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

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**Abstract**

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.

*Keywords:* behavioral economics, bounded rationality, energy conservation, informational feedback, smart meters, residential electricity consumption

*JEL classification: C91, D11, D12, D14, D83*

## 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

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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[1]. 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[2]. 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.

[1] The smart meters may provide data with higher temporal resolution and device-specific information.

[2] In the US, up to 65% of households have electric space heating and thus a significant impact on electricity consumption is expected.

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.

The remainder of the paper is organized as follows. Section 2 provides the main literature background. In Section 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 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 5, and the respective results are discussed in Section 6. Finally, we draw conclusions in Section 7.

## 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 (Simon, 1986; Rabin, 1998).

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.[3] 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 and Veloza, 2008; Gillingham et al., 2006; McKinsey and Company, 2009). 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 and Sergici, 2010), Joskow and 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 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 and Rogers (2014) expand the analysis on social norms by using data from the Opower program,

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

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.

## 3. Identification Strategy

In the US, smart-meter[4] 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 1 depicts the status of smart-metering legislation across the US states.

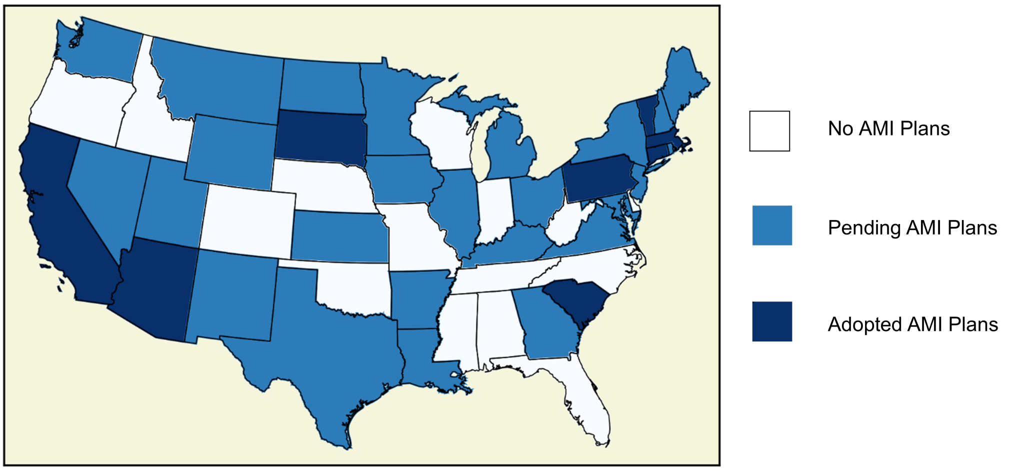



Figure 1: Smart-metering legislation across the US states (U.S. Energy Information Administration 2011)

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

[4]Such smart meters are part of the Advanced Metering Infrastructure (AMI). For more details on AMI see Appendix.1.

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.

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. 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 (Commission et al., 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 (Commission et al., 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 2, these IOUs cover more than 75% of all customer accounts[5] in California (2015).

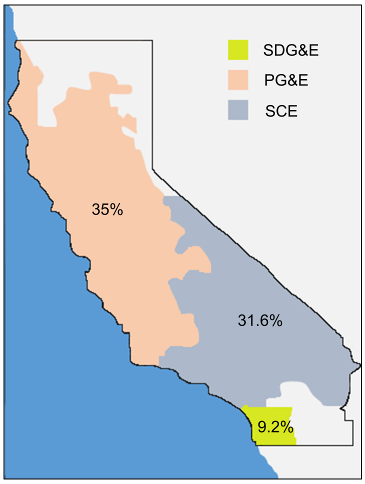



Figure 2: Investor-Owned Utilities (IOUs) and the respective share of Californian customer accounts (2015, Dec.)

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*

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

‘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.[6] 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 monthly variations of gas and electricity usage on daily and monthly levels.[7]

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.

As such, we suggest that the current electricity tariff design may primarily provide incentives for ‘load shifting’ rather than impacting overall consumption levels. Additionally, the implementation of real-time pricing has so far been ruled out as an option in California. We therefore assume that demand response measures do not effect a reduction in residential electricity consumption within the analyzed period.

*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.[8] 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.[9] Such incentives are particularly designed to reduce load through state-of-the-art devices. While the utility level remains constant with the

[6]We provide two simplified versions of residential tiered and time-of-use schedules in Section Appendix.7.

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

[8]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.

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

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 between 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.[10]

*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 3. The deployment of AMI began in 2008, and first achieved a penetration rate above 10% in 2009.

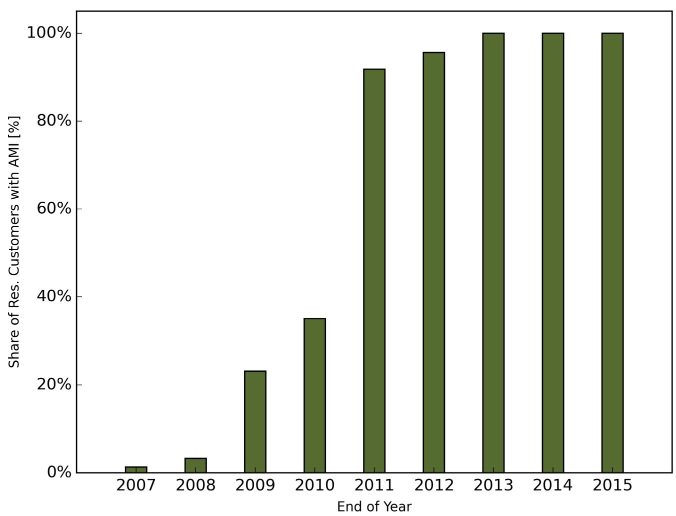



Figure 3: Share of total Californian households with AMI (smart meters) over time

As of 2011 the share of Californian households with AMI corresponds to the share of customer accounts

[10]For more details, see Section 5.

covered by the three major IOUs.[11]

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).

## 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.

### *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 1.

$$Demand_{m,s}^{res,adj} = Demand_{m,s}^{res,billed} + SelfConsumption_{m,s}^{res,PV} + Savings_{m,s}^{res,ee} \tag{1}$$

Our initial data on residential electricity consumption consists of monthly ($m$) state-specific ($s$) electricity sales in the residential sector, which we label $Sales_{m,s}^{res}$. 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. $> 70\%$) of residential customers in California, we assume that there is no loss of representative nature. In the next step, we divide $Sales_{m,s}^{res}$ by the respective number of customer accounts in order to get the average monthly electricity consumption per household for which consumers are billed

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

($Demand_{m,s}^{res,billed}$). 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 ($SelfConsumption_{m,s}^{PV,residential}$) has to be added to the basic electricity consumption data in order to get unbiased values.[12]

Second, we adjust our data for residential electricity savings that result from energy efficiency ($ee$) programs ($Savings_{m,s}^{res,ee}$). The respective data are collected from the individual service utilities in the US states and are listed in Table 1.[13] 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.[14] 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 2009. As there is a time lag between significant energy-efficiency savings beginning in 2006[15] 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 statewide 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[16] (Public Service Company New Mexico, 2016). An overview on the respective

[12]For more details on the calculation methodology, see Section Appendix.5.

[13]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 6.1.

[14]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).

[15]The development of energy-efficiency savings in California is illustrated in Figure .7 in Section Appendix.2.

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

data is provided in Table 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.

| 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 |

Table 1: Energy efficiency savings data

*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 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 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 (U.S. Energy Information Administration, 2016). 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).[17]

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 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 3 shows descriptive statistics for all variables used for our empirical estimations under Section 6.2.

## 6. Empirical Analysis

Following the identification strategy from Section 3, we use a two-stage empirical approach. First, we derive a control group by applying synthetic control methods.[19] In a second step, we conduct a Difference-in-Differences estimation to quantify the effect under analysis.

### *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

[17]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.

[19]The respective procedure is described in detail in Section 6.1.

| Label | Explanation | Resolution | Region[18] | 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 |
| $Customers^{res}_{m,s}$ | Total residential customer counts | Monthly | State-specific | Total | EIA |
| $Demand^{res,billed}_{m,s}$ | 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 |
| $Feedback^{PV}_{m,s}$ | 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 |
| $Price^{res}_{m,s}$ | 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 2: The exact references are: NOAA (National Oceanic and Atmospheric Administration, 2016), RECS (Energy Information Administration, 2016), EIA (U.S. Energy Information Administration, 2016), BLS (Bureau of Labor Statistics, 2016), NREL (National Renewables Energy Laboratory, 2016)

Table 2: List of variables and references

| 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 |

Table 3: Descriptive statistics

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 and 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 2.

$$\min_{w \in [0,1]} (X_1 - X_0 \cdot w)' V (X_1 - X_0 \cdot w) \tag{2}$$

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 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 (c.f. Figure 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 (see, e.g., Abadie and Gardeazabal (2003)), we rely on a regression-based technique in order to derive $V$.[20] 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.

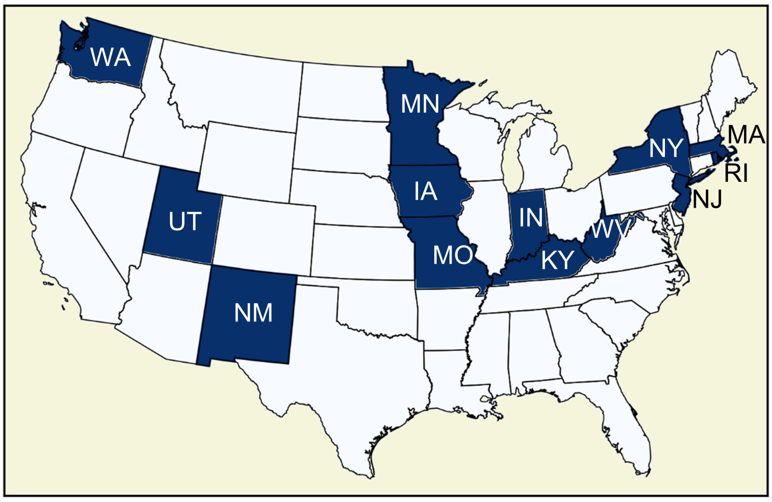


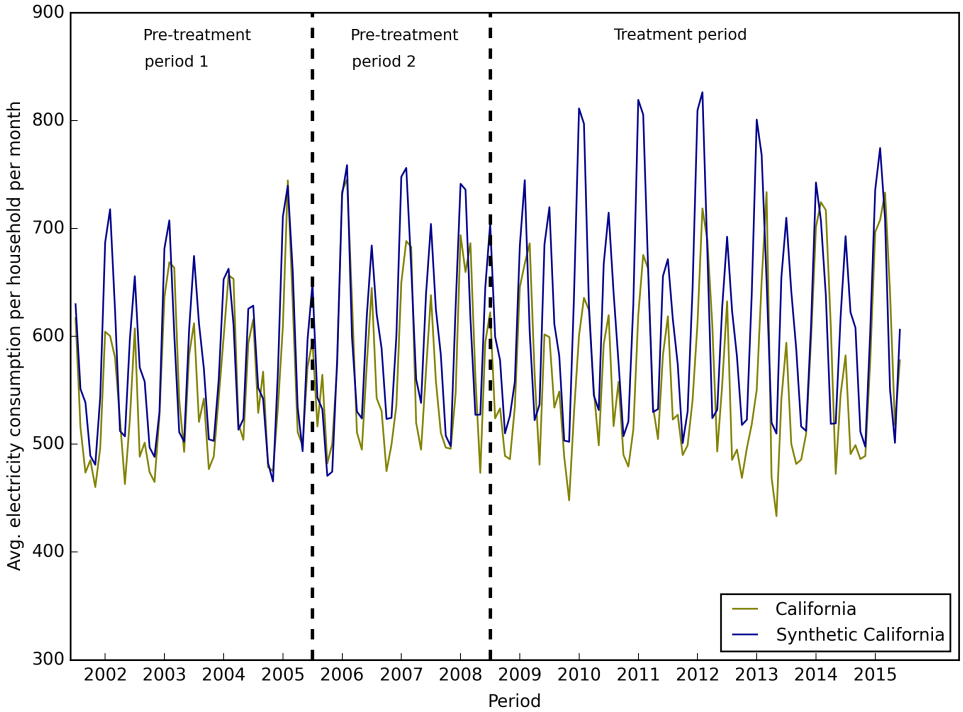

Figure 4: Candidate states with low AMI penetration

As a result, we obtain Synthetic California, which combines the states of New York and New Mexico,

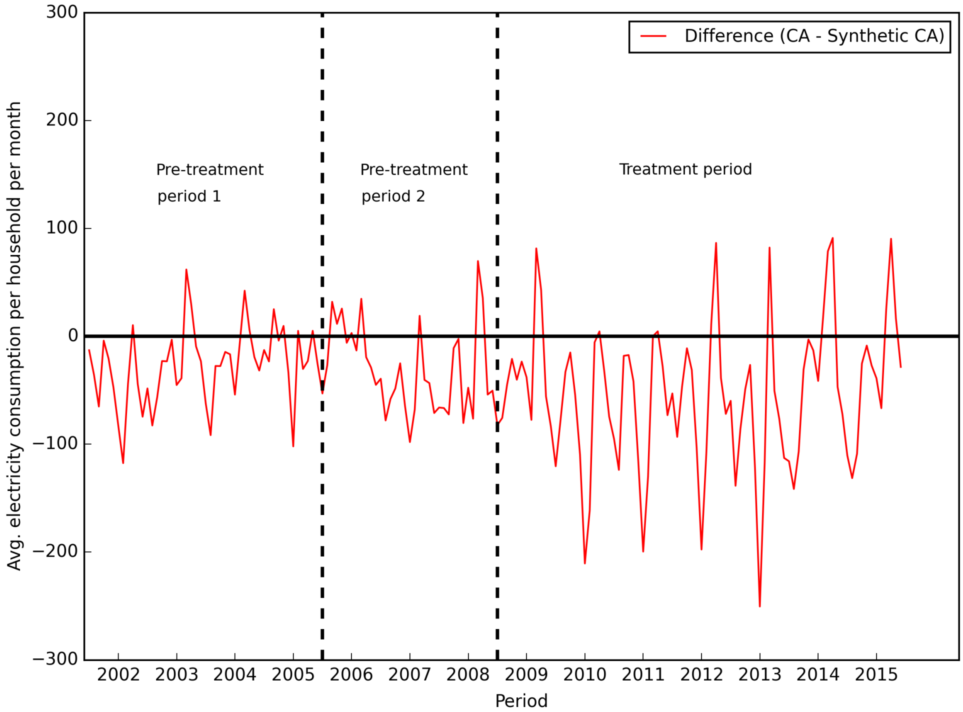
[20]Details on weights are listed in Section Appendix.4.

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 $X_0w$. The resulting development of residential electricity consumption is depicted in Figure 5(a), where we highlight the three periods that we differentiate. For illustration purposes, Figure 5(b) depicts the respective difference plot. In order to support the claim of a suitable control group, it is crucial 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.




(a) Synthetic controls: Descriptive comparison




(b) Synthetic controls: Difference plot

Figure 5: Descriptive comparison and differences between the development of residential electricity consumption in California and 'Synthetic California'

*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 (3). We aim to estimate the coefficient $\gamma$ to shed light on whether or not a significant decrease of residential electricity consumption due to smart-meter deployment has been achieved. 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.[21] 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 $\mu_m$ 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.

$$\begin{aligned} \Delta Demand_m^{res,adj} = \; & \alpha_1 Dummy_{Pre-Treatment1} + \alpha_2 Dummy_{Pre-Treatment2} \\ & + \gamma \Delta AMI_m \\ & + \beta_1 \Delta Price_m^{res} \\ & + \beta_2 \Delta CDD_m + \beta_3 \Delta HDD_m \\ & + \beta_4 \Delta Unemploymentlvl_m + \beta_5 \Delta Wage_m \\ & + \mu_m \end{aligned} \tag{3}$$

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[22] 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

[21] We provide an overview of the respective descriptive statistics in Section Appendix.3.
[22] A Kleiberger-Paap test indicates that the hypothesis of weak instruments may be rejected.

do not change on a monthly basis. We identify a high first-order autocorrelation of 96% in California and 76% in Synthetic California.[23] 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 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, 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 Appendix.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

[23] Lower values compared to California may be traced back to the use of a weighted combination of electricity prices.

| | | | | | |
|---|---|---|---|---|---|
| | | | | 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* | | |
| $\Delta$Share $AMI_{total,m}$ | -0.031*** | -0.042*** | -0.01 | | |
| | (0.01) | (0.01) | (0.01) | | |
| | | | | *Non-heating* | *Heating* |
| $\Delta$Share $AMI_{2009-2011,m}$ | | | | -0.020*** | 0.024 |
| | | | | (0.02) | (0.02) |
| | | | | *Non-heating* | *Heating* |
| $\Delta$Share $AMI_{2012-2014,m}$ | | | | -0.041*** | -0.008 |
| | | | | (0.013) | (0.016) |
| | | | | *Non-heating* | *Heating* |
| $\Delta$Share $AMI_{2015,m}$ | | | | -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) | |
| $\Delta CDD_m$ | 0.66*** | 0.67*** | | 0.68*** | |
| | (0.08) | (0.08) | | (0.081) | |
| $\Delta HDD_m$ | 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: 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.

Table 4: IV Estimates for DiD estimation

are expected to create incentives for reducing electricity consumption. However, the 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 appears to be lower in the first post-treatment period compared to the subsequent periods. From 2009 to 2011, we observe a relative reduction of residential electricity consumption of 3.3%, whereas the respective effect ranges from 6.1% to 6.4% between 2012 and 2015. We argue that these relations 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 periods, which yields a reduction estimate of about 6%. Compared to the literature, this is a little lower than the reductions gained from field experiments, as mentioned in Section 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 (Figure .7 in Section Appendix.2). Rather to the contrary, we identify coefficients that strongly comply with the temporal development of the share of AMI.

## 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.

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# Appendices

*Appendix.1. The General Functioning of the Advanced Metering Infrastructure*

Figure .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 (c.f. 'inductive process' from Section 2).

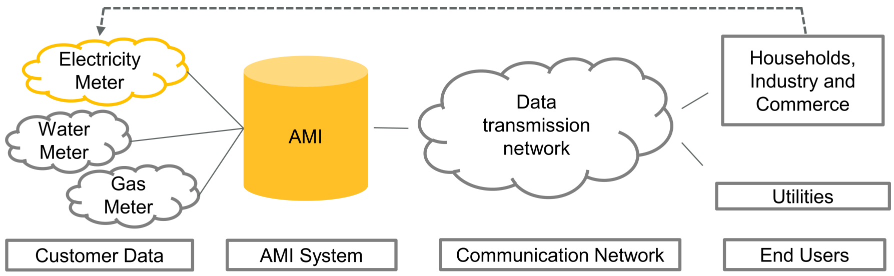


Figure .6: Simplified illustration of Advanced Meter Infrastructure (AMI) and its informational feedback

*Appendix.2. Development of Energy-Efficiency Savings in California*

Depicting the development of energy-efficiency saving estimates for California in Figure .7, we identify a significant and rather continuous impact of energy-saving measures beginning in 2007.

*Appendix.3. Descriptive Statistics: Difference-in-Differences Variables*

| Variable | N | Mean | SD | Min | 25% | Median | 75% | Max |
|---|---|---|---|---|---|---|---|---|
| $\Delta CDD_m$ | 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 |
| $\Delta HDD_m$ | 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 |
| $\Delta AMI_m$ | 168 | 0.393 | 0.444 | 0.000 | 0.000 | 0.131 | 0.954 | 0.997 |

Table .5: Descriptive statistics: Differences in levels (California minus Synthetic California)

*Appendix.4. Empirical Results: Weight Vector V for the Exogenous Variables*

The weight vector $V$ is presented in Table .6.

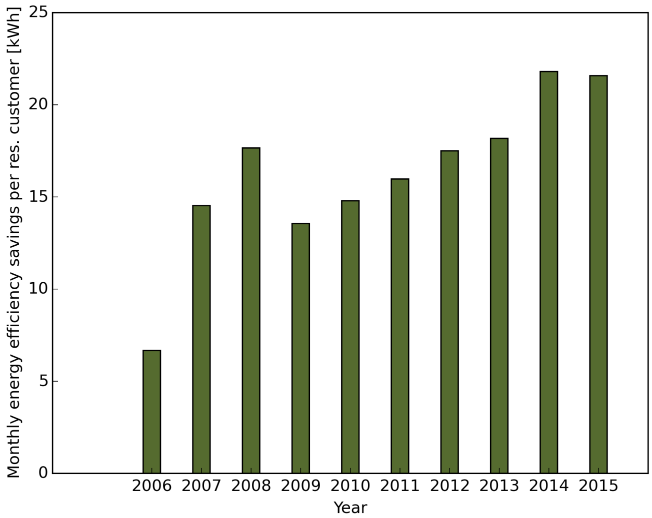


Figure .7: Development of energy-efficiency savings in California over time

| 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 |

Table .6: Weights of the exogenous variables

*Appendix.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) (U.S. Energy Information Administration, 2016). 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 $\frac{kWh}{m^2 d}$ 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 .1.

$$\begin{aligned} SelfConsumption_{m,s}^{res,PV} &= InstalledCapacity_{m,s}^{res,PV} \cdot \overline{Irradiation}_{m,s}^{GHI} \\ &\quad \cdot Days^{month} \cdot Efficiency^{PV} \cdot Area^{kWp} \\ &\quad - FeedBack_{m,s}^{res,PV} \end{aligned} \tag{.1}$$

*Appendix.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 .7. One may claim, therefore, that we identify no impact on residential electricity consumption other than that induced through the deployment of smart meters.

*Appendix.7. Simplified Residential Schedules*

Residential schedules from PG&E and SCE, as shown in Figure .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.

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.

| 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) |
| $\Delta$Share $AMI_{total,m}$ | -0.035*** |
| | (0.015) |
| $\Delta Price_m^{elec,res}$ | -0.42 |
| | (1.08) |
| $\Delta CDD_m$ | 0.70*** |
| | (0.09) |
| $\Delta HDD_m$ | 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 .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.

Table .7: IV Estimates for DiD estimation when controlling for yearly time dummies

**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 .8: Simplified schedules for tier and time-of-use in the residential sector