements in a range between 430 and 830 kWh/month. The figures show that the seasonal component, in particular, is reproduced accurately. As regards the differences in levels, the respective values in California and Synthetic California differ only slightly between the two pre-treatment periods. In more detail, whereas the residential electricity consumption in the first pre-treatment period is 11 kWh lower on average in California compared to Synthetic California, the respective average difference is -15 kWh in the second pre-treatment period. Even though there is no perfect pre-treatment match in both periods, the respective difference is rather constant until the treatment period. Additionally, the average difference in residential electricity consumption amounts to -36 kWh in the post treatment periods, which already indicates a significant treatment effect. We therefore assume that residential electricity consumption would have developed identically in California and Synthetic California if there had not been any additional treatment. Simply put, the assumption of parallel trends is valid. We now focus on the development of residential electricity consumption after the treatment. Essentially beginning in 2010, we observe a clear excess of negative differences, indicating a significant impact of AMI on electricity consumption. Furthermore, the absolute value of peak differences is doubled compared to the pre-treatment periods. To sum up, our descriptive results already indicate a negative influence of smart meters on residential electricity consumption. However, we address the question of causality and quantify the impact under analysis within the next section.

4.6.2 Difference-in-Differences Estimation Results

We define the yearly share of AMI as the treatment variable and thereby account for the respective deployment process. In more detail, there is a time lag between the decision for the smart-meter deployment and the ability of every household to use AMI which is directly reflected by the treatment variable. We apply a linear Difference-in-Differences estimation in levels according to Formula 4.3. We aim to estimate the coefficient γ to shed light on whether or not a significant decrease of residential electricity consumption due to smart-meter deployment has been achieved.



(i) Synthetic controls: Descriptive comparison



(ii) Synthetic controls: Difference plot

Figure 4.5: Descriptive comparison and differences between the development of residential electricity consumption in California and 'Synthetic California'

For our estimation, we rely on monthly data gathered over 14 consecutive years (2002-2015). According to the estimation approach, we directly use the differences between the respective values for California and Synthetic California.[51] Besides the treatment variable, we control for other potential impacting factors. We use the subset of variables that provide monthly observations, because data with a temporal variability different from that exhibited by the dependent variable would lead to distorted results and issues of collinearity. First, we include monthly average electricity prices ($Price_m^{res}$). Furthermore, we consider data for HDD_m and CDD_m to account for weather conditions. Finally, we account for macro-economic impact factors comprising wage data ($Wage_m$) and the development of the unemployment level ($Unemploymentlvl_m$). In addition to the explanatory variables, we estimate the error term μ_m using robust standard errors to account for heteroscedasticity. It is worth mentioning that we do not estimate an aggregate constant term but control for different periods.

$$
\begin{aligned}
\Delta Demand_m^{res,adj} = \; & \alpha_1 Dummy_{Pre-Treatment1} + \alpha_2 Dummy_{Pre-Treatment2} \\
& + \gamma \Delta AMI_m \\
& + \beta_1 \Delta Price_m^{res} \\
& + \beta_2 \Delta CDD_m + \beta_3 \Delta HDD_m \\
& + \beta_4 \Delta Unemploymentlvl_m + \beta_5 \Delta Wage_m \\
& + \mu_m
\end{aligned}
\tag{4.3}
$$

We conduct a two-stage least squares regression analysis to address issues related to endogeneity of electricity prices. In more detail, one may expect simultaneity of residential electricity consumption and the respective prices due to mutual bidirectional dependencies. We therefore use the lagged electricity price as an instrument[52] for the original explanatory variable. We argue that the electricity prices from past months affect the current prices ($cov[Price_{m-1}^{res}, Price_m^{res}] \neq 0$) since, for example, fixed price components do not change on a monthly basis. We identify a high first-order autocorrelation of 96% in California and 76% in Synthetic California.[53] At the same time, we do not expect the electricity price from the previous month to impact the current electricity consumption as it does not reflect the price that households

[51] We provide an overview of the respective descriptive statistics in Section 4.8.3.
[52] A Kleiberger-Paap test indicates that the hypothesis of weak instruments may be rejected.
[53] Lower values compared to California may be traced back to the use of a weighted combination of electricity prices.

are actually charged. Thus, there should be no direct impact on the decision rationale of households other than through its impact on the current electricity price and thus we assume that the exclusion restriction is valid ($cov[Price^{res}_{m-1}, \mu] = 0$). As well as the electricity price, it is relevant to comment on the other explanatory variables included. By default, weather conditions are a factor given exogenously and the economic variables such as wage data are most commonly assumed to have a unidirectional impact on electricity consumption as well. Moreover, we do not expect our estimation to be biased by omitted variables, since we include the most relevant variables that, according to prior literature, are assumed to have an impact on residential electricity consumption. Finally, we isolated the impact of AMI such that we do not expect any other policy measures to influence the artificial electricity consumption we use.

To investigate the impact of the treatment in question and to break down the respective temporal development, we depict estimates for three specifications, namely IV (1), IV (2), and IV (3). Put simply, IV (1) measures the aggregate impact of deploying AMI in California on the state-wide residential electricity consumption. Results for IV (1) are displayed in Table 4.4, where we find the treatment effect to be significant at the 1% level. A 100% diffusion rate of AMI triggers an average monthly residential electricity reduction of 31 kWh per household, which is equivalent to a relative reduction of 5.1%. These estimation results provide the first evidence of causality and both estimates which are controlling for significant differences in the pre-treatment periods are insignificant. However, additional insights and further evidence for causality are provided in Section 4.8.6. Thus, we claim that there is no systematic difference between the Californian and the Synthetic Californian development of residential electricity consumption other than that induced through the AMI.

All in all, the p-value of the model suggests significance. With regard to the additional explanatory variables included, both CDD and HDD reveal highly significant coefficients, and reduced regressions show that they constitute the major share of explanatory power. This is plausible as both variables reflect the need for electricity through, for example, air conditioning in non-heating periods and heating in colder months. In addition, we see a slightly significant negative impact of the unemployment level. An increasing unemployment rate tends to be accompanied by decreasing wages, which reduces the available budget for the electricity bill. Finally, we observe a negative coefficient for the electricity price, as increasing prices are expected to create incentives for reducing electricity consumption. However, the

Table 4.4: IV Estimates for DiD estimation

	Dependent variable: $\Delta Demand_m^{res,adj}$				
Explanatory variable	IV (1)	IV (2)		IV (3)	
Pre-Treatment1	-0.07	-0.002		-0.003	
	(0.007)	0.007)		0.007)	
Pre-Treatment2	-0.10	-0.006		-0.004	
	(0.008)	(0.008)		(0.008)	
		Non-heating	*Heating*		
ΔShare $AMI_{total,m}$	-0.031***	-0.042***	-0.01		
	(0.01)	(0.01)	(0.01)		
				Non-heating	*Heating*
ΔShare $AMI_{2009-2011,m}$				-0.020	0.024
				(0.025)	(0.02)
				Non-heating	*Heating*
ΔShare $AMI_{2012-2014,m}$				-0.041***	-0.008
				(0.013)	(0.016)
				Non-heating	*Heating*
ΔShare $AMI_{2015,m}$				-0.039**	-0.031
				(0.016)	(0.022)
$\Delta Price_m^{elec,res}$	-0.46	-0.48		-0.36	
	(0.51)	(0.49)		(0.57)	
ΔCDD_m	0.66***	0.67***		0.68***	
	(0.08)	(0.08)		(0.081)	
ΔHDD_m	0.04**	0.06***		0.05***	
	(0.02)	(0.02)		(0.02)	
$\Delta Unemploymentlvl_m$	-0.53*	-0.46		-0.88**	
	(0.20)	(0.24)		(0.36)	
$\Delta Wage_m$	0.05	0.04		(0.07)	
	(0.06)	(0.06)		(0.06)	
$observations$	167	167		167	
R^2	0.45	0.47		0.48	
F	23.8	22.91		17.17	
p-value	0.00	0.00		0.00	

Notes to Table 4.4: Robust standard errors in parentheses. * / ** / *** : significant at the 0.05 /0.02 / 0.01 error level respectively. We use data from January 2002 until December 2015.

respective estimate is insignificant, which may be traced back to the data availability. Furthermore, we do not directly use the electricity prices that households are actually charged; instead we use averages across all tariff periods and service areas.

In addition to IV (1), we specify IV (2) in order to investigate seasonal variations of the treatment effect under analysis. We differentiate between heating and non-heating periods, all of which are defined within the same year. We define heating periods to cover the months from January to March and from October to December. We observe a significant impact of AMI in non-heating periods, whereas there is no significant influence in colder months. The respective reduction in non-heating periods amounts to 42 kWh per household per month (6.7%). We expect some devices to be more likely to be substitutable in summer periods (such as air conditioning, dryers etc.), whereas electric heating in the heating period is a more basic need. As one main finding, we thus conclude that the potential for energy conservation can basically be leveraged by households in non-heating periods. At the same time, the average residential electricity consumption in the states under consideration tends to be higher in the non-heating periods. Thus, policy makers may achieve a slight reduction of the electricity consumption in peak months by deploying AMI. Such a finding is especially important in the light of the Californian energy crisis, which was the event triggering the deployment of smart meters. However, we are well aware that we do not control for the one-time peak load but focus on the overall electricity consumption.

In addition to IV (2), we specify IV (3) in order to analyze the temporal structure of the impact of smart meters on residential electricity consumption and to address the question of continuous effects. More precisely, we split up the post-treatment periods into three sub-periods and differentiate between heating and non-heating periods. Overall, we get similar results with respect to the influence of the climate factors CDD and HDD. Furthermore, the macroeconomic indicator is now significant at the 2% level and the respective estimate is slightly higher than in IV (1). As regards the treatment effect, we identify additional evidence for seasonality. The impact of AMI on residential electricity consumption is significant in non-heating periods only. Analyzing differences between the non-heating periods in all three post-treatment periods, we first find that the impact of AMI is insignificant in the first post-treatment period. We argue that this finding may be traced back to the introductory phase of deploying smart meters. In the first period, there are no observations available that reflect a state in which all households are able to access AMI. The aggregate effect in which we are interested may thus be derived instead from the last two post-treatment periods with AMI being fully deployed. From 2012 to 2015, we observe a relative reduction of residential electricity consumption that ranges from 6.1% to 6.4%. Compared to the literature, this is a little lower than the reductions gained from field experiments, as mentioned in Section 4.2. In addition, we find that this reduction potential related to AMI is rather continuous over time. We find no evidence that the impact under analysis comes to an abrupt end after some years. However, it may be worth considering an extended period of observation in future research. Finally, the temporal structure identified supports the hypothesis of causality. One may, in particular, assume that the methodology to isolate the impact of AMI from energy efficiency savings is imprecise. However, if that were the case, we would expect significant differences in electricity consumption before the deployment of smart meters was completed, as rather constant energy-efficiency savings were achieved from 2007 onwards (see Figure 4.7 in the Appendix). Rather to the contrary, we identify coefficients that strongly comply with the temporal development of the share of AMI.

4.7 Conclusion

One topic worth stressing in the light of climate targets and emission reduction goals focuses on energy conservation. Within the residential sector, the design of energy-saving programs has to account for unique behavioral aspects such as limited information and bounded rationality. Against this backdrop, we investigate how AMI is impacting on residential electricity consumption at the state level over time. Our identification strategy is based on a decision for statewide smart-meter deployment by the government of the state of California in 2005. As such, the treatment on which we are focusing is policy-driven and not based on a natural experiment or pilot program as predominantly studied in prior research. We are thus able to circumvent hindrances stemming from a lack of generality or Hawthorne effects. We aim at assessing the overall effectiveness of policy measures related to energy conservation. To the best of our knowledge, such a framework has not been studied so far.

We apply a two-stage empirical approach. First, we derive a control group as a weighted combination of US states using synthetic control methods. We find a combination of New York and New Mexico that reproduces the characteristics of California appropriately. We then descriptively depict the development of residential electricity consumption in California and its counterfactual, 'Synthetic California', and find an indication for a change in consumption after 2009 when introducing smart meters. In order to draw inferences regarding causality and significance, we apply a Difference-in-Differences estimation in a second step. Our results comprise two major findings, all of which contribute to the existing literature on energy conservation. First, we observe a significant reduction in electricity consumption induced through AMI in non-heating periods that essentially ranges from 6.1 to 6.4%. In contrast, there is no significant reduction in heating periods. Thereby we infer that reductions in electricity consumption induced by smart-meter deployment are linked to seasonality. Second, based on our empirical results, we find an indication that the impact of additional informational feedback on residential electricity consumption is continuous during the period analyzed. However, we are not able to draw a unique conclusion on persistence due to a lack of further periods of observation.

Summarizing our findings, we suggest that the Californian smart-meter deployment is effective in leveraging energy-saving potentials. We expect this finding to be mainly attributable to the additional informational feedback that smart meters provide. In essence, this information may be the cornerstone for altering consumption decisions that have been taken previously. Theory suggests that breaking the rationality boundaries improves decisions with respect to electricity savings. We find an indication that the impact of smart meters on consumption is continuous. However, for service utilities it may be worth implementing monitoring procedures in order to assess the long-term impact of smart meters. Furthermore, it may be worth considering supplementary informational feedback such as programs that focus on social comparisons. Finally, we find that the influence of AMI exhibits strong seasonal variations. Thus, it may be beneficial to consider complementary energy-saving measures.

4.8 Appendix

4.8.1 The General Functioning of the Advanced Metering Infrastructure

Figure 4.6 shows the simplified functioning of the AMI. As depicted, the AMI first enables the collection of consumption data differentiated by energy source. The consumption data are collected by a smart meter device that then processes and transmits the data via an electronic network to the end user. As such, the AMI could provide real-time consumption data with electricity price information, allowing users to curb electricity consumption if electricity prices are increasing. As information flows iteratively between the meter and the end user, we stress that such a system is a closed informational system allowing (potentially) for correction of consumption in a continuous manner (see 'inductive process' from Section 4.2).

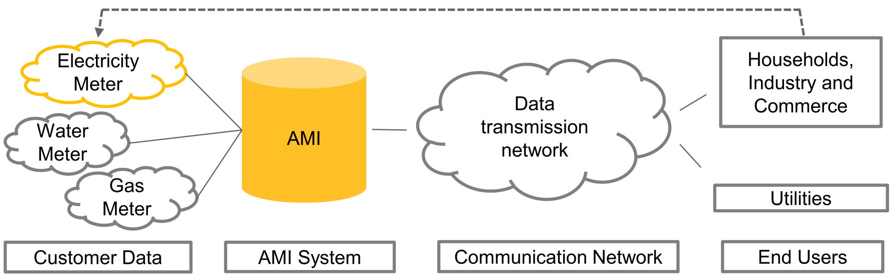


Figure 4.6: Simplified illustration of Advanced Meter Infrastructure (AMI) and its informational feedback

4.8.2 Development of Energy-Efficiency Savings in California

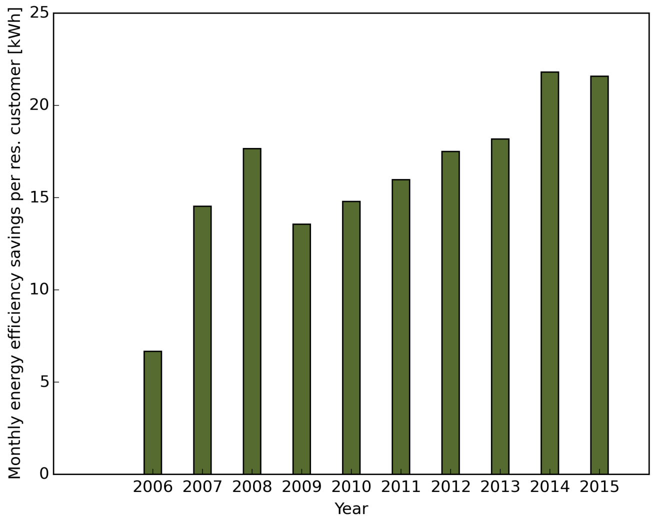


Figure 4.7: Development of energy-efficiency savings in California over time

Depicting the development of energy-efficiency saving estimates for California in Figure 4.7, we identify a significant and rather continuous impact of energy-saving measures beginning in 2007.

4.8.3 Descriptive Statistics: Difference-in-Differences Variables

Table 4.5: Descriptive statistics: Differences in levels (California minus Synthetic California)

Variable	N	Mean	SD	Min	25%	Median	75%	Max
ΔCDD_m	168	0.01	0.05	-0.12	0.00	0.005	0.002	0.18
$\Delta Demand_m^{res,adj}$	168	-0.02	0.05	-0.20	-0.05	-0.02	0.00	0.11
ΔHDD_m	168	-0.22	0.22	-0.83	-0.41	-0.18	-0.01	0.09
$\Delta Price_m^{res}$	168	0.005	0.015	-0.079	-0.003	0.006	0.014	0.039
$\Delta Unemployment_m$	168	0.016	0.012	0.00	0.00	0.01	0.027	0.04
$\Delta Wage_m$	168	0.03	0.05	-0.14	0.01	0.04	0.06	0.10
ΔAMI_m	168	0.393	0.444	0.000	0.000	0.131	0.954	0.997

4.8.4 Empirical Results: Weight Vector V for the Exogenous Variables

The weight vector V is presented in Table 4.6.

Table 4.6: Weights of the exogenous variables

Label	Weight
$CDD_{m,s}$	0.109
$Clothesdryer_{m,s}$	0.091
$Education_{m,s}$	0.008
$Elderlypeople_{m,s}$	0.010
$Floorspace_{m,s}$	0.071
$GDP_{m,s}$	0.119
$HDD_{m,s}$	0.263
$HeatingEquipment_{m,s}$	0.090
$MainHeating_{m,s}$	0.040
$Oven_{m,s}$	0.000
$Price^{res}_{m,s}$	0.042
$Refrigerators_{m,s}$	0.009
$Rooms_{m,s}$	0.083
$Unemployment_{m,s}$	0.000
$Wage_{m,s}$	0.149

4.8.5 PV Self-Consumption

In general, we calculate the quantity of self-consumed electricity generation as the difference between the total electricity generation by PV systems and the amount that is fed back into the grid. Monthly data with respect to the total electricity generation from renewable energy plants in the residential sector that is fed back into the grid are provided by the U.S. Energy Information Administration (EIA) (Energy Information Administration, 2016b). Furthermore, the EIA provides data on the total capacity of PV systems installed on a residential level. However, there are no publicly available monthly data on the total PV electricity generation in households. This is due to the concept of net metering. Thus, we use a heuristic approach in order to derive PV electricity generation data. More precisely, our approach is based on the monthly average global horizontal irradiance, which is given in $\frac{kWh}{m^2d}$ for each state by the National Renewable Energy Laboratory (National Renewables Energy Laboratory, 2016). The respective averages were derived from observations between 1998 and 2009 and do not vary across the years during our period of observation. We assume a typical efficiency of 13.2% for PV systems and a power density of $9m^2/kWp$. For illustration purposes, our calculation methodology is expressed in Equation 4.4.

$$\begin{aligned} SelfConsumption_{m,s}^{res,PV} = & InstalledCapacity_{m,s}^{res,PV} \cdot \overline{Irradiation}_{m,s}^{GHI} \\ & \cdot Days^{month} \cdot Efficiency^{PV} \cdot Area^{kWp} \\ & - FeedBack_{m,s}^{res,PV} \end{aligned} \tag{4.4}$$

4.8.6 Difference-in-Differences Estimation: Additional Evidence for Causality

By controlling for differences in electricity consumption apart from those related to AMI, we provide additional evidence for causality. In more detail, we include yearly time dummies in addition to the share of AMI to control for other impacting factors. All the respective time dummies yield insignificant coefficients as depicted in Table 4.7. One may claim, therefore, that we identify no impact on residential electricity consumption other than that induced through the deployment of smart meters.

Table 4.7: IV Estimates for DiD estimation when controlling for yearly time dummies

Dependent variable: $\Delta Demand_m^{res,adj}$	
Explanatory variable	IV (1)
2003	-0.003
	(0.008)
2004	-0.009
	(0.009)
2005	0.009
	(0.021)
2006	0.011
	(0.011)
2007	-0.006
	(0.01)
2008	0.022
	(0.028)
2009	0.049
	(0.034)
2010	0.056
	(0.050)
2011	0.078
	(0.052)
2012	0.041
	(0.037)
2013	0.035
	(0.029)
2014	0.002
	(0.034)
ΔShare $AMI_{total,m}$	-0.035***
	(0.015)
$\Delta Price_m^{elec,res}$	-0.42
	(1.08)
ΔCDD_m	0.70***
	(0.09)
ΔHDD_m	0.03***
	(0.02)
$\Delta Unemploymentlvl_m$	-0.22
	(0.13)
$\Delta Wage_m$	0.07
	(0.06)
$observations$	167
R^2	0.45
F	23.8
p-value	0.00

Notes to Table 4.7: Robust standard errors in parentheses. * / ** / *** : significant at the 0.05 /0.02 / 0.01 error level respectively. We use data from January 2002 until December 2015.

4.8.7 Simplified Residential Schedules

Residential schedules from PG&E and SCE, as shown in Figure 4.8, may not fully reflect the wide range of tariff designs provided by the IOUs. As one example, we do not consider schedules from the CARE program where customers are eligible for reduced tariffs. Moreover, rate structures may be subject to changes over time. Our data were collected in the first quarter of 2016. However, the samples below illustrate tier and time-of-use schedules in a simplified way.

PG&E

Residential Schedule E-1

	Tier 1 Baseline	Tier 2 101-200% baseline	Tier 3 >200% baseline
$/kWh	0.18	0.24	0.40

Residential Time-of-Use Rate Schedule E-7

$/kWh Summer (Winter)	Tier 1 Baseline	Tier 2 101-200% baseline	Tier 3 >200% baseline
Peak	0.38 (0.16)	0.44 (0.22)	0.60 (0.38)
Off-Peak	0.13 (0.13)	0.19 (0.19)	0.35 (0.35)

SCE

Domestic Schedule D

	Tier 1 Baseline	Tier 2 101-200% baseline	Tier 3 >200% baseline
$/kWh	0.16	0.23	0.29

Domestic Time-of-Use Schedule D

$/kWh	Summer (Winter)
Peak	0.44 (0.33)
Off-Peak	0.28 (0.28)
Super-Off-Peak	0.13 (0.14)

Figure 4.8: Simplified schedules for tier and time-of-use in the residential sector

Generally, tiers may be subject to change in terms of numbers, territory, and pricing as well. Significant differences in the tariff structure for time-of-use schedules stem from the definitions of peak and off-peak. In the above example, PG&E defines peak hours as ranging from 12 am to 6 pm, whereas all other hours are declared off-peak. For SCE, peak hours are defined as ranging from 2 pm to 8 pm. The off-peak period begins at 8 am and lasts until 2 pm. Additionally, the period from 8 pm to 10 pm is considered as off-peak. The 'super off-peak' period comprises the hours between 10 pm and 8 am, while peak is replaced by off-peak at weekends.

5 Electricity Reduction in the Residential Sector - The Example of the Californian Energy Crisis

Leveraging conservation potential within the residential sector is one important topic for countries aiming to save electricity. In this article, I study the conservation programs that were initiated in order to counteract electricity blackouts within the Californian Energy Crisis. By applying synthetic control techniques I first identify the overall electricity reduction for the residential sector. The effectiveness of conservation programs taken to leverage electricity reduction potential is then estimated with a treatment regression. I find that a reduction is jointly achieved by the mass media campaign and '20/20' rebate program resulting in quarterly reductions between 6% to 12%. I furthermore argue that despite the possibility of replacing electrical household equipment, some residential consumers must have been able to change consumption habits to uncover the majority of this potential.

5.1 Introduction

Efforts to encourage reductions in residential electricity consumption have a long history in the State of California. The starting point for an analysis of mechanisms targeting reductions has been the Energy Crisis when severe supply shortages caused electricity outages during the year 2000. As a consequence, the academic debate about the consumer's willingness and capability to reduce electricity consumption over short time horizons has been raised during the crisis and beyond. In a broader context the debate focuses today on identification strategies of potentially available electricity reductions and find ways to effectively leverage them.

In the residential sector, energy economic related research primarily considers electricity price-driven mechanisms, both theoretically and empirically, arguing that stronger electricity price signals reaching the consumer might effectively reduce consumption in 'stressed' electricity market situations. In this context real time pricing has been extensively discussed, however conclusive evidence on reduction effects is lacking so far. Empirically, findings are often based on field experiments that fall short of making general statements. By studying the unique events of the Energy Crisis, I contribute to the analysis of electricity prices impacts on an aggregated level and complement prior research by studying the impact of two state-induced conservation measures whose impact has so far only found minor attention and, to the best of my knowledge, not been quantified so far. In the particular case of California, the nationwide efforts to promote electricity savings through the mass media campaign and '20/20' rebate program mutually targeted a behavioral change for electricity usage as opposed to a monetary incentive program targeting a replacement of technical household equipment. As such it implicitly raised the question if electricity reductions over short time spans can be realized through a change in electricity use by encouraging residential consumers with monetary and non-monetary conservation programs.

The article at hand empirically analyzes the effectiveness of the two conservation programs jointly and covers a 48-month period that fits the events before and after the Energy Crisis. Such an analysis needs to be unbiased of other (technical) energy efficiency or other conservation programs than the ones analyzed, ruling out interactions with other programs over the same period. My analysis methodically makes use of constructing a synthetic control group leading me to the structural comparison of the residential consumption in the treatment (California) and control group state ('Synthetic Energy Crisis California'). The differences in residential electricity consumption allow to comment on an overall residential consumption reduction and have not been quantified so far. I then measure and evaluate the different sources impacting residential electricity reduction with a treatment regression.

I find that a reduction of residential electricity consumption in California ranges between 6% to 12% depending on the quarter of the respective post crisis year. Over the years 2001 and 2002 the quarterly reductions timely coincide with the mass media campaign and the '20/20' rebate program. By controlling for the influence of weather, economic indicators and the residential electricity price, my treatment regression results show overall higher residential electricity reductions from the conservation programs in 2001 compared to 2002 which I relate to the fade-out of the mass media campaign in 2002. Furthermore, residential electricity reduction occurred more strongly over the summer months compared to winter months providing some evidence that consumers willingness to give up a certain comfort level in winter is restricted. In total, the initially targeted 20% of electricity reduction for the residential sector has never been reached, neither by the '20/20' rebate program nor by the joint impact of the mass media conservation campaign and the '20/20' rebate program.

Overall, I conclude that the measured electricity reductions have been strongly supported by the '20/20' rebate program and the mass media campaign. The effectiveness of the two conservation programs has been enhanced by the design of each program. In particular, the mass media campaign and the rebate programs conveyed a clear and easy to understand message to the residential consumer facilitating information processing for the consumer as for instance compared to complex pricing schemes (Ito, 2014). My findings make a valuable contribution to the debates around electricity conservation programs and their effectiveness while accounting for the impact of residential electricity prices on consumption. Since residential electricity reductions based on the programs occurred, a portion of residential consumers must have been able to change certain habits that reduced electricity usage and thus uncovered electricity saving potential. At the same time it is reasonable to assume that no major change in household equipment stock occurred. I argue that this stems from the unique events of the crisis, the short time span and the non-existence of other fierce reduction programs targeting a replacement of household equipment.

The remainder of this article is organized as follows. Section 5.2 provides a literature background for the Energy Crisis from an economic and regulatory perspective and discusses electricity price impacts on residential electricity consumption. Section 5.3 discusses the conservation programs for the Californian market in detail. A data description is presented in Section 5.4 and Section 5.5 shows the used estimation approaches and discusses the estimation results. Section 5.6 concludes.

5.2 Literature

Literature surrounding the Californian Energy Crisis is divided into analyses attempting to understand the economic and regulatory factors leading to the Energy Crisis, the conservation programs taken to contain the Energy Crisis and demand responses in the Californian energy market. Furthermore, regulatory suggestions to prevent further crises are made.

Causes for the crisis in California have been analyzed in different articles. Economic and regulatory factors triggering the crisis are extensively studied by Woo (2001), Stenglein (2002), Blumstein et al. (2002) and Weare (2003), who all emphasize that such factors included a shortage of generating capacity while electricity demand sustained[54], bottlenecks in related (gas) markets, faulty market design and potential market power abuse. Whereas all of the above articles describe the root causes for the Energy Crisis in detail, Wolak (2003) and Borenstein (2002) stress regulatory-driven mitigation strategies that could prevent such crisis. In particular, Wolak (2003) argues that instant regulatory intervention is crucial to correct supply break downs in flawed markets and conservation programs have to be quickly implemented if a meaningful distressing effect on the energy balance is desired. In contrast to this rather short term focus of Wolak's article, Borenstein (2002) stresses that long term contracts between buyers and sellers in electricity markets may generally stabilize the market and thus provide a certain security of supply in the long run. Joskow (2001) adds to those factors the analysis of power procurement initiatives helping to stabilize in his view the energy market.

Besides the causes for the crisis, the effect of demand responses due to electricity prices in the Californian electricity market has been studied as well. The predominant motivation for that is that demand response programs target to relieve the demand side thereby triggering bill savings, contributing to a reliable electricity system through reduced outages and reducing potential market power. Albadi & El-Saadany (2008) provide a comprehensive summary of demand response options for electricity markets, distinguishing between incentive and price based programs. As opposed to direct load control programs, the latter contain electricity price based demand responses such as peak and off-peak, time-of-use and real time pricing that have strongly been discussed in the context of the Energy Crisis since their individual contributions remain debated. Herter et al. (2007), for instance, argue that peak pricing results in demand reductions, however the results are based on a rather small field experiment making an assertion claiming generality in a larger framework questionable. Borenstein (2002) stresses that a real time pricing scheme might stimulate instant demand and supply reactions, thereby benefiting the functioning of the market as a whole. However, his theoretical thoughts require from the residential consumer the processing of all information resulting from a non-linear pricing scheme, an argument that Ito (2014) takes up in his work. Contrary to the literature streams on demand-reducing impacts of real-time pricing, Ito (2014) argues that consumers faced with complex non-linear pricing schemes are not able to draw right conclusion from such complex schemes. As such he concludes that, if at all, consumer react to average rather than marginal prices, making non-linear

[54]The authors consistently argue these shortages are linked to the low hydro reservoirs during the Energy Crisis, the 16GW capacity revisions made at the end of the summer 2000, and the lack of investments into new capacity prior to the crisis.

pricing schemes in terms of electricity conservation useless. By studying the residential electricity consumption reduction in the San Diego's service area, Reiss & White (2003) argue that besides the price impacts consumers reacted to the broadcasted mass media campaign more than initially expected thereby extending price based arguments made in conjunction with residential electricity reduction.

It is worth stressing that during the Energy Crisis residential customers in California were charged for electricity usage based on two-tiered tariffs distinguishing between consumers using a static baseline consumption volume or a high volume. When faced with two-tiered tariffs, it remains questionable to argue that residential consumers reacted to the price changes, since neither a price signal is provided to the residential consumers, nor did consumers sign contracts reflecting instantaneous electricity price changes. Additionally, wholesale price increases were not fully passed on to the residential consumer during the Energy Crisis (Wolak, 2003). Furthermore, doubts on consumers willingness and ability to filter out the price effect amid all other sources impacting demand (i.e. weather) raises further doubts on the consumer's responsiveness to residential electricity prices. To sum up, evidence on factors such as electricity prices remains ambiguous and an analysis of the root causes for demand reduction during the Energy Crisis needs to incorporate all demand variation sources.

In my article, I therefore first determine the overall residential electricity reductions, which may be more broadly interpreted as reduction potential.[55] Surprisingly, this first step is so far lacking in the literature and provides a baseline against which all demand reducing efforts regardless of their origins can be assessed. Secondly, any electricity price effects resulting from price movements are taken into my analysis allowing me to comment on a electricity price-driven impact on residential consumption. Thirdly, by focusing on the effects of two residential conservation programs, I evaluate their consumption reducing effect for the residential sector through a treatment estimation. The two investigated residential conservation programs are unbiased of other efficiency programs and have so far found only minor attention in the literature which is partly due to the challenges that need to be overcome when constructing suitable control groups on a national level. Contrary to the issue of a potentially 'modest' price signal within the residential sector, the analyzed conservation programs provided a clear and simple consumption-reducing message directly addressing the consumer.

[55] A reduction potential describes an amount of electricity reduction that can be (theoretically) realized but might not be fully leveraged in reality due to, for instance, comfort issues and a consumer's sluggish adjustment with respect to secondary energy use.

5.3 The Energy Crisis and its containment through conservation programs

During the Californian Energy Crisis the Californian residents suffered from electricity outages not due to extreme weather conditions but rather low hydro reservoirs, and large undertaken capacity revisions during times when electricity demand increased (Energy Information Administration, 2017) and wholesale power prices spiked (CPEC, 2000). According to Weare (2003) electricity consumption increased by about 3 percent between 1998 and 2000 in California and from 2000 to 2001 by 6 percent (Energy Information Administration, 2016b). The resulting imbalance between an increased demand and unchanged generation capacity was also flagged by the Californian Independent System Operator (CAISO) which, as a consequence, in summer 2000 declared an emergency stage 1 alert for system security reasons.

As the events unfolded, the threat for outages continued and reached its peak shortly thereafter in November 2000 when 16 gigawatts of the total generation capacity were taken out of the market by Pacific Gas & Electric (PG&E), Southern California Edison (SCE) and San Diego Gas & Electric (SDG&E) due to servicing (c.f. Blumstein et al. (2002)).[56] The 16 GW reflected 35% of the total Californian generation capacity. Although servicing has been rationalized based on heavy plant running times during the summer 2000 by the three major investor-owned utilities (IOUs), other arguments for offline plants have been discussed, such as Joskow (2001) arguing that market manipulations may have played an important role.

Whatever the exact reasons have been, the threat for blackouts was severe and state leaders decided to throw considerable resources into promoting electricity conservation programs targeting a reduction in electricity usage from 2001 on. The undertaken conservation programs to contain the Californian Energy Crisis were accompanied by strong governmental policies (International Energy Agency, 2005). Over half a billion dollars were allocated in the beginning by the Californian legislature to fund these conservation programs as a short-term policy action for electricity conservation. One of those programs was a mass media campaign belonging to the marketing campaign 'Flex Your Power' that was coordinated through the State of California and the Consumer Services Agency (Todd & Wood, 2006). In January 2001 this conservation effort was signed and became active. It included voluntary partnerships working on the reduction of electricity consumption, the distribution of

[56] The Figure 5.4 of the Appendix provides a monthly comparison for capacity revisions between 1999 and 2000 shortly before the conservation programs for containment of the Energy Crisis unfolded.

informational material to consumers, the promotion of energy conservation lessons and small events promoting the future use of Energy Star appliances. The 'Flex Your Power' program however focused on the mass media broadcasts to promote a deliberate use of electricity during the Energy Crisis (Bender et al., 2002). The target of the 'Flex Your Power' campaign to reduce electricity consumption and peak demand over summer periods was encouraged by a series of television, radio and newspaper ads, as well as educational material. To induce a behavioral change in electricity usage, the campaign concretely promoted shifting laundry and dish washing from peak hours to off-peak hours, turning-off lights, unplugging equipment and adjusting thermostats of electricity intense air conditions (Lutzenhiser, 1993). The ads used were designed in a way to attract different target audiences defined by age, ethnicity and language spoken. The campaign particularly targeted the summer of 2001 and 2002, however it didn't come to a complete stop in other seasons. Except for two off-air periods in April 2001 and March-April 2002, the mass media campaign was conducted regularly until summer 2002 and with an initial frequency of 50 television and radio ads per week from February through mid-September 2001. After September the frequency for television and radio spots decreased to 25 times per week in 2001. Full-page newspaper ads ran one time per week from May through July 2001. For the rest of this first program year newspaper ads appeared every second week.

In parallel, the State of California launched a conservation rebate program in order to further contain the crisis. The '20/20' rebate program encouraged nationwide consumers conservation behavior and rewarded consumers for electricity savings. Therefore, the California Public Utility Commission (CPUC) passed on an executive order to the three largest Californian investor-owned utilities (IOUs) and urged all three to implement a rebate program. The program consisted of a 20% discount to customers on their monthly bills in June, July, August and September 2001 and in July, August, September and October 2002 respectively. Discounts were offered if the customers consumed 20% less electricity compared to the same months in 2000.[57] All customers who qualified participated automatically in this rebate program and were credited for conservation efforts by the internal billing system of each utility.

Figure 5.1 shows the two conservation programs and their implementation periods. Whereas the mass media campaign for electricity reduction continued over a longer time span, however with varying intensity, the '20/20' conservation rebate

[57] SDG&E customers had to reduce their residential electricity consumption by 15% compared to 2000. A residential sample bill accounting for conservation efforts under the '20/20' program is shown in Figure 5.3 of the Appendix.

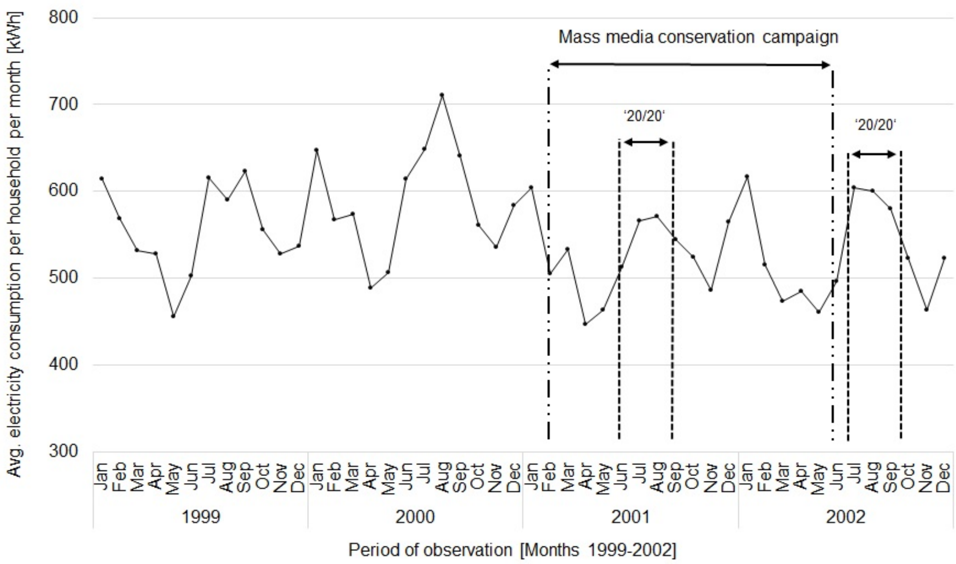


Figure 5.1: Californian residential electricity consumption and conservation programs

program targeted summer periods where residential electricity consumption was historically at high levels. The average electricity consumption per household displayed in figure 5.1 depicts the respective residential electricity consumption before the first signs the crisis in the summer of 2000 (Section 5.2). As such, Figure 5.1 also shows that the two state-induced conservation programs unfolded rapidly after the supply shortage in November 2000.

5.4 Data

My empirical analysis is based on a 48-month period starting in January 1999. Variables contain information on residential electricity consumption over time and account for differences between the states. These differences are reflected over time within the panel data set. Since some of the data used as explanatory variables display varying temporal and regional resolutions (see Table 5.1), I adjust the data in such a way that it first fits the monthly temporal resolution and second that it reflects state-specific data thereby extending prior data work of Paschmann & Paulus (2017). The adjustment is solely done for the household survey data obtained from Energy Information Administration (2016a).

5.4.1 Dependent Variable: Residential electricity consumption

I gather monthly residential electricity consumption data from the Energy Information Administration (2016b) in order to analyze the impact of electricity conservation programs within the context of the Energy Crisis. To measure conservation program impacts on residential electricity consumption during the Energy Crisis, other energy efficiency or conservation programs and their impacts on residential electricity consumption need to be thoroughly accounted for. The reason for this is that other programs might distort the impact of the analyzed conservation programs on residential electricity consumption. Fortunately, rigor programs targeting electricity reduction through energy efficiency or conservation programs have been implemented after and foremost as a consequence of the Energy Crisis leading to Energy Action Plans in 2003 and 2005 (California Energy Commission, 2003, 2005).[58] Energy efficiency and conservation programs for the residential sector before the Energy Crisis were thus negligible despite early implementation attempts for net metering in 2000 (CPUC, 2005).[59] Due to the lack of energy efficiency and conservation programs prior to the Energy Crisis, an adjustment of residential electricity consumption data is not needed.

The data on residential electricity consumption itself consists of monthly (m) state-specific (s) electricity sales in the residential sector including data for PG&E, SCE, and SDG&E. Residential customer of all three IOUs account for the major share of all Californian residential customers ($> 72\%$) and residential electricity consumption ($> 74\%$) over the respective period. This guarantees no loss of representative nature when assessing the impact of the analyzed conservation programs in the residential sector. Monthly state-specific electricity sales are then divided by the respective number of customers in order to derive the average monthly electricity consumption per household ($Demand^{res}_{m,s}$).

5.4.2 Explanatory Variables

Table 5.1 gives an overview of all variables used for the synthetic control group derivation and the two stage treatment regression. Electricity consumption is de-

[58]Both Energy Action Plans considered programs that provided explicit incentives for demand reduction and energy efficiency investments, fostered dynamic pricing, and issued additional energy conservation programs.

[59]Renewable capacity deployment with net metering was low, not reaching 25MW by 2005 for the residential sector. It took until the roll out of smart metering devices to accurately program residential fed-back electricity volumes.

pendent on the respective season, triggering the usage of a series of devices or applications within the residential sector. Thus, cooling degree days (CDDs) and heating degree days (HDDs) are calculated for all U.S. states from 1999 to 2002.[60] The meteorological data stems from the National Oceanic and Atmospheric Administration (NOAA). Other explanatory variables such as residential electricity consumption, sales, number of customers, and average electricity prices are taken from the U.S. Energy Information Administration (EIA). Data on the employment level and wages stem from the Bureau of Labor Statistics (BLS). All data from the EIA and the BLS is provided on a monthly and state-specific level.

In order to explain relative differences of residential electricity consumption between the U.S. states, I furthermore rely on household survey data for each U.S. state. The Residential Energy Consumption Survey (RECS) and the American Household Survey (AHS) provide suitable sources in which data for electricity intense households equipment and appliances such as the average number of refrigerators or electric ovens per household are published. Additionally, the survey gathers data on physical and demographic household characteristics such as for instance the average number of rooms or floorspace per household or the share of household members with a high school degree or higher as well as the average number of kids living in each state and household. All variables and thus all details including sources and temporal resolution are shown in Table 5.1. Raw data from RECS is converted into monthly values assuming no change over time until the next reference point.[61] For the given 48-months period analyzed, I am able to make use of two reference points in time. The data for these reference points stem from the national surveys in 2001 and 2005.

[60]To compute HDDs, all days showing differences between daily high and low temperatures above 65°Df are summed up for the month and standardized to 1000.

[61]Despite the fact that monthly data is not available in RECS, such a data conversion is applicable if monthly variation over time is assumed to be low, which may be the case for some variables (i.e. average floor space). All descriptive statistics used for the empirical estimations are shown in Table 5.3 of the Appendix.

Table 5.1: List of variables and references

Label	Explanation	Resolution	Region	Measure	Ref(2017)
$CDD_{m,s}$ $HDD_{m,s}$	Cooling degree days, Heating degree days	Monthly	State-specific	Total	NOAA
$Clothesdryer_{m,s}$	Share of electric clothesdryers	'01,'05	Census regions	Relative share	RECS
$Demand_{m,s}^{res}$	Elec sales per household	Monthly	State-specific	kWh	EIA
$Floorspace_{m,s}$	Avg. floor space per household	'01,'05	Census regions	m^2	RECS
$GDP_{m,s}$	Total real GDP divided by number of employees	Yearly	State-specific	USD	BLS
$Heating$ $Equipment_{m,s}$	Share of households using electric heating	'01,'05	Census regions	Percent	RECS
$MainHeating_{m,s}$	Share of households with electricity as main heating fuel	'01,'05	Census regions	Percent	RECS
$Oven_{m,s}$	Avg. number of electric ovens per household	'01,'05	Census regions	Total	RECS
$Price_{m,s}^{res}$	Avg. electric price for residential customers	Monthly	State-specific	Cents/ kWh	EIA
$Refrigerators_{m,s}$	Avg. number of refrigerators per household	'01,'05	Census regions	Total	RECS
$Rooms_{m,s}$	Avg. number of rooms per household	'01,'05	Census regions	Total	RECS
$Unemployment_{m,s}$	Unemployment level	Yearly	State-specific	Relative level	RECS
$Wage_{m,s}$	Avg. weekly wage	Monthly	State-specific	USD	BLS
$Kids_{m,s}$	Avg. number of children	Monthly	State-specific	Total	RECS

Notes to Table 5.1: Census regions include 9 regions and 4 states (CA, NY, FL, TX) if not otherwise stated. The exact references are: NOAA (National Oceanic and Atmospheric Administration, 2016), RECS (Energy Information Administration, 2016a), EIA (Energy Information Administration, 2016b), BLS (Bureau of Labor Statistics, 2016), NREL (National Renewables Energy Laboratory, 2016).

5.5 Empirical Application

I use a two-stage empirical approach to assess the impact of electricity conservation during the Energy Crisis based on the identified electricity reduction. First, I derive a synthetic control group reproducing Californian residential electricity consumption characteristics. As a result this control group resembles the Californian residential electricity consumption pattern, however the control group will not be exposed to events that happened in California during the post crisis years 2001 and 2002. Furthermore, I display the development of residential electricity consumption in the treatment state (California) and the control group state 'Synthetic Energy Crisis California' (SECC) on monthly basis. To link residential electricity reduction to its influencing factors, I then conduct a two stage least-squared treatment regression in a second step. The regression aims at analyzing the significance of state-level residential electricity conservation programs, i.e. the mass media campaign for electricity conservation and the '20/20' rebate program, and their mutual impact on residential electricity consumption.

5.5.1 Synthetic control group derivation and results

Residential electricity consumption varies substantially on a federal and regional level. Most of the difference are due to states' demographic structures with respect to age or family structure, climatic conditions, economic aspects as well as housing and social characteristics. Such a rich set of explanatory variables for residential electricity consumption imposes strong requirements on a potential control group state reflecting Californian characteristics before the Energy Crisis in California. Thus, a single state may not be able to capture Californian residential electricity consumption appropriately. As a consequence, I apply a synthetic control method for the Energy Crisis in order to resemble the residential electricity consumption in California before the Energy Crisis. As a result, the SECC resembles the Californian residential consumption pattern prior to the events of the Energy Crisis by using a weighted combination of all U.S. states. The derivation of the control group with synthetic control methods is mainly based on Abadie & Gardeazabal (2003), Abadie et al. (2010) and Abadie et al. (2015), however applications on energy-economic related topics remain rare except for Paschmann & Paulus (2017).

The individual weights (w) for the synthetic control group state are determined by minimizing the difference between Californian characteristics (Y_1) and the respective characteristics in the resulting control group ($Y_0 \cdot w$). Equation 5.1 provides the formal description for minimizing this difference with the following objective function

$$\min_{w}(Y_1 - Y_0 \cdot w)'V(Y_1 - Y_0 \cdot w). \tag{5.1}$$

Nonnegative synthetic control weights (w) reflect states with similar consumption characteristics of the treatment state. State weights w sum up to one and the all data described under Section 5.4 are used for the derivation of the synthetic control group state.[62] To account for the relative importance of the individual explanatory variables Y of each state, a vector V containing nonnegative components is determined with a standard regression technique, as described by Abadie & Gardeazabal (2003) or Abadie et al. (2010). Based on the regression, the V vector is chosen such that residential electricity consumption per household for California before the tipping point of the Energy Crisis is best reproduced by the synthetic control. The weight vector V is computed by using all periods prior to the events of the Energy Crisis, since V may vary before and after these events due to different underlying causal relations between the residential consumption and its explanatory variables.[63]

Before measuring and commenting on the impact of the two nationwide implemented conservation programs on Californian residential electricity during the Energy Crisis, I identify a suitable point in time allowing me to distinguish between the actual Californian residential electricity development and a synthetic one displaying a counter factual consumption development. Furthermore, this point in time, motivated by the Energy Crisis outages, enables me to relate back all consumption impacts in the following periods to this point in time. I identify the 16 gigawatts capacity revisions of November 2000 as triggering event for the synthetic controls state since the November events constituted the peak of all destabilizing effects in the electricity market up to that point. It therefore supports the argument that supply shortages destabilized the electricity market to a point of 'no return'. As such, the chosen point in time additionally coincides with an official statement from the Federal Energy Regulatory Commission (FERC) which in November 2000 announced that the Californian Energy System is 'flawed' (Wolak, 2003).

As states for the control group should display similar residential consumption pat-

[62]Temporal resolution of the data is to some extend neglected within the synthetic control method, since the method is based on average values of the explanatory variables over all pre-treatment periods, regardless of the selected pre-treatment period.

[63]Details on weights are listed in Table 5.4 of the Appendix.

terns prior to events of the Energy Crisis, consumption patterns across all states are thoroughly analyzed before the use of the synthetic control. Clearly, the heterogeneity of consumption patterns across all U.S. states is large, showing states with consumption patterns differing in levels and monthly cycles. Thus, the set of suitable states for the synthetic control is naturally restricted since some states exhibit similar residential electricity consumption patterns and increases over the summer periods in 2000. Comparing year-over-year residential consumption increases in California with others states indicates that states with similar patterns and demand increases, i.e. between 5% to 10%, are Colorado, Missouri, Nebraska, New Mexico, Oklahoma, Texas and Utah.[64]

Not surprisingly, the synthetic control state 'Synthetic Energy Crisis California' (SECC) combines a subset of the above states. As a result, the synthetic control group states are Texas, Colorado and New Mexico, where Texas has a weight of 4%, Colorado has a weight of 13% and the weight of New Mexico amounts to 83%. A first comparison based on meteorological data such as average, maximum and minimum temperature, HDDs and CDDs reveals that New Mexico and Colorado have similar climate conditions and Texas resembles some of California's economic indicators such as average weekly wages or relative real income for the analyzed period. Robustness checks supporting the use of a synthetic control have been performed, in particular with respect to pre-period time selection and parallel trends. Varying the data base prior to the Energy Crisis leaves post treatment synthetic control state patterns as shown in Figure 5.2. Variations with respect to consumption patterns are below 1%. Additionally, a test to verify the parallel trends assumption for residential electricity consumption has been carried out. By splitting the entire pretreatment period into sub-periods, the test shows that the assumption of parallel trends is valid.[65]

Figure 5.2 shows that prior to the treatment, the residential electricity consumption pattern of 'Synthetic Energy Crisis California' resembles the actual Californian pattern. This is especially true when comparing both seasonality patterns and consumption levels. Californian residential consumption exhibits upwards and downwards movements in a range between 460 $kWh/month$ and 705 $kWh/month$. Similar seasonal patterns in levels are found for 'Synthetic Energy Crisis California' with residential electricity consumption per household ranging between 480 $kWh/month$

[64] Residential electricity consumption for those states over the 48-month period are depicted in Figure 5.6 of the Appendix.

[65] A detailed description on the test is provided in Section 5.7.6.

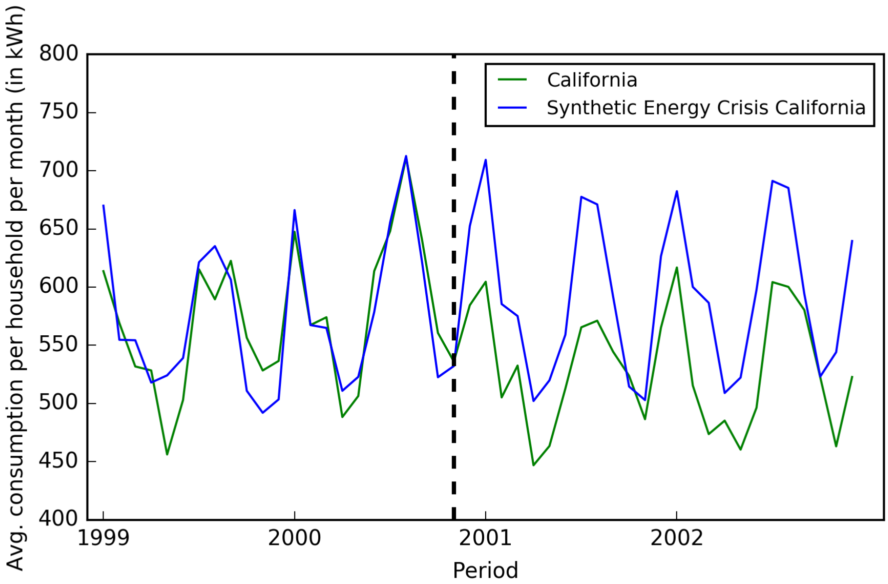


Figure 5.2: Descriptive Comparison for the 'Synthetic Control Group'-State (SECC) and California

and 705 $kWh/month$. On average, residential electricity consumption of 'Synthetic Energy Crisis California' is 4 $kWh/month$ lower than the pattern for California over the pre-treatment months. Thus, the synthetically derived SECC state reflects an accurate however not perfect match.

Periods after the treatment continue to show fluctuating patterns of positive and negative differences. However, after the year 2000 larger differences are observable in Figure 5.2. The residential consumption pattern for California shows an excess of negative differences (see Figure 5.5 of the Appendix) of on average -65kWhs. Taken together, the comparison is indicative of the negative influences on residential electricity consumption in the post treatment years 2001 and 2002. Nevertheless, the statistically negative excess of electricity has yet to be analyzed and put into perspective considering the conservation programs taken during the post treatment years 2001 and 2002.

5.5.2 Two-stage least-squared treatment regression and results

To quantify residential reduction stemming from the conservation programs, I conduct a two-stage least-squared treatment regression. By empirical design, the impact of the conservation impact is jointly analyzed using data for California and for

SECC. The effect of the conservation is jointly analyzed since both, the media campaign and the ‘20/20’ rebate program, occurred over the same time and mutually targeted a behavioral consumption change rather than the replacement of technical, more efficient, household equipment. The treatment term in the regression captures the electricity conservation within the Californian residential sector by interacting the observations of California and quarterly time periods within the Energy Crisis years 2001 and 2002. By applying a two-stage least-squared treatment regression, I am furthermore able to address endogeneity issues within electricity markets where electricity prices and residential electricity consumption are mutually dependent, especially if time horizons coincide. Although I expect the electricity price data used to be largely independent from the consumption since the electricity price I compute is averaged across IOUs and over the month thereby not clearly linking regional residential prices and consumption, endogeneity may not be completely ruled out. Another reason for that is that reverse causality may also stem from the ‘20/20’ rebate program itself since the program intended to achieve lower consumption levels based on the respective residential price in that month. Lutzenhiser (1993) and Hass et al. (1975), for instance, argue that consumer’s consciousness with respect to consumption and prices is more sensible in stressed situations increasing the likelihood to react to the conservation programs. I thus apply a two-stage least-squared treatment regression in order to first ‘disconnect’ the consumption in month m from the residential electricity price in the same month and secondly from indirect price sensitivity originating from the ‘20/20’ rebate program. The Equation 5.2 shows the first stage of the regression with residential electricity price lags

$$\ln p^{res}_{s,m} = intercept_1 + \gamma' \ln p^{res}_{s,m-1} + \epsilon_{s,m}, \tag{5.2}$$

where $\ln p^{res}_{s,m}$ is the logarithmic residential electricity price of the state s in month m and $\ln p^{res}_{s,m-1}$ is the logarithmic electricity price from the previous month. Furthermore, the standard instrument variable requirement, such as $cov[p^{res}_{s,m}, p^{res}_{s,m-1}] \neq 0$ has been verified, confirming the overall high autocorrelation (>0.8) among residential prices.[66]

The Equation 5.3 displays the second stage that accounts for other explanatory variables besides the instrumented residential electricity price. This log-linear esti-

[66]Testing for validity, expressed by $cov[demand^{res}_{s,m}, \mu] = 0$, is not feasible since the model is exactly identified. However, supporting qualitative evidence for supply shocks other than those discussed impacting the error term after the treatment is not present.

mation equation

$$\ln demand^{res}_{s,m} = intercept_2 + \alpha' Dummy_m + \delta' treatment_{qrty,y} + \beta_1' Y1_{s,m} + \beta_2' \ln Y2_{s,m} + \mu_{s,m} \tag{5.3}$$

allows me to comment on relative effect and captures both, linear and logarithmic explanatory variables, expressed by $Y1_{s,m}$ and $\ln Y2_{s,m}$. For linear explanatory variables, I choose weather conditions that are by definition exogenous. More precisely, I use heating and cooling degree days (HDD, CDDs) in order to infer on weather influences altering residential electricity consumption. For logarithmic explanatory variables, average weekly wage and the estimated residential electricity price from Equation 5.2 is used. Other influences on consumption arise from physical housing characteristics, however those are highly correlated to wage providing a good proxy for physical housing characteristics.[67] On the left hand side of the Equation 5.3, the logarithmic dependent variable $\ln demand^{res}_{s,m}$ reflecting the residential state-specific consumption is displayed. The treatment coefficient δ' will provide insights into the residential electricity reduction during the Californian Energy Crisis years 2001 and 2002 on a quarterly basis. Since I account for a general time trend with respect to residential electricity consumption by using monthly dummies ($Dummy_m$) over the 48-months period, the treatment term covers quarterly time horizons for each year in order to filter all other effects not related to monthly time trends.[68]

The estimation results reveal some interesting insights that are summarized in Table 5.2. First, I find that the cooling or heating degree days positively impact the residential electricity consumption through either the usage of air conditioning or electric heating within the residential sector. The magnitudes of the coefficients for CDDs and HDDs are low and significant at the 1% level contributing thus to the explanatory power of the overall regression model.[69] Furthermore, weekly wages reflect the purchasing power per state on a monthly basis. Those wages can partially be spent for electrical household equipment or more generally reflect the consumer's attitude towards residential electricity consumption by accounting for their income.

[67]Other explanatory variables such as family size or consumers' education have been analyzed and neglected for the estimation due to overall little variation within the data over the analyzed short time period.

[68]Variation for the estimation with respect to treatment time selection have been tested. Monthly treatment terms can be neglected, since high correlations between the monthly dummies and the treatment occur leading to estimation bias. The highest temporal resolution is thus obtained by quarterly treatment terms.

[69]R-squared is 90%.

As a monetary variable, wage is also closely linked to macro-economic indicators such as the gross domestic product (GDP) that similarly influences the electricity consumption pattern over the year. Additionally, wage is likely to relate to housing characteristics, such as housing size or even family size (i.e. number of children per household). As such the impact of wage on residential electricity consumption accounts for multiple factors. In the estimation, the coefficient for weekly wage is significant and shows a high positive influence on residential consumption.

Contrary to that, the estimation results reveal that the residential electricity price does not statistically impact the residential electricity consumption. This seems plausible since Californian residential electricity prices lacked instantaneous adjustment to wholesale price movements and, more importantly, residential consumers were not on real time pricing schemes during the Energy Crisis and rather signed contracts with their utilities for two-tiered tariffs over longer time periods.

I observe a significant impact of quarterly treatment terms whereas the impact of the treatment term differs with respect to the quarters of the years 2001 and 2002, as shown in Table 5.2. The respective electricity reduction in the first quarter is 9.1% which amounts to a reduction in levels of on average 50 kWhs per month and household.[70] The reduction effect coincides from a temporal perspective with the launch and thus the fierce promotion of electricity conservation within the mass media campaign in January 2001. In the second quarter of 2001 my results are indicative of a 11.0% reduction (52 kWhs) whereas from a timely perspective the potential conservation effects arising from the media campaign and the '20/20' rebate program overlap solely in June 2001. The treatment term for the 3rd quarter, $treatment_{Q3,2001}$, fully covers the '20/20' rebate program and the impact of the media campaign showing a maximum reduction of 12.1% reduction (68 kWhs). The first, second and third quarterly treatment effects within 2001 are furthermore significant at the 1% level. During the fourth quarter in 2001, no significant electricity reduction occurs which I relate to consumers' comfort issue preferring warm housing environments during winter. As radio, newspaper and television spots for electricity conservation continued, however with lower frequency, my estimation results reveal further electricity reductions for the following year. The quarterly treatment coefficients are however overall lower in terms of magnitude and decrease over time compared to 2001. The reduction in 2002 is 9.0% (down by 0.1%) in the first quarter, 6.4% (down by 4.6%) in the second quarter and 8.1% (down by 4.0%) in the third quarter. Thus, policy makers may achieve a reduction of electricity consump-

[70]The treatment coefficient δ is transformed by using [exp(δ)-1].

tion in on and off-peak months by implementing conservation programs whereas the impact of conservation programs is more strong in summer months.

Table 5.2: Determinants of monthly residential electricity consumption: IV estimation results

Dependent variable: $lndemand^{res}_{m,s}$		
Explanatory variable	Coefficient	Std. error
$CDD_{m,s}$	0.0008***	(0.000)
$HDD_{m,s}$	0.0002***	(0.000)
$lnWage_{m,s}$	0.2172***	(0.070)
$lnPrice^{res}_{m,s}$	-0.1199	(0.103)
$treatment_{Q1,2001}$	-0.0956***	(0.025)
$treatment_{Q2,2001}$	-0.1169***	(0.027)
$treatment_{Q3,2001}$	-0.1290***	(0.035)
$treatment_{Q4,2001}$	-0.0128	(0.023)
$treatment_{Q1,2002}$	-0.0938***	(0.038)
$treatment_{Q2,2002}$	-0.0666**	(0.031)
$treatment_{Q3,2002}$	-0.0845***	(0.034)
$treatment_{Q4,2002}$	-0.0446	(0.033)
$intercept_2$	-2.226***	(0.683)
monthly controls	yes	
$observations$	96	
R^2	0.897	
F	59,73	

Notes: Robust standard errors in parentheses. Instruments for 2SLS: Price lag (m-1) variable.***, ** and *: significant at the 1%-, 5%-, and 10%-level.

5.6 Conclusion

As a consequence of electricity outages that occurred in California in 2000, the State of California decided to curb electricity consumption with the help of two state-promoted conservation programs in the Energy Crisis targeting the years 2001 and 2002. With a potential residential consumption reduction, policy makers were hoping to contain the Energy Crisis and its electricity blackouts. Although the mass media campaign and the ‘20/20’ rebate program faced some initial critique, the Californian Government implemented both on a national level targeting behavioral changes for electricity usage in order to reduce residential electricity consumption.

The article at hand empirically analyzes the effectiveness of the two conservation programs jointly by conducting an empirical analysis in two consecutive steps. First, I make use of constructing a synthetic control group, called ‘Synthetic Energy Crisis California’ (SECC), not exposed to governmental conservation programs that resulted from the Energy Crisis. The resulting synthetic control group state leads me to the structural comparison of a treated and untreated state, whereas I interpret the resulting difference between the consumption patterns as reduction potential, that without the crisis would not have been revealed and has so far not been quantified. In a second empirical step, I conduct a two stage least-squared treatment regression assessing the effectiveness of the implemented conservation programs. By controlling for weather, electricity prices and economic indicators, I specifically filter out the conservation effect for all four quarters of the years 2001 and 2002.

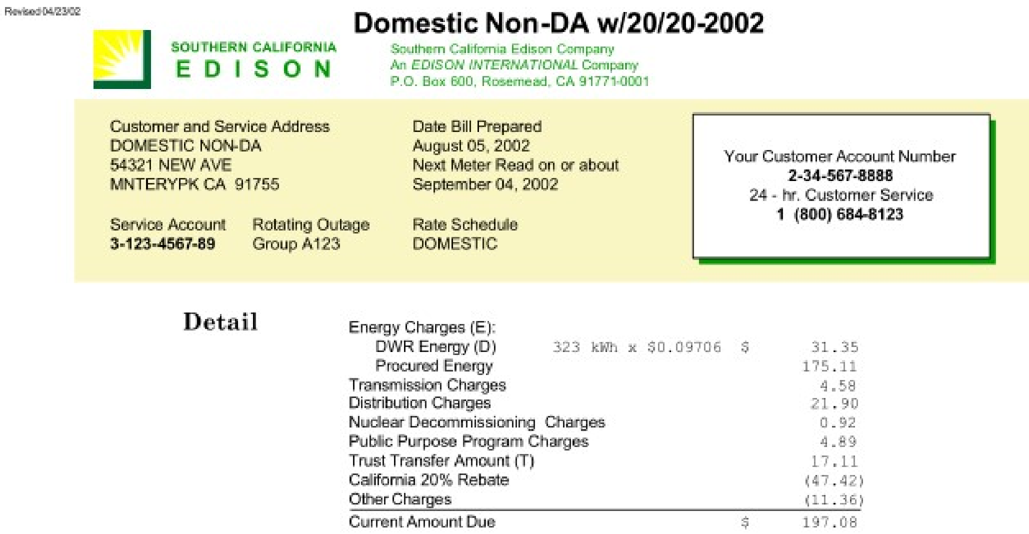
As expected, I find that heating or cooling increase residential consumption as well as the purchasing power of households, expressed by the significant positive coefficient of the wage indicator. I relate the positive impact of wages on residential consumption to the fact that wage is a good proxy for purchasing power interacting with a variety of influences on residential electricity consumption, such as housing and family size or conservation attitude itself. I furthermore find that residential consumption reductions temporally overlap with the conservation efforts in a consistent manner. Electricity reductions occur more strongly in 2001 compared to 2002 ranging between 6% and 12% depending on the analyzed quarter. Since the mass media ran with lower frequency in 2002 and was put into a broader energy saving context, this downward trend seems to be plausible. My result furthermore show that an envisaged residential electricity reduction of 20% has never been achieved neither by the ‘20/20’ rebate program or by the rebate program itself nor jointly by the rebate program and the mass media conservation campaign. Reasons for that are that not all customers, if at all, reacted likewise to the conservation incentives. Furthermore, I argue that an electricity consumption change driven by a structural replacement of household equipment was not present during the Energy Crisis and in particular not in the years 2001 and 2002. Firstly because no fierce policy incentivized residential consumers to replace equipment in the short time span and secondly attention was channeled towards conservation through altering electricity use. Thus, some residential consumers were rather able to change consumption habits in order to reduce electricity usage.

Nevertheless the estimation results need to interpreted with care, since I do not specifically control for the mass media campaign and the '20/20' rebate program. This is primarily driven by not finding suitable control variable data for the mass media campaign and the '20/20' rebate program that would explicitly account for the impact on residential electricity consumption. Additionally, some residential electricity reduction may also stem from other factors; an example for that could be a residential electricity consumer who made efforts to reduce electricity consumption during the Energy Crisis however was neither influenced by the media campaign nor participated in the rebate program due to not reaching the threshold of 20%.

Also, reductions in electricity consumption that resulted from the Energy Crisis cannot be generalized to other states in the U.S. or different countries. An argument to bring forward is that households and consumer (behavior) differ when analyzing other regions. Besides differences due to macro economic and geographically aspects on a country level, further differences stem from socio-economic and physical characteristics of households, as well as to the preference ordering of the individual household members when it comes to comfort issues. Nevertheless an analysis on obtrusive policy events can be carried out separately for other countries and sectors by thoroughly applying synthetic control techniques in order to address impacts on consumption in larger frameworks with lacking control groups.

5.7 Appendix

5.7.1 Exemplary residential sample bill from Southern California Edison (SCE)



Revised 04/23/02

SOUTHERN CALIFORNIA EDISON

Domestic Non-DA w/20/20-2002

Southern California Edison Company
An *EDISON INTERNATIONAL* Company
P.O. Box 800, Rosemead, CA 91771-0001

Customer and Service Address
DOMESTIC NON-DA
54321 NEW AVE
MNTERYPK CA 91755

Date Bill Prepared
August 05, 2002
Next Meter Read on or about
September 04, 2002

Your Customer Account Number
2-34-567-8888
24 - hr. Customer Service
1 (800) 684-8123

Service Account
3-123-4567-89

Rotating Outage
Group A123

Rate Schedule
DOMESTIC

Detail

Energy Charges (E):		
DWR Energy (D)	323 kWh x $0.09706 $	31.35
Procured Energy		175.11
Transmission Charges		4.58
Distribution Charges		21.90
Nuclear Decommissioning Charges		0.92
Public Purpose Program Charges		4.89
Trust Transfer Amount (T)		17.11
California 20% Rebate		(47.42)
Other Charges		(11.36)
Current Amount Due	$	197.08

Figure 5.3: Sample bill including '20/20' rebate for residential customers. [Source: Southern California Edison, 2017]

5.7.2 Total capacity revisions by the major three IOUs in 1999 and 2000

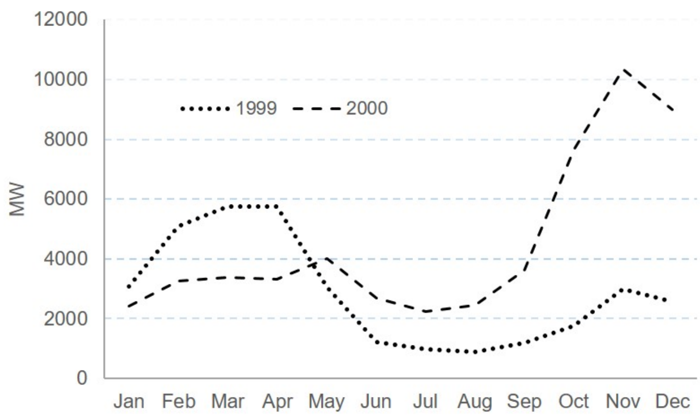


Figure 5.4: Un- or scheduled capacity revisions by IOUs in MW. [Source: Blumstein et al., 2002]

5.7.3 Descriptives for synthetic control and regression data

Table 5.3: Descriptive Statistics

Variable	N	Mean	SD	Min	25%	Median	75%	Max
$CDD_{m,s}$	490	111	163	0	0	16	177	651
$Clothesdryer_{m,s}$	490	0.8	0.117	0.472	0.758	0.806	0.869	0.94
$Demand_{m,s}^{res,adj}$	490	0.857	0.318	0.432	0.615	0.77	1.012	1.947
$Floorspace_{m,s}$	490	1980	236	1568	1757	1977	2277	2289
$GDP_{m,s}$	490	0.003	0	0.002	0.003	0.003	0.003	0.004
$HDD_{m,s}$	490	390	377	0	30	296	663	1504
$HeatingEquipment_{m,s}$	490	0.259	0.109	0.108	0.177	0.237	0.65	0.475
$MainHeating_{m,s}$	490	0.186	0.149	0.031	0.111	0 .179	0.247	0.5
$Oven_{m,s}$	490	1.066	0.011	1.043	1.058	1.064	1.076	1.081
$Price_{m,s}^{res}$	490	0.078	0.018	0.052	0.066	0.074	0.086	0.147
$Refrigerators_{m,s}$	490	1.205	0.0458	1.139	1.179	1.2	1.233	1.295
$Rooms_{m,s}$	490	5.728	0.233	5.134	5.597	5.809	6.948	6.014
$Unemployment_{m,s}$	490	4.404	1.085	2.7	3.4	4.4	5.3	6.8
$Wage_{m,s}$	490	614	86	475	549	593	669	837
$Kids_{m,s}$	490	0.694	0.044	0.648	0.648	0.696	0.738	0.738

5.7.4 Synthetic weight vector V for the exogenous variables

Table 5.4: Weights of the exogenous variables

Label	Weight
$CDD_{m,s}$	0.041
$Clothesdryer_{m,s}$	0.012
$Floorspace_{m,s}$	0.181
$GDP_{m,s}$	0.041
$HDD_{m,s}$	0.129
$HeatingEquipment_{m,s}$	0.135
$MainHeating_{m,s}$	0.017
$Oven_{m,s}$	0.023
$Price_{m,s}^{res}$	0.121
$Refrigerators_{m,s}$	0.116
$Rooms_{m,s}$	0.044
$Unemployment_{m,s}$	0.106
$Wage_{m,s}$	0.029
$Kids_{m,s}$	0.002

5.7.5 Difference Plot - Synthetic Control Group State 'SECC' and California

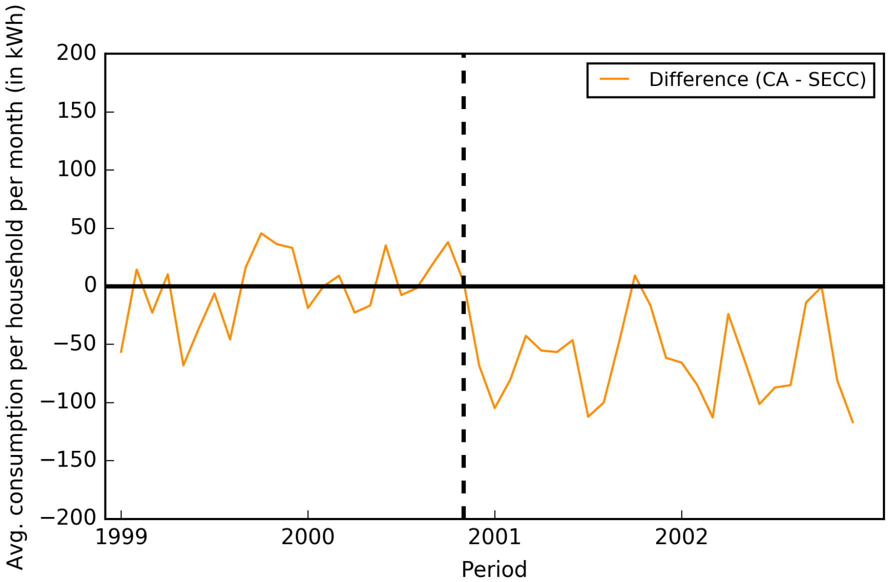
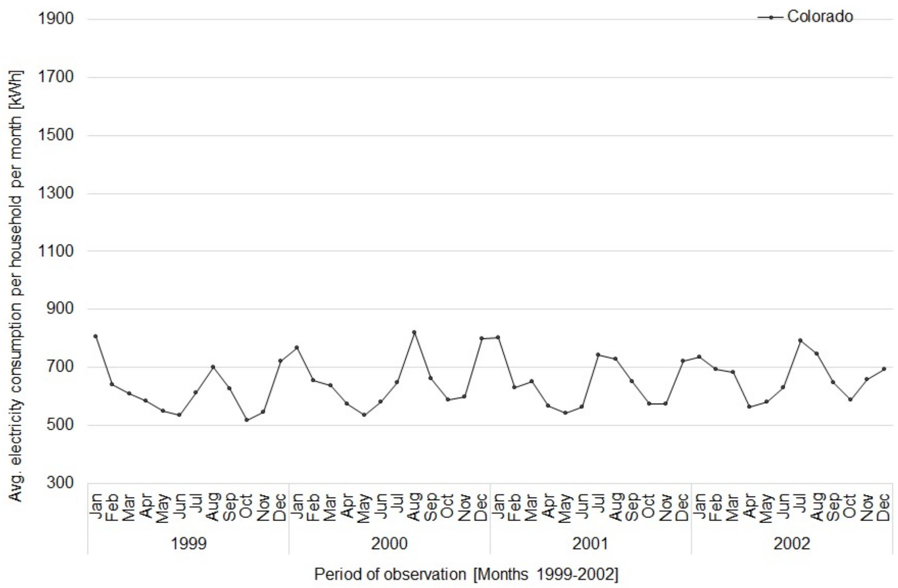
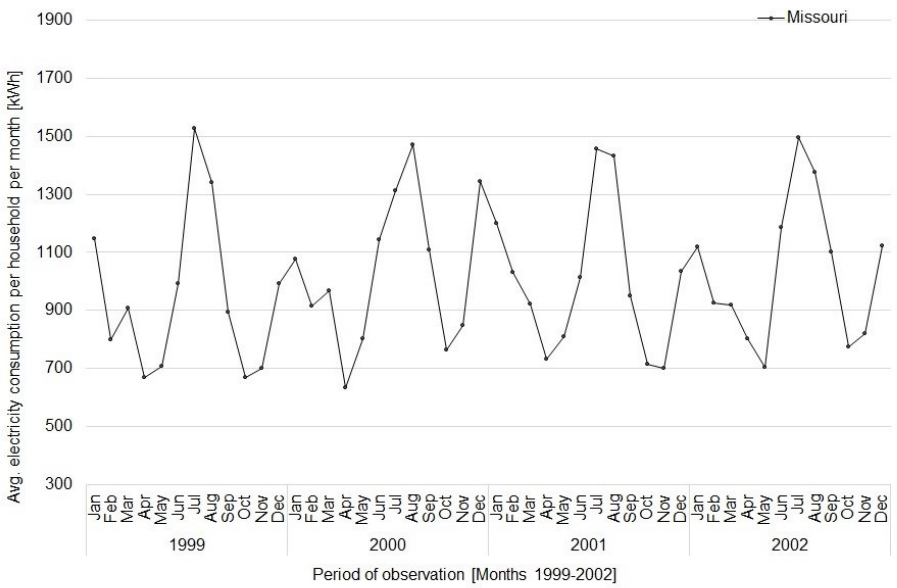


Figure 5.5: Synthetic Control Results - Difference Plot

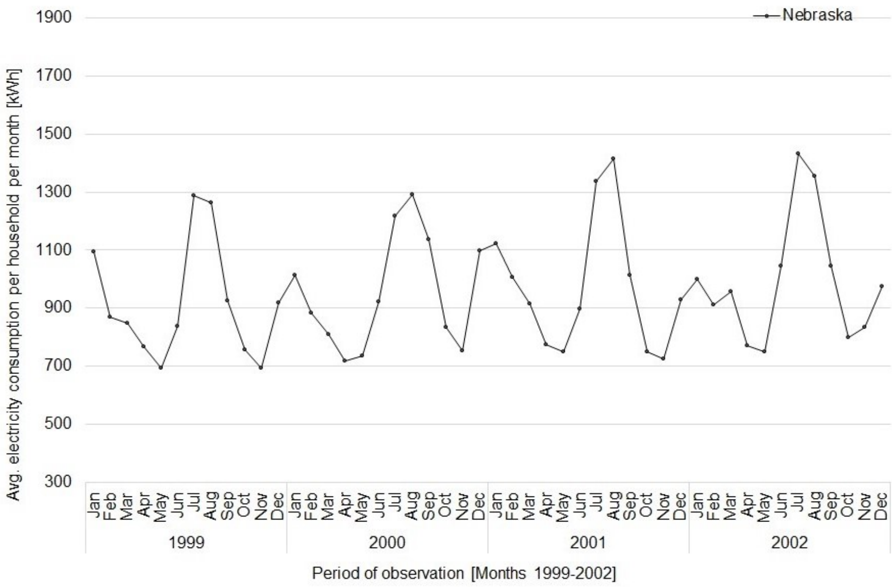
Development of residential electricity consumption in pre-selected states



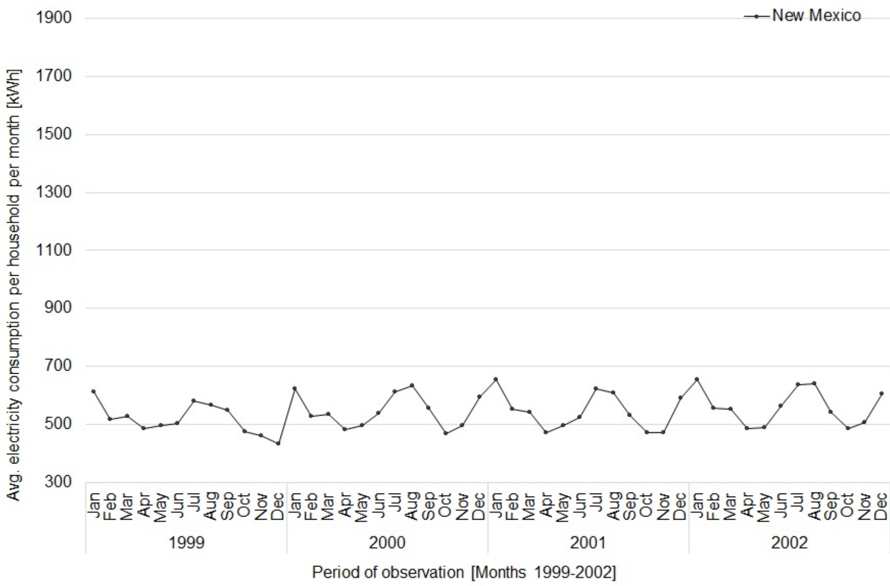
(i) Colorado



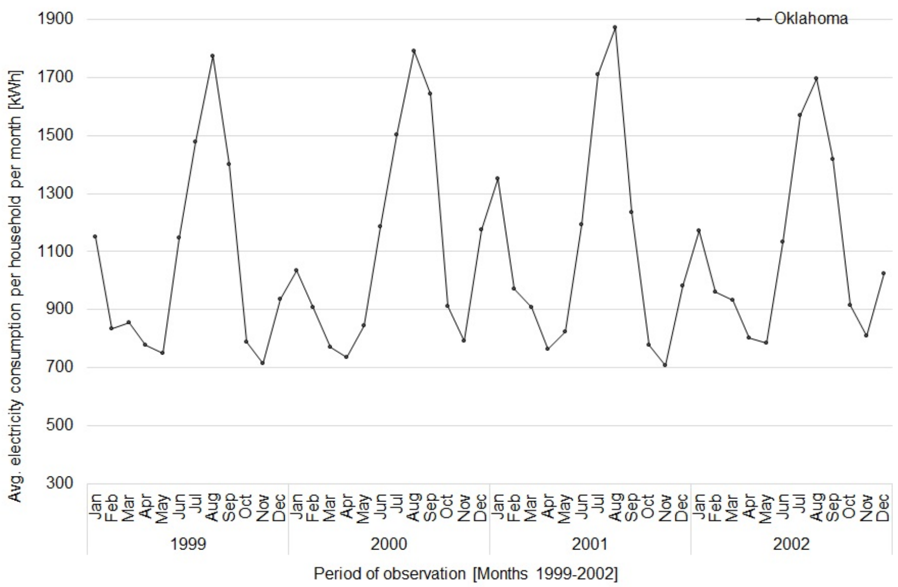
(ii) Missouri



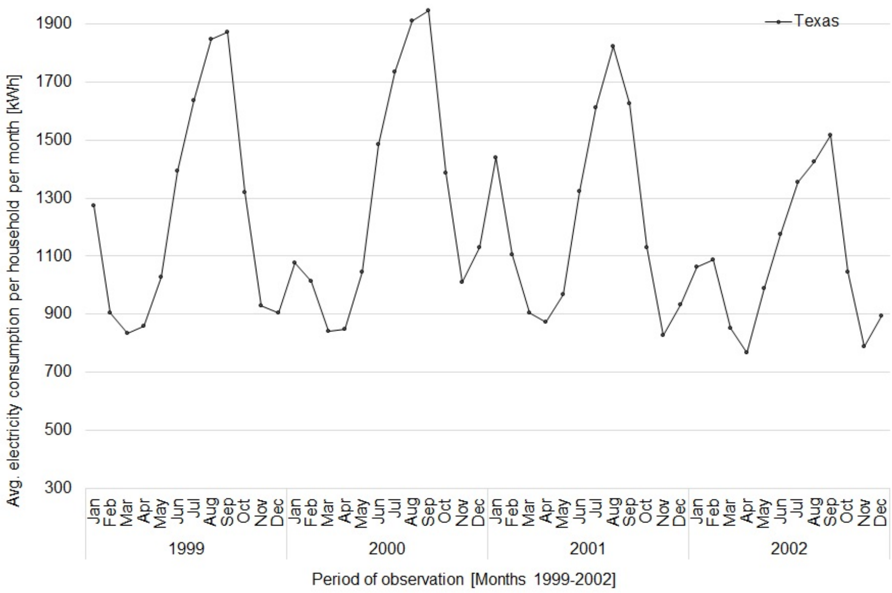
(iii) Nebraska



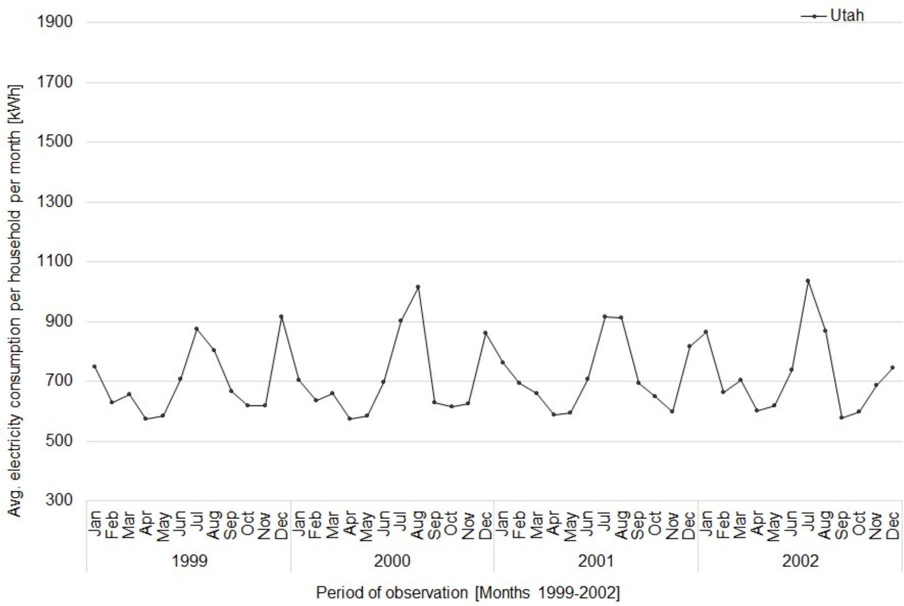
(iv) New Mexico



(v) Oklahoma



(vi) Texas



(vii) Utah

Figure 5.6: Residential consumption in pre-selected states over 48-month period

5.7.6 Parallel trends test

Testing for parallel trends assures that the use of the consumption patterns for California and the derived control group state is indeed following similar patterns before the crisis, unbiased of any other consumption-reducing influences (i.e. other programs or events). Therefore, I make use of using a difference-in-difference estimation based on data for the treated and untreated state. As explanatory variables, I use HDD, CDD, unemployment level, wages, lagged residential electricity prices, pre-treatment (pre_trt), interim-treatment (int_trt) and post-treatment ($post\_trt$) time dummies. The respective time dummies reflect the months in 1999 (pre_trt), 2000 (int_trt) and 2001-2002 ($post\_trt$). Among others, estimates for the treatment dummies are provided in Table 5.5. Two meaningful insights for the synthetic control approach can be derived; first, I can neglect other consumption reducing impacts shortly before the Energy Crisis due to the non-significant coefficient of the interim-treatment time dummy (int_trt). Thus, the parallel trends assumption is valid. Second, the negative impact on residential electricity consumption of the $post\_trt$ time dummy (-0.158, significant at the 5% level) provides first evidence for an aggregated reduction through conservation programs that are studied in more depth in Section 5.5.2.

Table 5.5: IV Estimates when controlling for pre- and post crisis treatment time dummies

Dependent variable: $\Delta Demand_m^{res}$	
Explanatory variable	IV
pre_trt	-0.085
	(0. 699)
int_trt	-0.108
	(0.0934)
$post\_trt$	-0.158**
	(0.0830)
$\Delta Price_m^{elec,res}$	-1.4904
	(2.4594)
ΔCDD_m	0.0003***
	(0.0001)
ΔHDD_m	0.0001*
	(0.0001)
$\Delta Unemploymentlvl_m$	0.0639
	(0.0616)
$\Delta Wage_m$	0.0006
	(0.0004)
$observations$	48
R^2	0.70
F	29.3
p-value	0.00

Notes to Table: Robust standard errors in parentheses. * / ** / *** : significant at the 0.1 / 0.05 / 0.01 error level respectively. Data used covers a 48-month period from January 1999 until December 2002.

Bibliography

Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of the American Statistical Association*, 105(490), 493–505.

Abadie, A., Diamond, A., & Hainmueller, J. (2015). Comparative Politics and the Synthetic Control Method. *American Journal of Political Science*, 59(2), 495–510.

Abadie, A. & Gardeazabal, J. (2003). The Economic Costs of Conflict: A Case Study of the Basque Country. *American Economic Review*, 93(1), 113–132.

Adair, J. G. (1984). The Hawthorne effect: A Reconsideration of the Methodological Artifact. *Journal of Applied Psychology*, 69(2), 334–345.

Al-Faris, A. R. F. (2002). The demand for electricity in the GCC countries. *Energy Policy*, 30(2), 117–124.

Albadi, M. H. & El-Saadany, E. F. (2008). A summary of demand response in electricity markets. *Electric Power Systems Research*, 78(11), 1989–1996.

Allcott, H. (2011). Social norms and energy conservation. *Journal of Public Economics*, 95(9), 1082–1095.

Allcott, H. & Rogers, T. (2014). The Short-Run and Long-Run Effects of Behavioral Interventions: Experimental Evidence from Energy Conservation. *American Economic Review*, 104(10), 3003–3037.

Arthur, W. B. (1991). Designing Economic Agents that Act like Human Agents: A Behavioral Approach to Bounded Rationality. *The American Economic Review*, 81(2), 353–359.

Arthur, W. B. (1994). Inductive Reasoning and Bounded Rationality. *The American Economic Review*, 84(2), 406–411.

Bardazzi, R., Oropallo, F., & Pazienza, M. G. (2015). Do manufacturing firms react to energy prices? evidence from italy. *Energy Economics*, 49, 168–181.

Bender, S. L., Moezzi, M., Gossard, M. H., & Lutzenhiser, L. (2002). Using Mass Media to Influence Energy Consumption Behavior: California's 2001 Flex Your Power Campaign as a Case Study. In Proceedings of the 2002 ACEEE Summer Study on Energy Efficiency in Buildings 8: 15-28: Washington D.C.: American Council for an Energy-Efficient Economy.

Bernstein, M. A., Griffin, J. M., & Infrastructure, S. (2006). *Regional differences in the price-elasticity of demand for energy*. National Renewable Energy Laboratory.

Bjørner, T. B. & Jensen, H. H. (2002). Energy taxes, voluntary agreements and investment subsidies—a micro-panel analysis of the effect on Danish industrial companies' energy demand. *Resource and Energy Economics*, 24(3), 229–249.

Blumstein, C., Friedman, L. S., & Green, R. J. (2002). The History of Electricity Restructuring in California. *Journal of Industry, Competition and Trade*, 2(1), 9–38.

Boisvert, R., Cappers, P., Neenan, B., & Scott, B. (2004). Industrial and commercial customer response to real time electricity prices. *http://eetd.lbl.gov/sites/all/files/publications/boisvert.pdf, accessed 2016-01-11*.

Bönte, W., Nielen, S., Valitov, N., & Engelmeyer, T. (2015). Price elasticity of demand in the epex spot market for electricity: New empirical evidence. *Economics Letters*, 135, 5–8.

Borenstein, S. (2002). The Trouble with Electricity Markets: Understanding California's Restructuring Disaster. *The Journal of Economic Perspectives*, 16(1), 191–211.

Boshell, F. & Veloza, O. P. (2008). Review of Developed Demand Side Management Programs Including Different Concepts and their Results. In Proceedings of the 2008 IEEE/PES Transmission and Distribution Conference and Exposition: Latin America: IEEE.

Bundesnetzagentur (2016). Monitoring Report 2015.

Bureau of Labor Statistics (2016). Quarterly Census of Employment and Wages. *http://www.bls.gov/cew/, accessed 2017-04-06*.

Bushnell, J. B. & Mansur, E. T. (2005). Consumption Under Noisy Price Signals: A Study of Electricity Retail Rate Deregulation in San Diego. *The Journal of Industrial Economics*, 53(4), 493–513.

California Energy Commission (2003). Energy Action Plan I. *http://www.energy.ca.gov/energy_action_plan/, accessed 2016-08-31*.

California Energy Commission (2005). Energy Action Plan II. *http://www.energy.ca.gov/energy_action_plan/, accessed 2016-08-31*.

California Public Utilities Commission (2016). California Energy Efficiency Statistics. *http://eestats.cpuc.ca.gov, accessed 2016-06-28*.

CPEC (2000). Price Movements in California Power Exchange Markets: Analysis of Price Activity: May-September 2000.

CPUC (2005). Update on determining the costs and benefits of California's Net Metering Program as required by Assembly Bill 58.

Davito, B., Tai, H., & Uhlaner, R. (2010). The smart grid and the promise of demand-side management. *McKinsey and Company*.

Dergiades, T. & Tsoulfidis, L. (2008). Estimating residential demand for electricity in the United States, 1965–2006. *Energy Economics*, 30(5), 2722–2730.

DiClemente, C. C., Marinilli, A. S., Singh, M., & Belliono, L. E. (2001). The Role of Feedback in the Process of Health Behavior. *American Journal of Health Behavior*, 25(3), 217–227.

Energy Information Administration (2016a). Residential Energy Consumption Survey. *http://www.eia.gov/consumption/residential/, accessed 2017-04-06*.

Energy Information Administration (2016b). U.S. Electricity Data. *http://eia.gov/electricity/data/, accessed 2017-02-30*.

Energy Information Administration (2017). Wholesale Electricity and Natural Gas Market Data. *https://www.eia.gov/electricity/wholesale/, accessed 2017-05-08*.

EPEX Spot (2016). Epex spot annual report 2015.

Eurostat (2016). Eurostat electricity price statistics. *http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nrg_pc_204_c&lang=en, accessed 2016-05-25*.

Farrell, M. J. (1957). The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society. Series A (General)*, 120(3), 253–290.

Faruqui, A. & Sergici, S. (2010). Household response to dynamic pricing of electricity: a survey of 15 experiments. *Journal of Regulatory Economics*, 38(2), 193–225.

Faruqui, A., Sergici, S., & Sharif, A. (2010). The impact of informational feedback on energy consumption d A survey of the experimental evidence. *Energy*, 35, 598–1608.

Førsund, F. R. (2008). Good modelling of bad outputs: Pollution and multiple-output production.

Fowlie, M., Greenstone, M., & Wolfram, C. (2015). Do Energy Efficiency Investments Deliver? Evidence from the Weatherization Assistance Program. *NBER Working Paper No. 21331*.

Färe, R., Grosskopf, S., Norris, M., & Zhang, Z. (1994). Productivity Growth, Technological Progress, and Efficiency Change in Industrialized Countries. *American Economic Review*, 84(1), 66–82.

Färe, R., Grosskopf, S., & Pasurka, C. (2013). Joint Production of Good and Bad Outputs with a Network Application. In J. F. Shogren (Ed.), *Encyclopedia of Energy, Natural Resource, and Environmental Economics*, volume 120 (pp. 109–118). Waltham: Elsevier.

Färe, R., R. & Primont, D. (1995). *Multi-Output Production and Duality: Theory and Applications*. Kluwer Academic, Boston.

Gans, W., Albernini, A., & Longo, A. (2013). Smart meter devices and the effect of feedback on residential electricity consumption: Evidence from a natural experiment in Northern Ireland. *Energy Economics*, 36, 729–743.

Garcia-Cerrutti, L. M. (2000). Estimating elasticities of residential energy demand from panel county data using dynamic random variables models with heteroskedastic and correlated error terms. *Resource and Energy Economics*, 22(4), 355–366.

Genc, T. (2014). Market Power Indices and Wholesale Price Elasticity of Electricity Demand. *University of Guelph Discussion Paper*.

Gillingham, K., Newell, R., & Palmer, K. (2006). Energy Efficiency policies: A Retrospective Examination. *Annual Review of Environment Resources*, 31, 161—-192.

Gillingham, K., Rapson, D., & Wagner, G. (2015). The Rebound Effect and Energy Efficiency Policy. *Review of Environmental Economics and Policy*, 10(1), 68–88.

Growitsch, C., Paulus, S., & Wetzel, H. (2017). Competition and Regulation as a Means of Reducing CO2-Emissions: Experience from U.S. Fossil Fuel Power Plants. *EWI Working Paper Series No. 17/03*.

Halicioglu, F. (2007). Residential electricity demand dynamics in Turkey. *Energy Economics*, 29(2), 199–210.

Hampf, B. & Rødseth, K. L. (2015). Carbon dioxide emission standards for U.S. power plants: An efficiency analysis perspective. *Energy Economics*, 50, 140–153.

Hass, J. W., Bagley, G. S., & Rogers, R. W. (1975). Coping with the Energy Crisis: Effects of Fear Appeals upon Attitudes Toward Energy Consumption. *Journal of Applied Psychology*, 60(6), 754–756.

He, Y., Yang, L., He, H., Luo, T., & Wang, Y. (2011). Electricity demand price elasticity in China based on computable general equilibrium model analysis. *Energy*, 36(2), 1115–1123.

Herter, K., McAuliffe, P., & Rosenfeld, A. (2007). An exploratory analysis of california residential customer response to critical peak pricing of electricity. *Energy*, 32(1), 25–34.

Holtedahl, P. & Joutz, F. L. (2004). Residential electricity demand in Taiwan. *Energy Economics*, 26(2), 201–224.

Hosoe, N. & Akiyama, S.-i. (2009). Regional electric power demand elasticities of Japan's industrial and commercial sectors. *Energy Policy*, 37(11), 4313–4319.

International Energy Agency (2005). Saving electricity in a hurry dealing with temporary shortfalls in electricity supplies. *https://www.iea.org/publications/freepublications/publication/savingelec.pdf, accessed 2017-04-26*.

Ito, K. (2014). Do consumers respond to marginal or average price? evidence from nonlinear electricity pricing. *American Economic Review*, 104(2), 537–563.

Joskow, P. L. (2001). California's Electricity Crisis. *Oxford Review of Economic Policy*, 17(3), 365–388.

Joskow, P. L. & Wolfram, C. D. (2012). Dynamic Pricing of Electricity. *American Economic Review*, 102(3), 381–385.

Knaut, A. & Paulus, S. (2016). When are consumers responding to electricity prices? An Hourly Pattern of Demand Elasticity. *EWI Working Paper Series No. 16/07*.

Krupnick, A., Wang, Z., & Wang, Y. (2013). Sector effects of the shale gas revolution in the United States. *Resources for the Future Discussion Paper 13-20*.

Lijesen, M. G. (2007). The real-time price elasticity of electricity. *Energy Economics*, 29(2), 249–258.

Lutzenhiser, L. (1993). Social and Behavioral Aspects of Energy Use. *Annual Reviews of Energy Environment*, 18, 247–289.

NASA (2016). GMAO MERRA: Modern Era Retrospective-Analysis for Research and Applications. *http://gmao.gsfc.nasa.gov/merra/, accessed 2016-05-06*.

National Oceanic and Atmospheric Administration (2016). Climate at a Glance. *http://www.ncdc.noaa.gov/cag/, accessed 2017-03-11*.

National Renewables Energy Laboratory (2016). Solar Data. *http://www.nrel.gov/gis/data_solar.html/, accessed 2017-02-12*.

New York Office of Information Technology Services (2016). Energy Efficiency Portfolio Standard (EEPS) Program Estimated Energy Savings Data. *https://data.ny.gov/Energy-Environment/Energy-Efficiency-Portfolio-Standard-EEPS-Program-/vqmi-95p7/, accessed 2016-09-05*.

New York State Department of Public Service (2016). New York Standard Approach for Estimating Energy Savings from Energy Efficiency Programs. *https://data.ny.gov/Energy-Environment/Energy-Efficiency-Portfolio-Standard-EEPS-Program-/vqmi-95p7/, accessed 2016-09-05*.

North, D. C. (1994). Economic Performance Through Time. *The American Economic Review*, 84(2), 359–368.

Office of Energy Efficiency and Renewable Energy (2016). Energy Incentive Programs. *https://www.smartgrid.gov/document/smart_grid_and_promise_demand_side_management, accessed 2016-06-28*.

Oggioni, G., Riccardi, R., & Toninelli, R. (2011). Eco-efficiency of the world cement industry: A data envelopment analysis. *Energy Policy*, 39(5), 2842–2854.

Paschmann, M. & Paulus, S. (2017). The Impact of Advanced Metering Infrastructure on Residential Electricity Consumption - Evidence from California. *EWI Working Paper Series No. 17/08*.

Pastor, J. T. & Lovell, C. A. K. (2005). A global Malmquist productivity index. *Economics Letters*, 88(2), 266–271.

Paulus, S. (2017). Electricity Reduction in the Residential Sector: The Example of the Californian Energy Crisis. *EWI Working Paper Series No. (forthcoming)*.

Public Service Company New Mexico (2016). PNM Energy Efficiency Program Annual Reports. *http://www.pnmresources.com/investors.aspx/, accessed 2016-09-22*.

Rabin, M. (1998). Psychology and Economics. *Journal of Economic Literature*, 36(1), 11–46.

Rapanos, V. T. & Polemis, M. L. (2006). The structure of residential energy demand in Greece. *Energy Policy*, 34(17), 3137–3143.

Reiss, P. C. & White, M. W. (2003). Demand and Pricing in Electricity Markets: Evidence from San Diego During California's Energy Crisis. *NBER Working Paper No. 9986*.

Reiss, P. C. & White, M. W. (2005). Household Electricity Demand, Revisited. *The Review of Economic Studies*, 72(3), 853–883.

San Diego Gas and Electricity (2016). About smart meters. *http://www.sdge.com/residential/about-smart-meters/, accessed 2016-06-28*.

Schaffer, M. E. (2012). xtivreg28: Stata module to perform extended IV/2SLS, GMM and AC/HAC, LIML and k-class regression for panel data models (version 8). Statistical Software Components, Boston College Department of Economics. *https://ideas.repec.org/c/boc/bocode/s457436.html, accessed 2016-03-13*.

Selten, R. (1998). Features of experimentally observed bounded rationality. *European Economic Review*, 42(3), 413–436.

Shephard, R. W. (1953). *Cost and Production Functions*. Princeton University Press.

Shephard, R. W. (1970). *The Theory of Cost and Production Functions*. Princeton University Press.

Shephard, R. W. & Färe, R. (1974). The Law of Diminishing Returns. *Zeitschrift für Nationalökonomie*, 34, 69–90.

Simon, H. (1957). *Models of Man: Social and Rational; mathematical essays on rational human behavior in society setting*. Wiley, New York.

Simon, H. A. (1986). Rationality in Psychology and Economics. *The Journal of Business*, 59(4), S209–S224.

Southern California Edison (2017). Southern California Edison Sample Bill. *https://www.sce.com/NR/sc3/tm2/pdf/1631-E.pdf, accessed 2017-04-20*.

Stenglein, M. (2002). The Causes of California's Energy Crisis. *Natural Resources and Environment*, 16(4), 237–273.

Sueyoshi, T. & Goto, M. (2013). Returns to scale vs. damages to scale in data envelopment analysis: An impact of U.S. clean air act on coal-fired power plants. *Omega*, 41(2), 164–175.

Sueyoshi, T., Goto, M., & Ueno, T. (2010). Performance analysis of US coal-fired power plants by measuring three DEA efficiencies. *Energy Policy*, 38(4), 1675–1688.

Taylor, T. N., Schwarz, P. M., & Cochell, J. E. (2005). 24/7 hourly response to electricity real-time pricing with up to eight summers of experience. *Journal of regulatory economics*, 27(3), 235–262.

Todd, A. M. & Wood, A. (2006). "Flex Your Power:" Energy Crises and the Shifting Rhetoric of the Grid. *Atlantic Journal of Communication*, 14(4), 211–228.

U.S. Energy Information Administration (EIA) (2015a). Electric Power Annual, Detailed State Data (Release date: October 2015). *http://www.eia.gov/electricity/data/state/, accessed 2016-06-05*.

U.S. Energy Information Administration (EIA) (2015b). State Energy Data System (SEDS): 1960-2013 (complete) (Release date: July 24, 2015). *http://www.eia.gov/electricity/data/state/, accessed 2016-06-05*.

U.S. Energy Information Administration (EIA) (2016a). Monthly Energy Review, Table 9.9 (April 2016). *http://www.eia.gov/totalenergy/data/monthly/index.cfm, accessed 2016-06-05*.

U.S. Energy Information Administration (EIA) (2016b). Monthly Energy Review, Tables 7.2b and 12.2-12.6 (April 2016). *http://www.eia.gov/totalenergy/data/monthly/index.cfm, accessed 2016-06-05*.

U.S. Environmental Protection Agency (EPA) (2015). FACT SHEET: Overview of the Clean Power Plan. *https://www.epa.gov/cleanpowerplan/fact-sheet-overview-clean-power-plan, accessed 2016-03-20*.

Wang, Q., Chen, X., Jha, A. N., & Rogers, H. (2014). Natural gas from shale formation – The evolution, evidences and challenges of shale gas revolution in United States. *Renewable and Sustainable Energy Reviews*, 30, 1–28.

Weare, C. (2003). *The California Electricity Crisis: Causes and Policy Options*. Public Policy Institute of California.

Welch, E. & Barnum, D. (2009). Joint environmental and cost efficiency analysis of electricity generation. *Ecological Economics*, 68(8-9), 2336–2343.

Wolak, F. A. (2003). Diagnosing the California Electricity Crisis. *The Electricity Journal*, 16(7), 11–37.

Woo, C.-K. (2001). What went wrong in California's electricity market? *Energy and Environmental Economics*, 26, 747–758.

Zhang, N. & Choi, Y. (2014). A note on the evolution of directional distance function and its development in energy and environmental studies 1997-2013. *Renewable and Sustainable Energy Reviews*, 33, 50–59.

Zhou, P., Ang, B., & Poh, K. (2008). A survey of data envelopment analysis in energy and environmental studies. *European Journal of Operational Research*, 189(1), 1–18.

Zhou, P., Ang, B. W., & Han, J. Y. (2010). Total factor carbon emission performance: A Malmquist index analysis. *Energy Economics*, 32(1), 194–201.

Ziramba, E. (2008). The demand for residential electricity in South Africa. *Energy Policy*, 36(9), 3460–3466.

Curriculum Vitae

Simon Paulus

PERSONAL DATA

Date of Birth	25 April 1985
Place of Birth	Lennestadt, Germany

EDUCATION

09.2015 - current	**Institute of Energy Economics** and **Department of Energy Economics, University of Cologne** Ph.D. student in economics under the supervision of Prof. Van Anh Vuong, Ph.D and Prof. Dr. Marc-Oliver Bettzüge.
10.2004 - 01.2010	**Eberhard Karls Universität Tübingen, Germany** Graduate International Economics (Diplom Volkswirt)
08.2008 - 03.2009	**University of Denver, Colorado, USA** Semester abroad
09.2006 - 01.2007	**Université de Lumière II & Lyon III, France** Semester abroad
06.2004	**Gymnasium Schmallenberg, Germany** University Entrance Examination (Abitur)

WORKING EXPERIENCE

09.2015 - current	**Department of Energy Economics, University of Cologne** Research Associate
09.2012 - 12.2016	**ewi Energy Research & Scenarios gGmbH** Lead Research Associate
02.2010 - 08.2012	**General Electric Inc, GE Energy** Financial Analyst

LANGUAGES

German	Mother tongue
English	Mastery (C2)
French	Vantage (B2)
Spanish	Breakthrough (A1)

PUBLICATIONS AND PRESENTATIONS

Articles in refereed journals:

- A. Knaut, C. Tode, D. Lindenberger, R. Malischek, S. Paulus, J. Wagner (2016). The Reference Forecast of the German Energy Transition – An Outlook on Electricity Markets. *Energy Policy*, 92.
- S. Paulus (2013). Potential developments for the German renewables support scheme until 2018. *Zeitschrift für Energiewirtschaft (ZfE)*.

Working papers:

- S. Paulus (2017). Electricity Reduction in the Residential Sector - The Example of the Californian Energy Crisis. *EWI Working Paper* (forthcoming).
- M. Paschmann, S. Paulus (2017). The Impact of Advanced Metering Infrastructure on Residential Electricity Consumption - Evidence from California. *EWI Working Paper* 17/08.
- C. Growitsch, S. Paulus, H. Wetzel (2017). Competition and Regulation as Means Against CO2 Emissions – Experience from U.S. Fossil Fuel Power Plants. *EWI Working Paper* 17/03.
- A. Knaut, S. Paulus (2016). When Are Consumers Responding to Electricity Prices? An Hourly Pattern of Demand Elasticity. *EWI Working Paper* 16/07.

Conference presentations:

- Synthetic California and the Influence of Informational Feedback on Residential Electricity Consumption. *Young Energy Economists and Engineers Seminar 2016*, Edinburgh, United Kingdom.
- Competition and Regulation as Means Against CO2 Emissions: Experience from U.S. Fossil Fuel Power Plants. *14th European Workshop on Efficiency and Productivity Analysis (EWEPA 2014)*, Helsinki, Finland.

WORK IN PROGRESS

- Pathways for Decarbonizing the Road Transport Sector – The Example of Germany (with B. Helgeson and J. Peter)

JOURNAL REFEREE

Networks and Spatial Economics (Springer)
Zeitschrift für Energiewirtschaft