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Essays on energy economics and policy: Price elasticity, policy evaluation and potential savings

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"*If you torture the data long enough, it will confess to anything*"
– Ronald Coase

Summary

This thesis is composed of three essays on the residential electricity demand and its efficient use. In order to design and implement effective energy policy measures it is important for policy makers and utilities to have information on the response of consumers to an increase in electricity prices, on the impact of current and past energy efficiency programmes on the electricity demand as well as on the potential of electricity savings in the residential sector. The goal of this thesis is to provide more information on the price elasticity of residential electricity demand, to evaluate demand-side management programmes introduced by some Swiss utilities and to estimate the potential of electricity savings in Swiss households.

In **Essay 1** we estimate the long- and short-run price elasticities of residential electricity consumption in Switzerland from a household survey that includes information on appliance stock and its price as well as information on the amount of energy services, such as the number of cooked meals or number of washing cycles, consumed within a household. We create an index of the stock of household appliances by aggregating the information on the major household appliances. The index is used to estimate the impact of appliances on residential electricity demand in the short-run and to estimate the appliance stock demand in the long-run. Furthermore, we also use energy services to estimate the electricity demand. We adopt an instrumental variables approach to obtain consistent estimates of the price elasticity to account for potential endogeneity concerns with the average price as well as the appliance stock and its price.

Our results in **Essay 1** indicate that the price elasticity in the short-run is around -0.4 while in the long-run it ranges between -0.4 and -0.6. We also find that estimates of the electricity demand when we substitute the usual residential characteristics with energy services are very similar. Therefore, from the point of view of policy makers, pricing policy as an instrument may have a small impact in the short run. However, since the estimates of the long-run price elasticity of electricity consumption are generally higher this indicates that households will be influenced by pricing policy even though the impact may not be as substantial as needed and a combination of policies may be necessary to affect long-term electricity demand.

In **Essay 2** we use data from a survey conducted on 30 Swiss utilities from 2006 to 2012 to estimate the impact of demand-side management (DSM) activities on residential electricity demand using DSM spending and an energy efficiency score. The energy efficiency score measures a utility's commitment to implement DSM among their residential customers. Using the variation in DSM activities within utilities and across utilities over time we identify the impact of these programmes. If we consider the amount of monetary spending, a continuous measure, a 10% increase in DSM spending causes around a 0.14% reduction in per customer residential electricity consumption. A 10% increase in the energy efficiency score causes around a 0.36% reduction in per customer residential electricity consumption. To check for the robustness of this result we also consider a binary variable to denote the presence or absence of these programmes and find that they reduce per customer residential electricity consumption. We then conduct several robustness checks for potential endogeneity issues of the policies and conclude that current DSM practices in Switzerland

are statistically significant and have a negative effect.

The results of the econometric analysis of current DSM activities in Switzerland on residential electricity consumption indicate that the impact appears to be statistically significant. Using the results of the econometric estimation we perform a simple counterfactual exercise to obtain an estimate of the cost of saving a unit of electricity that would have been produced in the absence of DSM programmes. We find that, on average, the cost of saving a kilowatt hour is around CHF 0.04. This is a rough estimate and should be treated with caution due to our relatively small sample of utilities and the possible measurement error of the DSM spending variable. The range of our estimate for this cost is from a low of CHF 0.03 to CHF 0.09 while the current cost of producing and distributing electricity in Switzerland is higher than this range. Given our findings, it appears that DSM programmes may be a valuable option as Switzerland pursues its goals in *Energy Strategy 2050*.

In **Essay 3** we use the same sample of Swiss households as in **Essay 1** to measure the level of efficiency in the use of electricity in households. Since the demand for residential electricity is a derived demand, it can be modelled as a production process whereby households combine electricity and capital goods as inputs to provide services. This production process may be inefficient and to measure this inefficiency in the use of electricity in households we estimate a stochastic frontier model. As this dataset includes information on the amount of energy services consumed within a household, we are able to estimate a sub-vector input distance function using the household survey data. To the best of our knowledge, this is the first study that includes energy services in the frontier model and adopts a distance function approach on a disaggregated level to estimate the level of technical efficiency in the use of energy based on a microeconomic foundation.

The analysis of the level of efficiency in the use of electricity in Swiss households in **Essay 3** shows an average inefficiency of around 20%. From the point of view of policy makers we conclude that there is a considerable amount of possible improvement in the efficient use of electricity in some households. Comparing our results to a earlier bottom-up economic-engineering approach, our estimates lie at the upper end.

Zusammenfassung

Diese Disseration besteht aus drei Essays über den Haushaltsstromverbrauch und dessen effizienten Verbrauch. Um effektive energiepolitische Instrumente zu entwerfen und einzuführen, ist es wichtig, dass politische Entscheidungsträger und Stromversorgungsunternehmen über Informationen verfügen, wie Konsumenten auf eine Preiserhöhung reagieren, dass sie die Wirkung von aktuellen und vergangenen Energieeffizienzmassnahmen kennen und das Potential von Stromeinsparungen im Haushaltssektor abschätzen können. Ziel dieser Dissertation ist es, einerseits die Preiselastizität von Konsumenten in Bezug auf den Strompreis zu schätzen, andererseits die Energieeffizienzmassnahmen von Schweizer Stromversorgern zu evaluieren und das Potential von Stromeinsparungen in Haushalten abzuschätzen.

Im **ersten Essay** schätzen wir die kurz- und langfristige Strompreiselastizitäten von Schweizer Haushalten unter Verwendung einer Haushaltsumfrage, welche sowohl Informationen über die vorhandenen Haushaltsgerät und deren Preise, als auch Informationen über die konsumierten Energiedienstleistungen, wie zum Beispiel die Anzahl gekochter Mahlzeiten oder die Anzahl Waschmaschinenladungen, in den Haushalten enthält. Wir erstellen einen Haushaltsgeräteindex durch die Aggregation der wichtigsten Haupthaushaltsgeräte. Diesen Index benutzen wir um den Einfluss des Gerätebestands auf den kurzfristigen Stromkonsum zu messen und um die langfristige Haushaltsgerätenachfrage zu schätzen. Zudem berücksichtigen wir auch Energiedienstleistungen in unserer Schätzung. Für die Schätzung verwenden wir die Methode der Instrumentenvariablen um potentiellen Endogenitätsproblemen des Durchschnittspreises, des Geräteindex und der Gerätepreise vorzubeugen und um so eine robuste Schätzung der Preiselastizität zu erhalten.

Unsere Schätzungen im **ersten Essay** ergeben eine kurzfristige Preiselastizität von -0.4 und eine langfristige Preiselastizität von -0.4 bis -0.6. Zudem erhalten wir ähnliche Resultate, wenn wir die in so einer Schätzung üblichen Haushaltscharakteristika durch die Energiedienstleistungen ersetzen. Deshalb könnte, aus der Sicht der politischen Entscheidungsträger, eine Preispolitik auf kurze Sicht einen kleinen Effekt auf die Stromnachfrage haben. Auf lange Sicht hingegen haben wir eine höhere Preissensibilität festgestellt, was zeigt, dass die Haushalte langfristig eher auf eine Preispolitik reagieren. Es kann sein, dass der Effekt dennoch nicht so gross ist wie erforderlich, weshalb ein Instrumenten-Mix verwendet werden sollte, um die langfristige Stromnachfrage von Haushalten zu beeinflussen.

Im **zweiten Essay** verwenden wir Daten einer Umfrage, die auf einem Sample von 30 Schweizer Stromversorgern basiert und Daten von 2006 bis 2012 abfragt, um den Effekt von Demand-Side Management (DSM) Aktivitäten auf den Stromverbrauch zu schätzen. Dazu verwenden wir einerseits die Ausgaben für DSM-Programme und andererseits einen Energieeffizienz-Score. Der Energieeffizienz-Score misst das Engagement eines Stromversorgers für die Realisierung von DSM Massnahmen bei dessen Haushaltskunden. Mit Hilfe der Variation der DSM-Aktivitäten unter den Stromversorgern und über die Zeit versuchen wir die Wirkung dieser Programme zu identifizieren. Wenn wir die Ausgaben für DSM-Programme heranziehen, finden wir bei einer Erhöhung von 10% der Ausgaben für DSM einen Rückgang von 0.14% des Verbrauchs. Bei einer Erhöhung von 10%

des Energieeffizienz-Score resultiert einen Rückgang von 0.36% des Verbrauchs. Um die Robustheit dieses Resultats zu überprüfen, schätzen wir zusätzlich ein Model mit einer binären Variable, welche die An– oder Abwesenheit eines DSM-Programms misst. Auch hier finden wir einen signifikanten und negativen Effekt (Rückgang des Stromverbrauches). Um potentielle Endogenitätsprobleme des politischen Instruments zu testen führen wir verschiedene Robustheitsprüfungen durch. Aus diesem dritten Teil können wir folgern, dass aktuelle DSM Aktivitäten in der Schweiz einen statistisch signifikanten negativen Effekt auf den Stromverbrauch von Haushalten haben.

Aus dem ökonometrischen Teil dieser Analyse können wir folgern, dass aktuelle DSM-Aktivitäten in der Schweiz einen statistisch signifikanten Effekt auf den Stromverbrauch von Haushalten haben. Mit der Hilfe der Resultate aus der ökonometerischen Schätzung schätzen wir durch eine simple kontrafaktische Überlegung die Kosten einer gesparten Einheit Strom, die in Abwesenheit des DSM Programms produziert worden wäre. Wir erhalten durchschnittliche Kosten von 0.04 CHF für eine eingesparte Kilowattstunde. Hier muss man betonen, dass es sich nur um eine grobe Abschätzung handelt, und mit Vorsicht betrachtet werden muss, da unsere Stichprobe relativ klein ist, und wir möglicherweise Messfehler der DSM-Ausgaben nicht ausschliessen können. Die Bandbreite für diese Kosten liegt zwischen 0.03 CHF und 0.09 CHF, die Kosten für die Produktion und Verteilung von Elektrizität in der Schweiz liegen jedoch über dieser Bandbreite. Angesichts unserer Ergebnisse scheint es, dass DSM Programme eine wertvolle Option für die Schweiz sein kann um die Ziele der *Energiestrategie 2050* zu verfolgen. Abschliessend empfehlen wir in Zukunft regelmässig detailliertere Informationen über die Versorgungsunternehmen und ihre DSM Anstrengungen zu sammeln. Dies wird es den Forschern ermöglichen die Daten zu analysieren um anschliessend Regulatoren, politischen Entscheidungsträger und andere Interessenten über den Fortschritt der *Energiestrategie 2050* zu informieren.

Im **dritten Essay** verwenden wir dieselben Daten wie im **ersten Essay** um das Level der Effizienz in der Verwendung von Elektrizität in Haushalten zu messen. Da die Stromnachfrage der Haushalte eine abgeleitete Nachfrage ist, kann diese als einen Produktionsprozess modelliert werden, wobei Haushalte Elektrizität und Kapitalgüter als Produktionsfaktoren benutzen um Dienstleistungen bereit zu stellen. Dieser Produktionsprozess kann von Ineffizienzen geprägt sein und um diese Ineffizienz in der Verwendung von Elektrizität in Haushalten zu messen, benutzen wir eine Stochastische Frontier-Analyse. Weil der Datensatz auch Informationen über die im Haushalt konsumierten Energiedienstleistungen enthält, können wir für die Haushalte eine sub-vektor Input-Distanzfunktion schätzen. Nach unserem besten Wissen, ist dies die erste Studie, welche Energiedienstleistungen in einer Frontier-Analyse benutzt und einen Distanzfuntion-Ansatz wählt um das Effizienzlevel in der Verwendung von Energie mit disaggregierten Daten auf Basis von mikroökonomischer Grundlage zu schätzen.

In der Analyse des Effizienzlevels in der Verwendung von Elektrizität in Schweizer Haushalten im **dritten Essay** resultiert eine durchschnittliche Ineffizienz von 20%. Aus der Sicht von politischen Entscheidungsträgern können wir folgern, dass es eine beträchtliche Menge an möglichen Verbesserungen in der effizienten Verwendung von Elektrizität gibt, zumindest für einige Haushalte. Vergleichen wir unsere Resultate mit einer früheren ökonomisch-ingenieurtechnischen Bottom-up Analyse, liegen unsere Resultate am oberen Ende.

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Nina Boogen, February 2016

Für Mama und Papi

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Introduction

Policies to increase energy efficiency have been promoted since the oil crises of the 1970s. However, in recent years with the global issue of climate change increasing energy efficiency has been a part of the strategy of several industrialised nations in order to reduce their emissions of CO_2 and other greenhouse gases. Worldwide discussions about the security of nuclear power plants and other energy policy issues gathered momentum after the Fukushima Daiichi nuclear accident on 11 March, 2011. In Germany, chancellor Angela Merkel imposed a moratorium for three months on announced extensions for existing nuclear power plants and shut down seven of its 17 power plants within days after the accident. Afterwards, the government announced that all existing power plants will be phased out by 2022. Italy had already closed down all its nuclear power plants after the Chernobyl accident, the last in 1990. However, the government planned to construct a new nuclear power plant. The referendum for this took place in June 2011, just after the Fukushima incident, and a majority voted against this plan (Jorant, 2011). In Switzerland the Federal Council decided to suspend the approvals process for new nuclear reactors. The Council subsequently decided to make the ban on new nuclear reactors permanent. Furthermore, it was decided that the country's five existing nuclear reactors would continue producing electricity until they are gradually phased out with no replacements.[1] The implications of a switch in electricity generation from nuclear to other sources are important for a country like Switzerland which is, at the moment, heavily reliant on its nuclear reactors. In 2011 almost 40% of Switzerland's electricity was produced from nuclear energy.

Even before the Fukushima incident the way forward for Switzerland in terms of its energy and climate policies has been discussed since 2004 when work started on *Energy Perspectives 2035* by the Swiss Federal Office of Energy. The results of the *Energy Perspectives 2035* led to the introduction of the Swiss Electricity Supply Law (StromVG) in 2007 as well as the start of liberalisation in the Swiss electricity market. The Swiss Federal Council and Swiss Parliament also discussed and worked on new energy policies. The Fukushima incident led to further debate on the future direction of Swiss energy policies. The Federal Council proposed the *Energy Strategy 2050* that sets out the future for Switzerland very clearly by stating that it "is focusing on increased energy efficiency, the expansion of hydropower and use of new renewable energy, and in a second step the Council wants to replace the existing promotion system with a steering mechanism". With regard to the focus on energy efficiency, the *Energy Strategy 2050* includes an initial package of measures with mandatory efficiency goals for utilities and, in a later phase, a possible ecological tax reform. The latter will introduce an energy tax to provide incentives for a more responsible use of resources and to stabilize the consumption of electricity by 2050.

In order to design and implement effective energy policy measures it is important for policy makers and utilities to have information on the response of consumers to an increase in electricity prices, on the impact of current and past energy efficiency programmes on the electricity demand as well as on the potential of electricity savings in the residential sector. The goal of this thesis is to provide

[1] This decision is not final yet because it has not gone through the parliament yet and there is a possibility of a referendum.

more information on the price elasticity of residential electricity demand, to evaluate demand-side management programmes introduced by some Swiss utilities and to estimate the potential of electricity savings in Swiss households. This dissertation is a cumulative dissertation and comprises three essays.

Essay 1: Estimating residential electricity demand in Switzerland: New empirical evidence

In order to find out the effectiveness of an energy tax on electricity consumption it is important to obtain credible estimates of the responsiveness of electricity demand to its price. In Essay 1, we are interested in investigating three issues. Firstly, we want to estimate the price elasticity of residential electricity consumption in order to assist to the design of appropriate pricing policies by utilities and the regulatory authorities to reduce electricity consumption. Secondly, we are interested in the effect of the stock of electrical appliances on the consumption of residential electricity. This will enable us to obtain a more precise estimate of the price elasticity. Finally, we analyse the impact of using energy services, such as the number of meals cooked at home, on the electricity consumption of a household. We want to analyse how the price elasticity of demand for electricity is affected if we use such measures instead of the usual method of approximating energy services with only household and socio-demographic characteristics.

The residential demand for electricity is considered to be a derived demand since electricity is consumed to provide us with services, e.g. a cloth washer providing clean clothes. We derive equations for the residential electricity and appliance demands by using a simplified version of household production theory whereby households combine electricity and capital goods to obtain energy services. We use data on characteristics of houses, demographics of households, the stock of appliances, rough characteristics of appliances, the amount of energy services consumed within a household and the annual electricity consumption of the household from a survey performed by the Verband der Schweizerischen Elektrizitätsunternehmen (VSE) to estimate the short- and long-run electricity demand and the long-run appliance stock demand.

This essay contributes to the existing literature in several ways. Firstly, we base our theoretical model on household production theory that posits electricity demand as being a derived demand for energy services. Therefore, we augment our basic models and estimate the electricity demand by using information on energy services. Secondly, we use detailed information from a household's stock of appliances and construct an appliance stock index that takes into account a measure of typical capacity. We also calculate a single index for the price of appliances as the average price, per Watt, of household appliances. Finally, we use an instrumental variables approach to account for the possible endogeneity of the average price of electricity as well as the price of the measure of household appliances to obtain consistent estimates of the price elasticity of residential electricity demand.

This essay is based on chapter 2 in the report "*An Evaluation of the Impact of Energy Efficiency Policies on Residential Electricity Demand in Switzerland*" (Boogen et al., 2015). Nina Boogen is the primary author of this essay in all regards.

Essay 2: Demand-Side Management by Electric Utilities in Switzerland: Analysing its Impact on Residential Electricity Demand

The proposal in the *Energy Strategy 2050* to include mandatory efficiency goals for utilities underlines the need to analyse existing policy instruments to promote energy efficiency. These policy instruments are usually considered to be a part of demand-side management (DSM) initiatives undertaken by governments and local utilities. DSM refers to the *"planning, implementing, and monitoring activities of electric utilities that are designed to encourage consumers to modify patterns of electricity usage, including the timing and level of electricity demand"* (EIA, 1999). In Switzerland, local utilities play an important role in the implementation of DSM programmes.

In order to perform a qualitative analysis of utility DSM efforts in Switzerland as well as an empirical analysis on the impact of DSM on electricity consumption in this essay, we collected data on the measures introduced by Swiss electric utilities using a survey. For this purpose, we sent out questionnaires to 105 utilities in Switzerland between April and November, 2013. We emailed a questionnaire to the 50 largest utilities and to a random sample of 55 mid-sized utilities. The objective of the survey was to gather information on the electricity delivered to residential customers as well as to quantify any efforts made by utilities on demand-side measures to reduce electricity consumption. The survey covered questions about the quantity of electricity consumed by residential customers, number of customers, electricity tariffs, utility characteristics and DSM activities. We use information from the survey to develop an energy efficiency score that measures a utility's commitment to promote energy efficiency among their residential customers.

Our primary identification strategy to estimate the effectiveness of DSM efforts by Swiss utilities is to use the variation in DSM measures within utilities over time and across utilities. In effect, we are using the method of difference-in-differences. We also use the method of instrumental variables as a robustness check.

This paper contributes to the public policy debate about the degree to which DSM programs can reduce the demand for electricity in the residential sector as well as influence the adoption of energy efficiency measures. A second major contribution of this paper is that, to our knowledge, this is the first econometric estimation of aggregate DSM efforts in a European country. Another contribution is that we construct a scorecard to measure the energy efficiency activities of individual utilities and correlate changes in the scorecard to to changes in the residential electricity consumption. Lastly, we use two alternative robustness checks to investigate the sample selection bias.

This essay is based on chapter 4 in the report "*An Evaluation of the Impact of Energy Efficiency Policies on Residential Electricity Demand in Switzerland*" (Boogen et al., 2015). This chapter represents joint work with Souvik Datta and Massimo Filippini.

Essay 3: Estimating the potential for electricity savings in Swiss households

The *Energy Perspectives 2050* forecasts an end-use electricity consumption of around 69 TWh in 2050 for the business-as-usual scenario (Prognos, 2012). The *Energy Strategy 2050* seeks to reduce this figure to 53 TWh by 2050 (SFOE, 2013b).[2] Since a third of the total end-use consumption originates from households, the residential sector may be an important driver of energy efficiency savings. Therefore, an important question is how large the actual potential of electricity saving in the residential sector is. Prognos (2011) uses an economic-engineering approach based on bottom-up models in order to derive an estimate for the potential for energy savings in Switzerland. They find that the electricity consumption for households can be reduced by almost 15% by 2035 and 20% by 2050 compared to the reference scenario. This essay, on the other hand, follows a top-down approach using stochastic frontier analysis based on microeconomic production theory to measure the level of technical efficiency in the use of electricity in Swiss households.

This essay makes use of the same dataset as in Essay 1. Since the demand for residential electricity is an input demand in the production of energy services at home, it can be represented as a production function. This production process may be inefficient and to measure this inefficiency in the use of electricity in Swiss households, we estimate a stochastic frontier model for residential electricity demand. The dataset includes information on the appliance stock and its price as well as information on the amount of energy services consumed within a household. Due to this, we are able to estimate a sub-vector input distance function. Traditionally, the stochastic frontier function is used in production theory to empirically measure the economic performance of production processes. The main concept of the stochastic frontier approach is that the frontier function estimates the maximum (or minimum) level of an economic indicator reachable by a decision making unit. In our case, the frontier gives the minimum level of electricity input used by a household for any given level of energy services. The difference between the observed input and the optimal input demand on the frontier represents inefficiency.

This paper has one major contribution to the existing literature. While the stochastic frontier approach has been used with aggregated energy data, we use disaggregated data since residential consumers are typically very heterogeneous and it can add more detail to the knowledge of consumer response. Since our dataset includes information on the amount of energy services produced within a household, we are able to estimate a sub-vector input distance function, similar to Zhou et al. (2012b), but using household survey data. Thus, to the best of our knowledge, this is the first study that includes energy services in the frontier model and adopts a distance function approach on a disaggregated level to estimate the level of technical efficiency in the use of electricity based on a microeconomic foundation.

[2] Per capita and year the *Energy Strategy 2050* aims to reduce the electricity demand by −3% by 2020 and −13% by 2035 compared to the year 2000.

1 Estimating residential electricity demand in Switzerland: New empirical evidence[3]

1.1 Introduction

1.1.1 Problem and Goals

In order to find out the effectiveness of an energy tax on electricity consumption it is important to obtain credible estimates of the responsiveness of electricity demand to its price. We ask three research questions in this paper. Firstly, what is the price elasticity of residential electricity consumption? This will enable the design of appropriate pricing policies by utilities and the regulatory authorities to reduce electricity consumption as well as provide a way to forecast demand and plan for generating capacity in the future. Secondly, how does the stock of electrical appliances affect the consumption of residential electricity? This will enable us to obtain a correct estimate of the price elasticity. Finally, what is the impact of using energy services, such as the number of meals cooked at home and the amount of time spent using personal computers and watching television, on the electricity consumption of a household? How is the price elasticity of demand for electricity affected if we use such measures instead of the usual method of approximating energy services with household and socio-demographic characteristics? This will indicate the difference, if any, between these two methods.

To answer these questions we use data from a survey of Swiss households served by seven electric utility companies and conducted by the Verband Schweizerischen Elektrizitätsunternehmen (VSE) in 2005 and 2011.[4] The survey contains information on a household's stock of appliances, use of appliances, and various socio-demographic characteristics. The survey also reports the electricity consumption of each household in the previous year. We find that Swiss households are price inelastic in electricity and the price elasticity in the short-run is around -0.4 while in the long-run it ranges between -0.4 and -0.6. These results can be used by policy makers and utility companies to design instruments to reduce and modify electricity consumption. Our results suggest that Swiss households are price inelastic in electricity prices. However, the estimated long-run values are higher than -0.5. These results can be used by policy makers and utility companies to design instruments to reduce and modify electricity consumption. We also find that the difference in the price elasticity of demand for electricity if we use energy services or if the usual method of approximating energy services with household and socio-demographic characteristics, is not very high and, therefore, using household and socio-demographic information are good measures of energy services.

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[3] This essay is based on chapter 2 in the report "*An Evaluation of the Impact of Energy Efficiency Policies on Residential Electricity Demand in Switzerland*" (Boogen et al., 2015). Nina Boogen is the primary author of this essay in all regards.

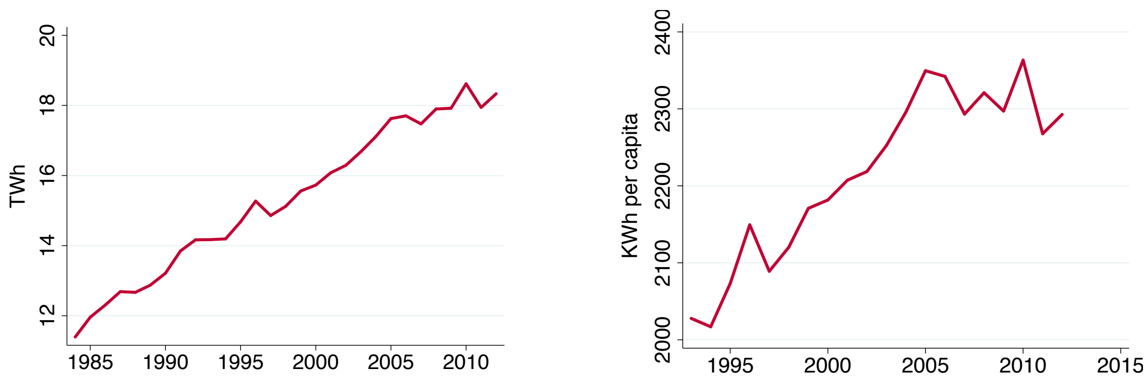
[4] The VSE is the Swiss Association of Electric Utilities.

1.1.2 Residential Electricity Demand in Switzerland

In Switzerland, 718 utility companies (as of September 2012) are involved in the production, distribution and supply of electricity (ElCom, 2013). Swiss utilities are very heterogeneous. There are different sizes of companies, from small municipal utilities to international operating companies. In 2011 these utilities sold 17.9 TWh to their residential customers. The average consumption in each household was 5,167 kWh and the average residential per capita consumption was 2,268 kWh (SFOE, 2013a). In Table 1.1 Switzerland can be compared to its neighbours, the EU average and the US using data from World Energy Council (2013). Whereas Italy, Germany and the EU (on average) use less electricity, both per household and per capita, France and Austria are comparable. Only US households use a lot more with double the consumption of Swiss households. Swiss total residential electricity demand is growing at a steady rate as can be seen in Figure 1.1 using data from SFOE (2013a). However, the growth for per capita demand shows a flattening from around 2005. Electricity demand is used to produce energy services. Therefore, in studying the demand for electricity, it is very important to also analyse the household's stock of appliances.

Table 1.1: Electricity consumption (in kWh) in European countries. Source: WEC (2013)

	per capita	per hh
Switzerland	2,268	5,167
Germany	1,714	3,454
France	2,277	4,977
Austria	2,212	4,931
Italy	1,153	2,735
European Union	1,611	3,888
United States	4,569	11,789



(a) Total residential electricity demand in TWh. (b) Residential electricity demand per capita in kWh.

Figure 1.1: Residential electricity demand in Switzerland (Source: SFOE, 2013).

1.1.3 Previous work

There are a number of studies that estimate long- and short-run price elasticities for residential electricity demand using aggregated data.[5] However, using data at a more disaggregated level can add great detail to the knowledge of consumer response due to the heterogeneity of residential consumers. As noted by Dubin & McFadden (1984), using disaggregated data avoids misspecification error caused by aggregation bias from using aggregate electricity consumption and prices. Table 1.2 provides an overview of some selected estimated price elasticities for electricity using disaggregated data in the literature. For example, Reiss & White (2005) use a sample of about 1,300 Californian households from the Residential Energy Consumption Survey (RECS) for 1993 and 1997 to estimate price and income elasticity using marginal price and a set of appliances. They find considerable amount of heterogeneity in the estimated elasticities across income and other demographic characteristics. Yoo et al. (2007) use survey data from 380 households in Seoul and a bivariate model to account for sample selection. They find significant sample selection bias and also find that a plasma TV or an air conditioner has a significant positive impact on residential consumption. However, the electricity demand estimated by using the average price appears to be price (-0.25) and income inelastic (0.06).

Conversely, Alberini et al. (2011) find a much higher price response by residential consumers (-0.67 to -0.86). They use a mix of panel data and multi-year cross-sectional household-level data from over 70,000 households in the 50 largest metropolitan areas in the United States from 1997 to 2007. To correct for a possible mismeasurement problem the average electricity price is instrumented with state-level electricity and gas prices or lagged electricity prices. In contrast to Reiss & White (2005), they find no evidence of significantly different price elasticities for households with electric and gas heating systems. Fell et al. (2014) use monthly data from a consumer expenditure survey collected between 2006 and 2008 to estimate the price elasticity. Using expenditure data and state-level average electricity prices to compute the quantity of electricity consumed they are faced with two possible sources of endogeneity that they solve with a GMM approach. The estimated price elasticity is near -0.50 and at the upper end compared to other cross-sectional studies. They explain this with the fact that they use average price and not marginal price as used in most other studies. Krishnamurthy & Kriström (2015) estimate price elasticity in a cross-country study using data from households in 11 OECD countries for 2011 and find a high price elasticity of between -0.27 and -1.4 in most countries.

There are only a few previous studies in Switzerland using disaggregated data. Table 1.2 also provides an overview of disaggregated studies within Switzerland. Among the first studies using disaggregated data were those by Dennerlein & Flaig (1987) and Dennerlein (1990). Dennerlein & Flaig (1987) use pooled cross-section data from almost 6,000 households collected with an expenditure survey from 1975 to 1984. This survey also includes information about the ownership of some appliances. The authors estimate the electricity demand as well as two separate probit

[5] Studies using aggregated data estimate a price elasticity from -0.07 in the short run and -0.19 in the long run (Blázquez et al., 2013) to -0.27 in the short run and -0.54 in the long run (Narayan & Smyth, 2005). The last analysis performed for Switzerland, Filippini (1999), estimates a long-run price elasticity of -0.3. Studies using aggregated data estimate, on average, lower price elasticities than studies using disaggregated data.

models for the ownership of electric stove and TV. Moreover, they also control for the ownership of electric stove, electric water and space heating and TV and find short-run elasticities between −0.2 and −0.4 and long-run elasticities of between −0.4 and −0.6. Dennerlein (1990) uses the same database but from 1977 to 1986 and finds slightly higher short-run (−0.5) and long-run (−0.7) elasticities using average prices. However, both these studies may suffer from potential simultaneity issues because the choice of appliances may depend on the consumption of electricity.

Zweifel et al. (1997) use data from around 1,300 households for different years (1989–92) and group them into three different pools depending on whether households have a single-tariff structure, a time-of-use structure and a time-of-use structure by choice. These households are customers of utilities that have either both structures or a time-of-use scheme. For the first group, the price elasticity is very small and not significant. But for the second and third groups the elasticities, estimated by OLS, are significant and −0.66 and −0.59 respectively. Excluding the city of Zürich in the third group reduces the elasticity to −0.42. However, the variation of electricity price in this study is based on only three utility companies and is, therefore, low. Since the 1990s there has been no study using disaggregated data in Switzerland to estimate the price elasticity of residential electricity demand and this paper provides an update using a unique household survey.

Table 1.2: Selected price elasticities using disaggregated data in the literature.

<table>
<tr><th>Author</th><th>Location</th><th>Short-run</th><th>Long-run</th></tr>
<tr><td>International</td><td></td><td></td><td></td></tr>
<tr><td>Tiwari (2000)</td><td>Mumbai</td><td>-0.61 to -0.84</td><td></td></tr>
<tr><td>Halvorsen & Larsen (2001)</td><td>Norway</td><td>-0.433</td><td>-0.442</td></tr>
<tr><td>Reiss & White (2005)</td><td>California</td><td>-0.39</td><td></td></tr>
<tr><td>Yoo et al. (2007)</td><td>Seoul</td><td colspan="2">-0.25</td></tr>
<tr><td>Alberini et al. (2011)</td><td>US</td><td>-0.74</td><td>-0.81</td></tr>
<tr><td>Fell et al. (2014)</td><td>US</td><td>-0.50</td><td></td></tr>
<tr><td>Krishnamurthy & Kriström (2015)</td><td>Cross-country</td><td colspan="2">-0.27 to -1.4</td></tr>
<tr><td>Switzerland</td><td></td><td></td><td></td></tr>
<tr><td>Dennerlein & Flaig (1987)</td><td>CH</td><td>-0.2 to -0.4</td><td>-0.4 to -0.6</td></tr>
<tr><td>Dennerlein (1990)</td><td>CH</td><td>-0.5</td><td>-0.7</td></tr>
<tr><td>Zweifel et al. (1997)</td><td>CH</td><td colspan="2">-0.42 to -0.66</td></tr>
</table>

All the studies mentioned above have certain drawbacks. Firstly, they use individual appliance dummy variables to control for the effect of appliances except for Krishnamurthy & Kriström (2015) who use a count variable to represent the appliance stock. The drawback to using this approach is that the appliance dummy variables and the count variable are not able to distinguish between appliances of various vintages and sizes and, hence, the precision for measuring appliance capacity is limited. In contrast to this approach, Tiwari (2000) estimates the residential electricity demand in Bombay by using an appliance index. This appliance index is composed of the average power requirement of a television, iron, video cassette recorder, tape recorder, radio and refrigerator owned by the household relative to the maximum power. However, the study ignores the possible endogeneity problem caused by the simultaneity bias when using an appliance index. This is another drawback since the choice of appliances may depend on the consumption of electricity. Therefore, we need to consider the residential electricity demand as being jointly determined with the demand for electrical appliances. There are two different strands of literature on this issue.

Firstly, Dubin & McFadden (1984) use a discrete-continuous approach with two steps. In the first step, they estimate the choice of a space and water heating system by using a multinomial logit model. In the second step, they estimate the electricity consumption with an OLS model using the predicted choice of space and water heating system as independent variables. They conclude that the unobserved factors influencing the choice of water and space heating system and the unobserved factors of the intensity of use are not independent. Therefore, the traditional single-equation approach leads to biased results.

Secondly, Garbacz (1983, 1984) develops a three-equation model with an electricity demand equation, an appliance stock equation and an equation for the electricity price. He uses a 2SLS procedure to estimate the three-equation model. He constructs an index of appliances as an alternative to several endogenous dummy variables for measuring the appliance stock. Garbacz (1983) mentions that using such an appliance index has two advantages. Firstly, one does not need to use a logit model and, secondly, his method allows him to get an estimate of the size of the appliance, which is an important factor when measuring the intensity of use. However, this appliance index is based on typical electricity use of the individual appliances in kWh and not a measure of typical capacity. In addition, the prices of appliances are not included in this model.

Our paper contributes to the existing literature in several ways. Firstly, we use a unique survey of households conducted in Switzerland that includes detailed information on a household's annual electricity consumption, residential and socio-demographic characteristics, its stock of appliances, and its use of these appliances. Secondly, we base our theoretical model on household production theory that posits electricity demand as being a derived demand for energy services. Therefore, we augment our basic models and estimate the electricity demand by using information on energy services, e.g., the amount of washing done by a household. Thirdly, we use detailed information from a household's stock of appliances and follow the approach of Garbacz (1983) by constructing an appliance stock index but use an alternative method that takes into account a measure of typical capacity and not typical electricity use as in Garbacz (1983). Unlike Garbacz (1983) we also calculate a single index for the price of appliances as the average price, per Watt, of household appliances. Finally, we use an instrumental variables approach to account for the possible endogeneity of the average price of electricity as well as the price of the measure of household appliances and obtain consistent estimates of the price elasticity of residential electricity demand.

The rest of the chapter is organized as follows. In the next section we provide the motivation for using a modified model of household production to derive a model for estimating electricity demand and demand for appliance stock and, following that, a description of our empirical strategy. Section 1.3 describes the household survey as well as other sources of data. The penultimate section presents the results of our different specifications while the final section has concluding remarks.

1.2 Model and Empirical Strategy

The demand for electricity is considered to be a derived demand since it is consumed to provide us with services, e.g. an electric heater providing warmth. Therefore, electricity is not demanded *per se* but as an input in the production of these services. In section 1.2.1, we shortly introduce the household production theory and how it can be used to obtain the residential electricity and appliance stock demand. In section 1.2.2 we derive equations for the long- and short-run residential electricity demands and the long-run appliance stock demand by using a simplified version[6] of household production theory whereby households combine electricity and capital goods to obtain energy services.

1.2.1 Household Production Theory

Household production theory was introduced by Becker (1965) and Muth (1966). A good description can also be found in Deaton & Muellbauer (1980). Applications to electricity demand analysis can be found in Dubin (1985), Flaig (1990) and Filippini (1999).

The optimal input demand functions of energy (E) and capital (K) and the resulting demand of produced energy services, S, can be found if one assumes that the household maximizes utility from the consumption of the energy service S and other goods X while taking the individual budget constraint and the production function of S into account.

$$\max \quad U(S, X) \quad \text{s.t.} \quad M = P^X X + P^K K + P^E E \quad \text{and} \quad S = f(E, K) \tag{1}$$

We can then write the Lagrangian function to the optimization problem stated above as:

$$L = U(S, X) + \lambda_1 \left(M - P^X X - P^K K - P^E E \right) + \lambda_2 \left(S - f(E, K) \right) \tag{2}$$

where U is a well-behaved[7] utility function with the consumption of the energy service S and other goods X as arguments. The household faces two constraints when maximising its utility. Firstly, it faces a budget constraint when spending the income M on input factors energy E and capital K with prices P^E and P^K but also on other goods X. We normalise the price of other goods P^X to unity. Secondly, the household faces a production technology $f(E, K)$ that is well-behaved in the same sense as the utility function which has inputs energy and capital and yields an output being the energy service S.[8]

After the optimization process we will get a demand system for the inputs E and K and the demand

[6] Note that there is no labour and time input in this version of the household production model.

[7] "well-behaved" means that utility is strictly increasing with S and X. That is $\frac{\partial U}{\partial S} > 0$, $\frac{\partial U}{\partial X} > 0$ and is concave in the sense that $\frac{\partial_2 U}{\partial_2 S} > 0$, $\frac{\partial_2 U}{\partial_2 X} > 0$.

[8] Assuming constant returns to scale in production , the price of energy services remains constant. This assumption allows to solve the optimisation problem.

for other goods that depend on the input prices and the quantity of energy services S:

$$E = E(P^E, P^K, S) \tag{3a}$$
$$K = K(P^K, P^E, S) \tag{3b}$$
$$X = X(P^E, P^K, S). \tag{3c}$$

The amount of energy services produced itself would then be a function of input prices and income.

$$S = S(P^E, P^K, M) \tag{4}$$

Substituting for S we get:

$$E = E(P^E, P^K, M) \tag{5a}$$
$$K = K(P^K, P^E, M) \tag{5b}$$
$$X = X(P^E, P^K, M). \tag{5c}$$

In summary, the process of household production is described as a utility maximisation process, optimised with respect to the amount of energy service S, the consumption of other goods X, the input use of energy E and capital K while taking two constraints into account: the budget constraint and the production function. This leads to the cost-efficient input demands for K and E that we are interested in estimating. To do this, we can estimate the cost-efficient input quantities for K and E in equation (3a) and (3b) given an amount of energy service S if we have information on the consumed energy services. In most cases, such information is not available and we can estimate the input demand functions using the equations (5a) and (5b).

1.2.2 Model

With the above discussion in mind, we now present the short- and long-run electricity and capital stock demand models used in this chapter. Solving the optimization procedure we obtain the demand function for electricity, E, as being determined by the prices of electricity and capital as well as the energy services consumed by a household:

$$E^* = E(P^E, P^K, S^*(P^E, P^K, M, Z)) \tag{6a}$$
$$= E(P^E, P^K, M, Z), \tag{6b}$$

where P^E and P^K are the prices of electricity and capital, respectively, S is the amount of energy services consumed, M is the household income and Z is a matrix of socio-demographic and residential characteristics. Equation (6a) indicates that electricity consumption depends on the electricity price, prices of the stock of appliances and the equilibrium amount of energy services consumed. This implies that, if we can obtain measures of the price variables and the quantity of energy services consumed, we will be able to estimate the electricity demand. Typically, the amount of energy services, as in equation (6a), are not measured and are, instead, approximated by including residential and socio-demographic characteristics. Therefore, we can also use equation (6b) to estimate the electricity demand. This represents electricity consumption as a function of electricity price, price of the stock of appliances and household income. It is also a function of other household characteristics.

The demand function for household appliance stock, or capital, K is also determined by the prices of electricity and capital as well as the energy services consumed by a household:

$$
\begin{aligned}
K^* &= K(P^E, P^K, S^*(P^E, P^K, M, Z)) && \text{(7a)}\\
&= K(P^E, P^K, M, Z). && \text{(7b)}
\end{aligned}
$$

The equations for E^* and K^* represent the long-run equilibrium consumption amounts for a household. While it is empirically possible to estimate equations (6b) and (7b) simultaneously, researchers limit themselves to estimating equation (6b). However, our data allows us to estimate the long-run demand for both electricity and appliance stock.

Equations (6a) and (6b) are static models in the sense that the adjustment of electricity consumption is instantaneous if there is a change in any of the determinants of electricity consumption. It also reflects the fact that the rate of utilisation and the stock of appliances are adjusted instantaneously when there are changes in prices or income. However, the instantaneous adjustment of the stock of appliances may be a relatively strong assumption. For this reason, it is important to estimate the electricity demand also with a short-run perspective in which the stock of appliances can not be adjusted while it can be in the long run.

With the above discussion in mind we now present the short- and long-run electricity demand models used in our study. The short-run electricity demand equations corresponding to (6a) and (6b), respectively, can be written as

$$
\begin{aligned}
E^{SR} &= E^{SR}(P^E, K, S^*(P^E, K, M, Z)) && \text{(8a)}\\
&= E^{SR}(P^E, K, M, Z), && \text{(8b)}
\end{aligned}
$$

where K denotes a given stock of appliances and the superscript SR refers to the short run. Capital stock is assumed to be fixed in the short run.[9] One way to measure a household's stock of appliances is to construct an index by using the capacity of the major appliances owned by the household. Tiwari (2000) uses this method to get an approximate measure of the appliance stock owned by a household.

[9]Therefore, we do not estimate a separate appliance stock demand in the short-run.

In the long-run, however, the electricity and appliance stock demand equations corresponding to (6a), (6b), (7a) and (7b), respectively, can be written as

$$
\begin{aligned}
E^{LR} &= E^{LR}(P^E, P^K, S^*(P^E, P^K, M, Z)) && (9a)\\
&= E^{LR}(P^E, P^K, M, Z), && (9b)\\
K^{LR} &= K^{LR}(P^E, P^K, S^*(P^E, P^K, M, Z)) && (9c)\\
&= K^{LR}(P^E, P^K, M, Z), && (9d)
\end{aligned}
$$

where the superscript LR refers to the long run. Equations (9a) and (9b) indicate that the long-run electricity demand changes when the prices of electricity and appliance stock change, while equations (9c) and (9d) show how the appliance stock demand changes when the prices of electricity and appliance stock change. Obtaining an estimate of the price of the stock of appliances is key to estimating the long-run equilibrium of electricity consumption. A way to do this is to calculate the price index of the appliance stock by using the capacity of the major appliances owned by the household (the index mentioned above in the short-run estimation). This is adjusted with the price of the corresponding appliance to determine the price index of the appliance stock.

We can then estimate the short- and long-run price elasticity of electricity consumption by utilising stock and price information of the appliances, respectively. We can also estimate the long-run price elasticity of capital stock demand. The previous discussion provides the motivation in terms of the explanatory variables for our econometric model specification. Using a log-log functional form, as is common in the literature, the long-run electricity and appliance stock demand function for household i can be written as

$$
\begin{aligned}
\log E_i^{LR} &= \alpha_0 + \alpha_1 \log p_i^E + \alpha_2 \log p_i^K + S_i\delta^{LR} + \epsilon_i && (10a)\\
\log E_i^{LR} &= \alpha_0' + \alpha_1' \log p_i^E + \alpha_2' \log p_i^K + M_i\delta'^{LR} + Z_i\gamma^{LR} + \epsilon_i, && (10b)\\
\log K_i^{LR} &= \gamma_0 + \gamma_1 \log p_i^E + \gamma_2 \log p_i^K + S_i\zeta^{LR} + \epsilon_i && (10c)\\
\log K_i^{LR} &= \gamma_0' + \gamma_1' \log p_i^E + \gamma_2' \log p_i^K + M_i\zeta'^{LR} + Z_i\eta^{LR} + \epsilon_i, && (10d)
\end{aligned}
$$

where α_1,α_1', γ_1 and γ_1' are the parameters to be estimated for the price of electricity p_i^E, α_2, α_2', γ_2 and γ_2' are the parameters to be estimated for the price of household appliances p_i^K, δ^{LR} and ζ^{LR} are vectors of parameters to be estimated for energy services S, δ'^{LR} and ζ'^{LR} are the parameters to be estimated for household income M_i, γ^{LR} and η^{LR} are vectors of parameters to be estimated for household characteristics Z_i, and ϵ_i is the usual error term, assumed to be independently and identically distributed. An advantage of using a log-log specification is that the coefficient of electricity price, e.g., α_1, is easily interpreted as the price elasticity of electricity demand. This means that a one percent change in electricity price will cause an α_1% change in the electricity consumption, keeping all else the same.

The short-run electricity demand function for household i can be written as

$$\log E_i^{SR} = \beta_0 + \beta_1 \log p_i^E + \beta_2 \log K_i + S_i\delta^{SR} + \epsilon_i. \tag{11a}$$

$$\log E_i^{SR} = \beta_0' + \beta_1' \log p_i^E + \beta_2' \log K_i + \delta'^{SR} M_i + Z_i\gamma^{SR} + \epsilon_i. \tag{11b}$$

where, similar to before, β_1 and β_1' are the parameters to be estimated for the price of electricity p_i^E, β_2 and β_2' are the parameters to be estimated for the stock of household appliances K, δ^{SR} is a vector of parameters to be estimated for energy services S, δ'^{SR} is the parameter to be estimated for household income M_i, γ^{SR} is a vector of parameters to be estimated for household characteristics Z_i, and ϵ_i is the usual error term, assumed to be independently and identically distributed. In contrast to the long-run equations, the short-run equations include the household's stock of appliances instead of the price of appliances since we assume that the appliance stock can not be changed in the short-run.[10] Therefore, we do not estimate a short-run version of the capital stock demand.

The method to calculate the electricity price is crucial to estimate the price elasticity of electricity. While the literature on this is substantial, the main approaches can be divided into two strands. The first approach uses average prices while the second uses marginal prices. Nordin (1976) suggests using the marginal price (and subtract the fixed fee from the income). Shin (1985), on the other hand, uses the average price. The average price of electricity is obtained by dividing the electricity bill with the quantity of electricity consumed. In our case, we use the marginal price and fixed fee, if any, to calculate the electricity bill by multiplying the electricity consumption with the marginal price and then adding the fixed fee.

The advantage of using the marginal price over the average price is its exogeneity, i.e. the marginal price of electricity will affect electricity consumption but not the other way round. Since the average price is calculated by dividing spending on electricity, that usually includes a fixed fee, with the quantity consumed there exists the problem of simultaneous causality which leads to the average price being an endogenous explanatory variable.[11] However, as has been discussed in the literature, the average price is probably more important than the marginal price since households are more concerned about their total electricity bill rather than the price of electricity at the margin (e.g., Shin (1985), Borenstein (2009) Fell et al. (2014) and Ito (2014)). We, therefore, use the average price in our analysis.[12] We use instrumental variables to account for the potential endogeneity issues stemming from using the average price.

As mentioned before, the way we incorporate a household's stock of appliances will enable us to estimate the long- and short-run price elasticities of demand for electricity. In our analysis, we use an index of the stock of appliances to estimate the short-run price elasticity as well as the long-

[10] An alternative approach is to estimate the long- and short-run price elasticities by using a partial adjustment model. Unfortunately, we can not use this approach since we do not have panel data. See Alberini & Filippini (2011) and Blázquez et al. (2013) for applications.

[11] For a more detailed discussion on this issue see Krishnamurthy & Kriström (2015)

[12] We do not use marginal prices because of very low variation of these prices across the utilities in our sample.

run appliance stock demand. The index is calculated by using the estimated capacities (in Watt) of a household's stock of major appliances. The appliance stock may suffer from simultaneity bias in the short-run since the choice of appliances may depend on the consumption of electricity (Dubin & McFadden, 1984). Therefore, the stock of appliances may be endogenous in the short-run estimating equation and we use instrumental variables to account for this. An advantage of constructing an aggregate index of individual appliances instead of using the appliances individually is the avoidance of using multiple instrumental variables to account for the potential endogeneity of the appliances. Since we consider many appliances it is very difficult to find instruments for multiple endogenous variables due to the possibility of weak instruments that will produce inconsistent estimates. Collapsing the multiple appliances to a single measurable index means that we need to find at least one instrumental variable. In addition, it enables us to estimate the long-run capital stock demand as a single regression.

In the long-run estimation we can estimate the demand for electricity independent from the demand for appliance stock. We estimate the long-run estimations in two ways. Firstly, by calculating a rental price for each major appliance and, secondly, by calculating a price index for the appliances, i.e. the price per estimated installed capacity. However, the price of appliances might be endogenous in both, electricity and appliance stock demand estimations. Since it might be the case that households with a higher electricity demand might be more interested in buying energy-efficient appliances, which are generally more costly. Also in this case we use instrumental variables to account for the potential endogeneity issues of the appliance price. However, we implement this only in the case where we use the price index for the appliances, as with the rental prices for each major appliance we are faced with a similar problem to find instruments for multiple endogenous variables.

In the rest of our analysis we estimate equations (10a), (10c) and (11a) as well as equations (10b), (10d) and (11b) where the parameters of interest are the long-run estimates of α_1 and α_1' and short-run estimates of β_1 and β_1', i.e. the price elasticities of residential electricity consumption in Switzerland. The goal is to estimate those elasticity parameters by taking into account the possible endogeneity of the average price, the appliance index and the price index for the appliances.

1.3 Data

The primary data comes from a household survey organized by the Verband der Schweizerischen Elektrizitätsunternehmen (VSE) while we use secondary data from the Swiss Federal Electricity Commission (ElCom), the Swiss price supervisor ("Preisüberwacher"), Schweizerische Agentur für Energie Effizienz (SAFE) and comparis, a Swiss price comparison website. The data are described below while Table 1.5 provides the summary statistics of all the variables.

1.3.1 VSE Survey

We use data from a survey performed by the Verband der Schweizerischen Elektrizitätsunternehmen (VSE). VSE conducted two surveys on around 2,400 Swiss households served by seven different utility companies. The first survey was conducted in 2005 and the second survey in 2011, both by telephone interviews. In both surveys data were collected from residential customers of five utilities for a total of 1,200 households. Three out of those five utilities were common to both the 2005 and the 2011 surveys but the households were not necessarily the same. Due to a confidentiality agreement, we are unable to list the names of the utility companies involved. However, these seven utilities account for around 25% of the residential electricity consumption in Switzerland. Variables collected include characteristics of houses (e.g., the number of rooms they live in), demographics of households (e.g., the gender and age group), the stock of appliances, rough characteristics of appliances (e.g. if older than 10 years), use of appliances (e.g., the hours switched on) and the annual electricity consumption of the household. We exclude households with a yearly consumption of less than 200 kWh and more than 30,000 kWh. This leaves us with 1,944 observations.

The survey reports the electricity consumption for the previous year. The household electricity consumption was not asked during the interview but was obtained from the last regular meter readings conducted by the respective utility company. Comparing the average total consumption in kWh per household and per capita in our sample to the Swiss Electricity Statistics (SFOE, 2013a) shows that both values in our sample are lower.[13] One possible explanation is that households with an electric heating systems are not part of our sample. Between 2000 and 2008 the share of electric heated homes in Switzerland decreased by 3.8%, but is still at a level of 6% (Prognos, 2008). The distribution of the electricity consumption for the utilities in 2005 and 2011 are provided in the kernel density plots in Figures 1.2 and 1.3, respectively. The upper graph in each figure is for the total electricity consumption and the lower graph is for its logarithmic transformation. Figure 1.3 shows that utilities 3 and 7 are quite different compared to utilities 1, 2, and 6. The customers of utilities 3 and 7 are all exclusively located in urban areas while the customers of utilities 1, 2, and 6 are distributed between rural and urban areas, as shown in Table 1.3.[14] Figure 1.2 also shows that utility 1 is very different compared to the other utilities in 2011. Therefore, we construct a dummy variable to control for a household belonging to utility 1 in year 2011.[15] Table 1.4 shows

[13] The values from the official statistics are 2268 kWh per capita and 5167 kWh per household.

[14] We define urban as an agglomeration area with more than 10,000 inhabitants.

[15] In Boogen et al. (2015) we perform robustness checks by excluding customers of utility 1 in 2011. We note that excluding households served by utility 1 in 2011 slightly reduces the price elasticity across all models.

the representativeness of our sample, comparing household income, number of rooms, abundance of children and household size to numbers from the Swiss Federal Statistical Office (BFS).[16] In our sample, the distribution of gross household income appears to be a little different from the distribution obtained from BFS. Since our data has only income groups it is difficult to make an appropriate comparison. Household size and percentage of households with children are comparable to the Swiss population. However, the sample is slightly under weighted in small homes (1–2 rooms) and overweighted in very large homes (6+ rooms). Nevertheless, we conclude that our sample is, more or less, representative.

Table 1.3: Rural versus urban households

Utility	**Rural**	**Urban**	**Total**
1	252	68	320
2	203	135	338
3	0	468	468
4	88	75	163
5	3	145	148
6	229	114	343
7	0	164	164
Total	775	1,169	1,944

Table 1.4: Representativeness of survey data

Variable	**BFS**	**VSE**
Gross Household Income in CHF per month†		
1st Quintile	4880	3750
2nd Quintile	7173	5250
3rd Quintile	9702	7500
4th Quintile	13170	12000
Number of rooms		
1-2 rooms	17.96%	11.28%
3-5 rooms	71.06%	72.85%
6 rooms or more	10.97%	15.86%
Household size		
1-2 persons	68.91%	66.44%
3-4 persons	25.54%	27.77%
5 persons or more	5.56%	4.79%
Children	32.25%	29.85%

†:VSE incomes are calculated using the mid-point of the income groups. 1 CHF (Swiss Franc) = 1.07 US Dollar, as of 4 May, 2015 (http://www.xe.com/#).
BFS: Bundesamt für Statistik is the Swiss Federal Statistical Office
VSE: Verband der Schweizerischen Elektrizitätsunternehmen is the Swiss Association of Electric Utilities

[16] http://www.bfs.admin.ch/bfs/portal/de/index/themen.html.

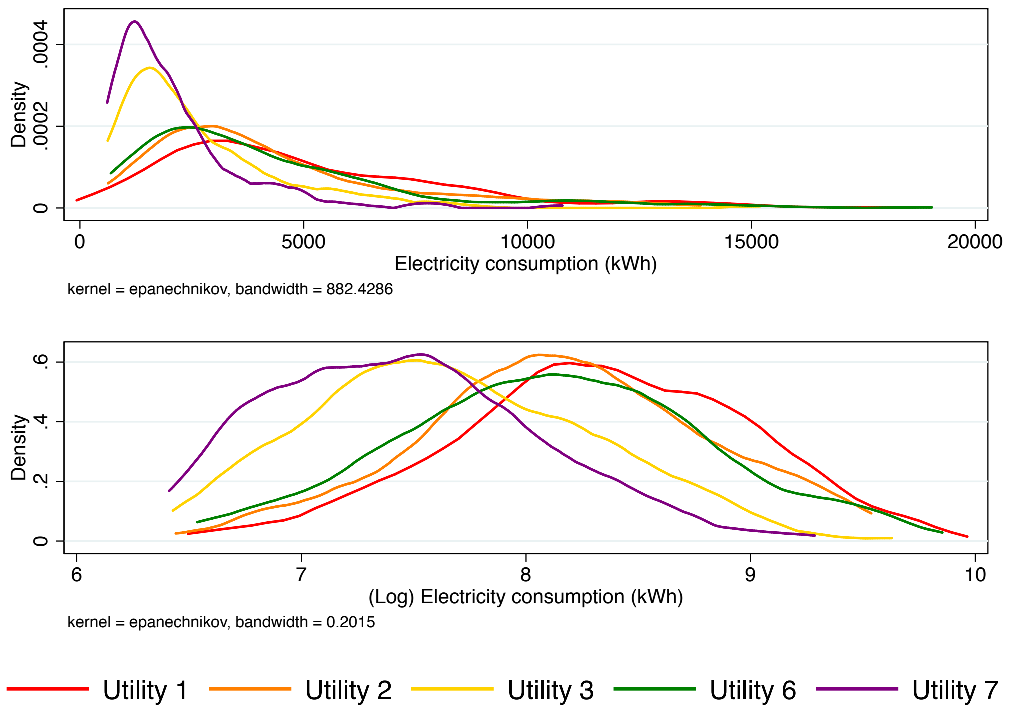


Figure 1.2: Kernel density plot for 2005

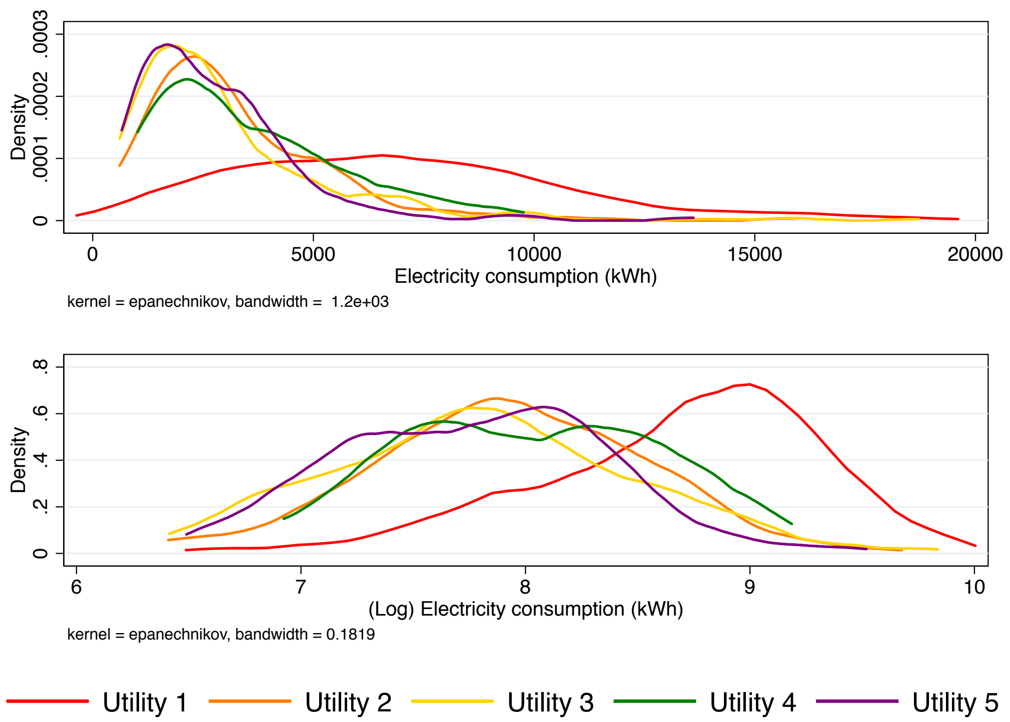


Figure 1.3: Kernel density plot for 2011

Table 1.5: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Consumption & Price					
Total consumption (in kWh)	3833.2	3123.27	247	29476	1944
Average Price (in Swiss Rappen)	17.28	5.73	2.83	62.8	1944
ElCom Price (in Swiss Rappen)	16.03	4.37	8.02	29.75	1844
Grouped Mean of Average Price (in Swiss Rappen)	17.28	5.03	10.9	33.04	1944
Neighbouring ElCom Price (in Swiss Rappen)	18.91	4.08	9.70	27.42	1844
Income Groups					
Income group 1	0.09	0.29	0	1	1944
Income group 2	0.17	0.37	0	1	1944
Income group 3	0.23	0.42	0	1	1944
Income group 4	0.29	0.46	0	1	1944
Income group 5	0.18	0.38	0	1	1944
Income group 6	0.04	0.20	0	1	1944
Midpoint income	7244.60	4459.63	1500	22500	1944
Household characteristics					
Number of rooms	4.15	1.49	1	9	1944
Household size	2.38	1.22	1	8	1944
Single family housing dummy	0.34	0.47	0	1	1944
Tenant dummy	0.55	0.50	0	1	1944
Children dummy	0.31	0.46	0	1	1944
Retired dummy	0.32	0.47	0	1	1944
Share of females	0.55	0.29	0	1	1944
Time-of-use dummy	0.77	0.42	0	1	1944
Urban dummy	0.6	0.49	0	1	1944
Dummy for utility 1 in 2011	0.08	0.27	0	1	1944
Year 2011 dummy	0.49	0.50	0	1	1944
Appliances					
Appliance Index (in Watts)	5191.88	2070.68	110	11605.1	1944
Freezer	0.55	0.50	0	1	1944
Electric boiler	0.32	0.46	0	1	1944
Clothes washer	0.55	0.50	0	1	1944
Dishwasher	0.72	0.45	0	1	1944
Electric stove	0.96	0.20	0	1	1944
Tumble dryer	0.58	0.49	0	1	1944
Microwave oven	0.52	0.50	0	1	1944
Separate oven	0.37	0.48	0	1	1944
No. of Refrigerators	1.14	0.38	1	3	1944
No. of Televisions	1.35	0.72	0	7	1944
No. of Personal computers	1.34	1.14	0	9	1944
Appliance User Costs (in CHF/Watt)					
Price per watt	0.43	0.38	0.14	7.24	1944
Average (Neighbouring) Price of Watt	0.43	0.07	0.35	0.58	1944
Price of Freezer	121.53	17.56	88.55	139.56	1944
Price of Electric boiler	81.8	16.61	58.39	156.8	1944
Price of Clothes washer	348.81	29.98	312.3	382.01	1944
Price of Dishwasher	281.01	26.96	238.94	329.6	1944
Price of Electric stove	138.18	18.63	109.48	167.22	1944
Price of Tumble dryer	178.56	49.85	124.92	231.53	1944
Price of Microwave oven	32.31	7.26	23.93	39.55	1944
Price of Oven	133.65	8.12	124.09	142.14	1944
Price of Refrigerator	154.83	45.17	83.28	231.53	1944
Price of Television	307.56	199.15	66.02	1598.12	1944
Price of Personal computer	373.17	143.63	109.49	610.71	1944
Energy Services					
No. of meals per day	2.39	1.03	0.14	13	1944
No. of hot water services per day	1.27	1.41	0	16.14	1944
No. of washing services per week	3.23	4.60	0	54	1944
Hours of entertainment per day	7.34	9.05	1	176	1944

1.3.2 Electricity Price

Apart from the survey, we also use electricity price data for 2004 from "Preisüberwacher"[17] and for 2010 from the Federal Electricity Commission (ElCom) as well as price data collected from VSE.[18] The average price of electricity is calculated by multiplying the electricity consumption of the household with the marginal price faced by the household, adding the fixed fee (if any) and dividing this total cost by the total electricity consumption.[19] Figure 1.4 shows the variation of the average price over the seven utilities. This price variable is endogenous due to the presence of the fixed fee and we correct for this endogeneity by using instrumental variables that will provide consistent estimates of the price elasticity. We need to find instrumental variables that will satisfy the relevance and exclusion criteria for instruments. In other words, the instrument should be correlated with the average price to satisfy the relevance condition but affect the electricity consumption only through its effect on average price to satisfy the exclusion criterion.

Since the introduction of the Swiss Electricity Supply Law (StromVG) in 2007, it is compulsory for Swiss utilities to report their electricity prices for customers in the basic supply to the regulator, ElCom, by the 31st of August every year.[20] Generally, the electricity price in Switzerland has three components: a price for grid utilisation, a price for the electricity itself, and federal and municipal duties. Table 1.6 shows the components of electricity price in Switzerland. In case the household does not have a time-of-use (TOU) tariff scheme, the energy price collapses to a single tariff system.[21] ElCom then calculates and publishes the average prices for different household or industry types (ElCom, 2013). The ElCom price is a weighted average price faced by a typical household with certain characteristics. It is calculated according to the consumption profile for each household type by taking into account summer and winter and four blocks during the day (6 a.m.– 12 p.m., 12 p.m.– 6 p.m., 6 p.m.– 10 p.m. and 10 p.m.– 6 a.m.). We consider the ElCom price as an instrument for the average price. The way we construct the ElCom price for each household is to match a particular household with certain characteristics, as given in Table 1.7, with the ElCom price faced by a typical household with similar characteristics serviced by the respective utility. For example, if a household in our sample lives in a flat and consumes 2000 kWh of electricity per year then it belongs to ElCom household type H2 and is assigned the corresponding ElCom price. Since the ElCom price is an average price faced by a typical household with certain characteristics it does not directly affect the consumption of a particular household but has an influence on the average price faced by a household. Since it does not suffer from a potential endogeneity problem, as in the calculated average price above, we will use this price as an instrument for the average price.

In section 1.4.4 we use two alternatives for the ElCom price as instrument. Firstly, the neighbouring

[17] `http://www.preisueberwacher.admin.ch/dokumentation/00073/00074/00203/index.html?lang=de`

[18] We refer to the 2004 electricity prices as ElCom prices to maintain consistency. ElCom was founded only in 2009 and started collecting data from then onwards. The 2004 prices from the "Preisüberwacher" are collected using the same methodology as the ElCom prices in 2010. Marginal price data were collected with the help of VSE.

[19] While a household may choose to use a particular tariff structure, e.g. electricity from renewables, we do not have this information and so consider the most common tariff that is provided by the respective electric utility.

[20] Customers in the basic supply (Grundversorgung) are not on the free market.

[21] Summary statistics of the price components in our sample can be found in Table A.9 in the Appendix.

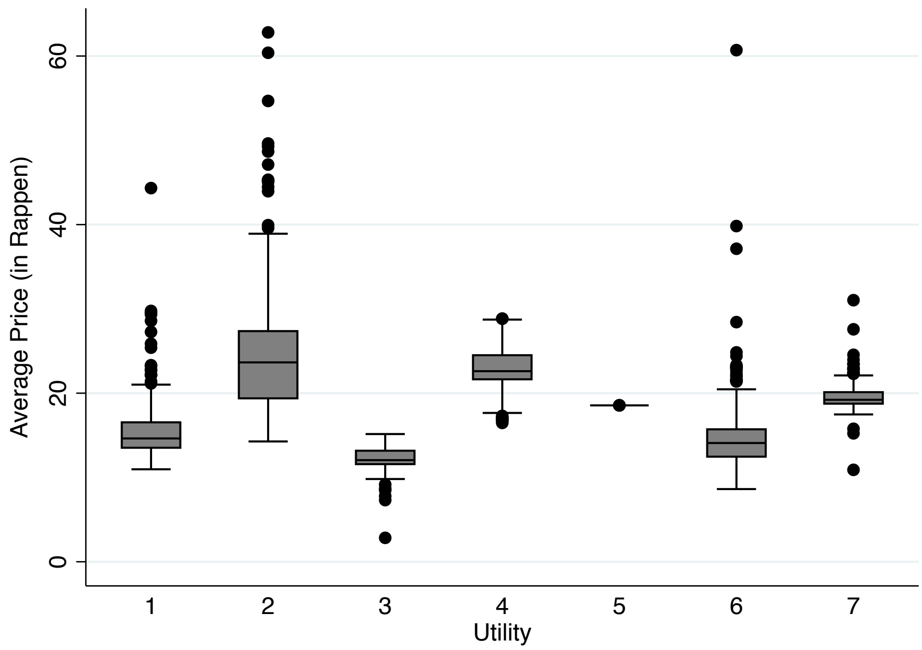


Figure 1.4: Variation of average electricity price over utilities

Table 1.6: Electricity price components for residential customers in Switzerland

1	**Grid utilisation**		
1a		Fixed fee	CHF/year
1b		Energy price (peak)	Rp./kWh
1c		Energy price (off-peak)	Rp./kWh
1d		Price for system services	Rp./kWh
2	**Energy**		
2a		Fixed fee	CHF/year
2b		Energy price (peak)	Rp./kWh
2c		Energy price (off-peak)	Rp./kWh
3	**Duties**		
3a		Duties to municipality	Rp./kWh
3b		Federal duties (KEV)	Rp./kWh

ElCom price and secondly, the grouped means of the average price. The reason for choosing the ElCom price of neighbouring utilities as an instrument is that it is very likely that the electricity price of a utility will be highly correlated with that of neighbouring utilities but the electricity consumption of a household in that particular utility will not be correlated with the price in a neighbouring utility. We choose utilities that are geographically near a particular utility and calculate the average ElCom price of those utilities. The grouped means of the average price are calculated as the mean of the average price among households that are within the same utility, the same year of the survey (2005 or 2011) and within the same ElCom household type. Using the mean value of the endogenous variable on a more aggregate level is another strategy to find an instrument. For example, Alberini et al. (2011) use state-level electricity prices as instrument for the average prices.

Table 1.7: ElCom Household Types

Type	Electricity [kWh/year]	Other	Number	%
H1	0-1,600	Flat	366	18.83%
H2	1,600 - 2,500	Flat	347	17.85%
H3	2,500 - 4,500	Flat + boiler	95	4.89%
H4	2,500 - 4,500	Flat + no boiler	301	15.48%
H5	0-7,500	Single Family House	484	24.90%
H6	13,000 - 25,000	Single Family House	36	1.85%
H7	7,500 - 13,000	Single Family House	137	7.05%
H8	$>$ 4,500	Flat	78	4.01%
Not matched			100	5.14%

1.3.3 Appliances

The VSE survey contains information on a number of appliances owned by a household. Schleich & Mills (2011) state that the major household appliances use 35% of residential end-use consumption of electricity in the EU 15 states. Figure 1.5 shows the most abundant home appliances and their share of electricity consumption in Switzerland. Kitchen appliances consume a big share with more than 40%. In this paper, we do not use the categories "other small appliances", "lighting" and "coffee machine" since the capacities and prices are very diverse within these categories. This will make it challenging to estimate reference values. We consider televisions (TVs) and personal computers (PCs) as being representative of the categories "home office" and "entertainment". Our analysis is restricted to 11 major appliances, namely, refrigerators, freezers, electric stoves, electric ovens, microwave ovens, dishwashers, clothes washers, tumble dryers, electric boilers, television sets and personal computers. We assume that a household possesses a tumble dryer and clothes washer only if their use is reflected in its own electricity bill.

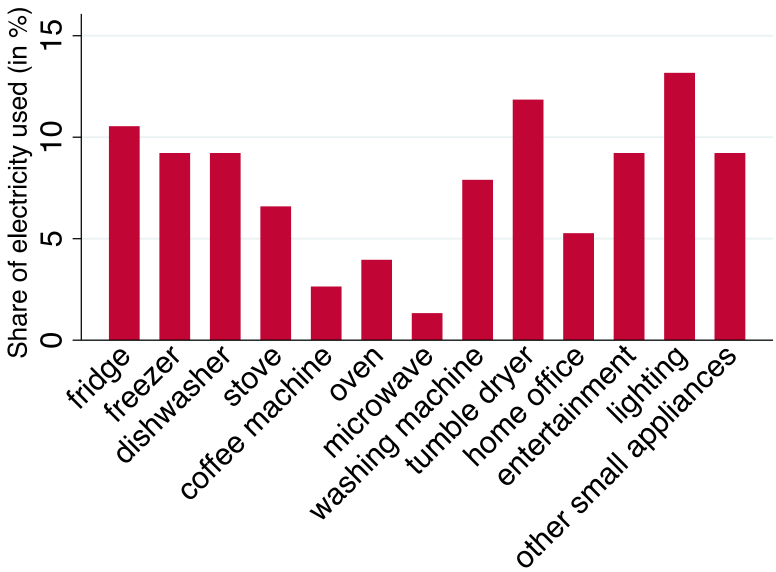


Figure 1.5: Share of electricity used by major household appliances. (Source: SAFE)

We construct an appliance index that aggregates the appliances owned by a household into one index that can be compared across the households in our survey. We do this by using a measure of the approximate power used by the major household appliances that we refer to as the "estimated capacity". The estimated capacity of the 11 major appliances is obtained by dividing the appliances into their vintage (older than 5 or 10 years) and size. The estimated capacity of an appliance is the average power used by the appliance while in use.[22] Electric boiler capacities are estimated by using the number of people in a particular household. See Table 1.8 for the detailed appliance characteristics used for the index. The advantage of using an appliance index is the relatively higher precision of the appliance capacity obtained when compared to using an aggregated count variable or individual appliance dummies. To the best of our knowledge, only a couple of studies have utilised such an appliance index. Garbacz (1984) develops a three-equation model with an electricity demand equation, an appliance stock equation and an equation for the electricity price. However, his appliance index is based on typical electricity use of the individual appliances in kWh and not a measure of typical capacity. Tiwari (2000), on the other hand, constructs an index based on average power requirement of the appliances.

We define the appliance index of household i, AI_i, as the sum of the estimated capacities, in Watt, of the 11 appliances:

$$AI_i = \sum_{k=1}^{11} \text{Estimated Capacity}_{i,k} \tag{12}$$

where k refers to appliance k. The estimated capacity is a function of the vintage, size and, for electric boilers only, household size.

Following Diewert (1974b) and Thomas (1987) we calculate the "user cost" of appliances that reflects the price of services obtained from a durable good even though it has been purchased by the household. Let us define this rental price or user cost of household appliances as P'_k. Thomas (1987, p. 26-27) defines the user cost as the difference between the purchase at the beginning of one period and the discounted price at the beginning of the next period after taking depreciation into account:

$$P'_{k,t} = P_{k,t} - \frac{(1-\delta_{lifetime})P_{k,t+1}}{1+r_{t,canton}} \tag{13}$$

where $P_{k,t}$ is the price of each appliance k [23], $\delta_{lifetime}$ is the annual rate of depreciation and $r_{t,canton}$ is the annual opportunity cost of capital. The interest rate $r_{t,canton}$ consists of cantonal mortgage interest rates.[24]

We can rewrite equation (13) as:

[22] The estimated reference capacities (in terms of Watt) have been provided by Schweizerische Agentur für Energie Effizienz (SAFE).

[23] These price estimates were also provided to us by SAFE. Similar to the measurement of the capacities for the 11 major appliances, these price estimates are approximate prices of the corresponding appliances by dividing the appliances into their vintage and size.

[24] The interest rate figures were provided by comparis, a Swiss price comparison website. The values for $\delta_{lifetime}$ and $r_{t,canton}$ are in Table A.10 and A.11 in the appendix.

$$P'_{k,t} = ((\delta_{lifetime} \cdot P_{k,t+1}) + (r_{t,canton} \cdot P_{k,t}) + (P_{k,t} - P_{k,t+1})) \cdot \frac{1}{1 + r_{t,canton}} \tag{14}$$

For simplicity, we assume that the initial value of the appliance is the same as in the next time period $(t+1)$, as there are no efficiency losses during the lifetime. This means that $P_{k,t} = P_{k,t+1}$. At the end of the appliance's lifetime the value will be zero instantly.[25] Therefore, we can simplify equation (14) to:

$$P'_{k} = (\delta_{lifetime} + r_{t,canton}) \cdot P_k \cdot \frac{1}{1 + r_{t,canton}} \tag{15}$$

Using the estimated capacity and price of the eleven appliance categories we can create a *price per installed capacity (in Watt)* for each household. We use this price per installed capacity in two ways. Firstly, as the price of appliance stock in the long-run estimation and, secondly, as an instrument for the household's stock of appliances in the short-run. The price per installed capacity is defined as:

$$PI_i = \frac{\sum_{k=1}^{11}(\text{Rental Price of Appliance}_{i,k})}{\sum_{k=1}^{11}(\text{Estimated Capacity}_{i,k})} = \frac{\sum_{k=1}^{11} P'_k}{AI_i}. \tag{16}$$

We choose this price index as an instrumental variable for estimating the short-run electricity demand. However, we use the neighbouring price index instead of a household's own price index. This is because we assert that the own price of a household's appliances will be directly correlated with the own electricity demand, thereby violating the exclusion restriction. The neighbouring price will not affect a particular household's electricity demand, thereby satisfying the exclusion restriction. However, the neighbouring price will affect a particular household's electricity demand through a spatial effect on its price for appliances, thereby satisfying the relevance condition. This spatial effect can be caused by similar households being close by. In our case, we have grouped the households by whether they are single family households or not.

Table 1.8 shows the appliance characteristics that we are able to incorporate into the appliance index. The fact that we are able to incorporate vintage and size among other characteristics makes our appliance index unique and more accurate than a set of appliance dummies. Figure 1.6 displays the appliance index as a histogram, while Figure 1.7 shows the variation over the different income groups. In the empirical analysis we use the appliance index because it measures the stock of appliances used in the production of energy services more accurately.

[25] There is also a simplified version of the user cost that assumes that the appliance is not sold in the next period but is kept till its value depreciates to zero. We have estimate our specifications using this version and the results remain unchanged.

Table 1.8: Capacity characterization of appliances

Appliance	Age class	Size class	Other Characteristics
Refrigerator	10 years	Small/large	Freezer compartment/combined
Freezer	10 years	Small/large	Upright/deep
Dishwasher	10 years		
Stove	10 years		
Oven	10 years		
Microwave oven	10 years		
Clothes washer	10 years		
Tumble dryer	10 years		
Television	5 years	Small/middle/large	Flat-screen
Personal computer	5 years	Small/middle/large	Flat-screen, laptop/desktop
Electric boiler			Household size

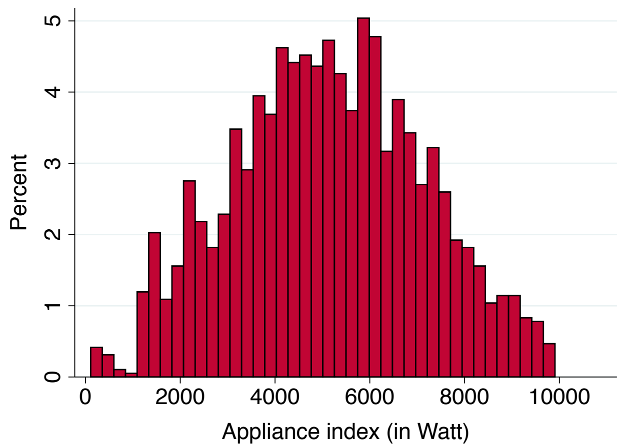


Figure 1.6: Histogram of appliance index.

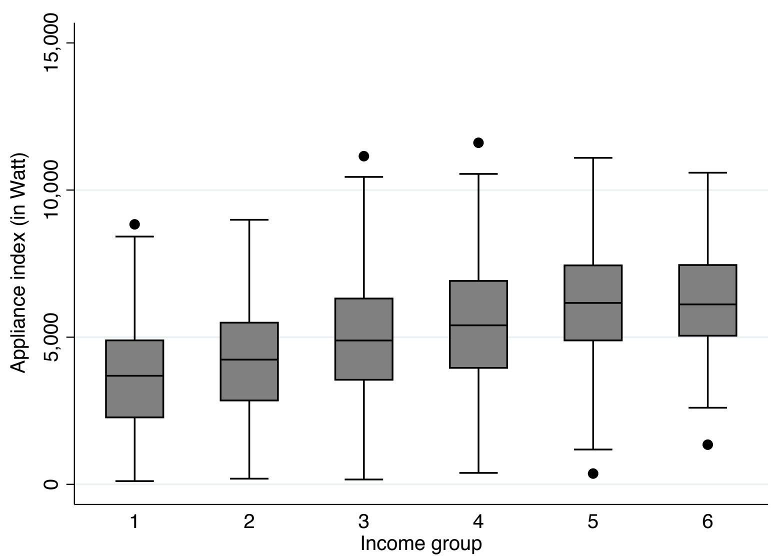


Figure 1.7: Variation of appliance index over income groups.

1.3.4 Energy Services

The VSE survey also contains information on some activities by households with regard to energy use in the week prior to the survey being undertaken. We combine energy use into four broad categories: the amount of washing, the amount of meals cooked at home, the number of hours spent on entertainment and the amount of hot water services. We combine the use of a clothes washer, tumble dryer and dehumidifier as representing the amount of washing. The amount of meals cooked at home is defined as the sum of breakfasts, lunches and dinners made at home. We obtain the number of hours spent on entertainment by adding the hours spent on a personal computer and on watching television. Hot water services are calculated by adding the number of showers and baths taken. Table 1.5 provides a summary of these variables. Lighting is also an important component of energy services. However, since we do not have information on the number of hours a household's lights are switched on we use the number of rooms as an approximation.

1.3.5 Income

As the VSE survey reports income of the households only in six bins, it is not possible to estimate income elasticities (see Table 1.9 for the definition of the six income groups as defined by the VSE survey). However, there are statistical methods in order to create a continuous income variable from the income bins. The most popular method is the midpoint estimator where one uses the average of the upper and lower bound of the bin as value for the continuous variable. Within each bin, the basic midpoint estimator assigns the n_b cases to the bin midpoint m_b:

$$m_b = \left(\frac{l_b + u_b}{2}\right)$$

where l_b is the lower bound and u_b is the upper bound of the bin. In order to calculate the midpoint of any bin, the bins need to be censored on both sides, meaning, there needs to be an upper and a lower bound for each bin. If the top bin is populated and has no upper bound, as in our case for income group 6, then its midpoint is undefined. We need to use an alternative statistic and the statistic should be some multiple of the top bin's lower bound l_B. In case there is evidence that the tail is longer, the value of the multiple should be larger (von Hippel et al., 2016).

In order to get an estimate of the length and shape of the tail, we assume that the incomes in the top two bins follow some parametric distribution. For example, one could assume that the top two bins follow a Pareto distribution with shape parameter $\alpha > 0$, which is an arbitrary but convenient assumption. Then, the mean μ_B of the top bin is a simple function of α:

$$\mu_B = \begin{cases} l_B \dfrac{\alpha}{\alpha - 1} & \text{if } \alpha < 1, \\ \infty & \text{if } \alpha \geq 1. \end{cases}$$

This is called the Pareto midpoint estimator. Von Hippel et al. (2016) mention that the Pareto midpoint estimator performs well in large samples but it is not robust or even usable in some small samples. The problem is due to the sensitivity of μ_B to the value of α. Therefore, von Hippel et al. (2016) suggest the robust Pareto midpoint estimator. Instead of the mean, μ_B, of the top bin they use the harmonic mean, h_B, which is less sensitive to α. The method of von Hippel et al. (2016) is implemented in Stata with the command `rpme`.

Of course, this method also has its critique. For example, Bhat (1994) mentions that the bias created with the midpoint estimator is especially large when bin sizes are large.

Table 1.9: Income groups as defined in the VSE survey (measured as (CHF/month)).

Income groups	Lower bound	Upper bound	Number of Obs.
1	0	3,000	177
2	3,000	4,500	321
3	4,500	6,000	451
4	6,000	9,000	570
5	9,000	15,000	342
6	15,000	n.d.	83
Total			**1,944**

1.4 Estimation Results

As mentioned previously, we have different variables that might be endogenous, namely the average electricity price, the appliance stock in the short-run and the appliance price in the long-run. In section 1.4.1 we firstly introduce the empirical challenges caused by the before mentioned problem. The second part of section 1.4.1 introduces the first stage estimation regressions in our case. We then present the results obtained by estimating models based on equations (10a), (10b), (10c), (10d), (11a) and (11b). The first set of results in section 1.4.2 estimates short-run models using the appliance index while the second set in section 1.4.3 estimates long-run models using the price index as calculated with equation (16) and then separately with the appliance user costs as estimated in equation (15). We first estimate the models using the set of household and socio-demographic characteristics and then estimate the models using energy services and a smaller subset of household and socio-demographic characteristics. Finally, in addition to the main analysis we add two smaller adjacent analysis: In section 1.4.4 we use two alternative instruments for average electricity price in order to do a robustness check and in section 1.4.5 we evaluate the effect of income on the price elasticity.

1.4.1 Empirical Challenges

Using Ordinary Least Squares (OLS), we need to make sure the five classical Gauss-Markov assumptions are met: linearity, independence, exogeneity, error variance and identifiability (Wooldridge, 2010). In this paper, as discussed previously, we need to discuss the assumption on exogeneity, also referred to as the zero conditional mean assumption. The violation of this assumption can be caused by an endogenous independent variable. An endogenous independent variable is defined as a variable that is correlated with the error term.

There are several reasons that can cause an endogeneity problem (Wooldridge, 2010):

- Measurement error
- Omitted variables
- Simultaneity and
- Sample selection errors

Several methods try to overcome this limitation of endogenous regressors, including instrumental variable regression. Broadly speaking, an instrumental variable is a variable that is used as substitute for the endogenous independent variable. It does not belong in the regression itself, but has to be correlated with the endogenous independent variable to work as a replacement. There are two main requirements for a valid instrument (Wooldridge, 2010):

1. *Instrument relevance condition*: The instrumental variable needs to be correlated with the endogenous independent variables.
2. *Instrument exogeneity condition*: The instrumental variable should not be correlated with the error term in the regression equation.

Once we have found one or several valid instruments for the endogenous variable, we can carry out our estimation using a *two stages least squared regression (2SLS)*.

In the case where we are faced with more than one endogenous regressor, we would have the same number of first stages as endogenous regressors.[26]

After the estimation using 2SLS we need to verify that we have used valid instruments. An instrument is valid if it satisfies the two assumptions mentioned above: instrument relevance and exogeneity. Firstly, the relevance of the instruments is tested in the first-stage regression. As a general rule of thumb, in case of a single endogenous regressor the F-statistic of a joint test whether all excluded instruments are significant should be bigger than 10.[27] This F-Test indicates the strength of the instrument. However, in case we have more than one endogenous regressor the F-statistic is no longer valid and the Cragg & Donald (1993) statistic should be used to evaluate the overall strength of the instruments. Stock & Yogo (2005) have tabulated critical values of the Cragg-Donald statistic for testing the strength of instruments. Instruments with low correlation between the endogenous regressors are called weak instruments.[28]

The second assumption for a valid instrument is that the instrumental variables need to be exogenous themselves. The exogeneity of the instruments can in general not be tested. If and only if an equation is overidentified[29], we may test whether the excluded instruments are independent of the error process as needed. Generally, in a test of overidentifying restrictions we regress the residuals from an 2SLS regression on all instruments in vector Z. Under the null hypothesis that all instruments are uncorrelated with the error term, the test has a large-sample $\chi_2(r)$ distribution where r is the number of overidentifying restrictions. This tests whether all instruments are exogeneous assuming that a least one of the instruments is exogenous. Therefore, it will not necessarily detect a situation in which all instruments are endogenous (Schmidheiny, 2015).

At the end we also would like to know whether our endogenous regressor is truly endogenous or not. This is usually tested by a Hausman test comparing IV and OLS estimates. However, note, that this test is dependent on the choice of instruments, if the instruments are not valid, the Hausman test is not valid either (Wooldridge, 2010).

In this chapter we have to deal with two endogenous variables in the short-run and two endogenous variables in the long-run estimation. We estimate four sets of short-run models. Out of those four, two models are estimated using instrumental variables. As discussed before, the endogenous variables are the average price of electricity and the stock of household appliances. Since we estimate one short-run model with the usual socio-demographic and household characteristics and another model with energy services we have two first-stage regressions for each short-run model.

[26] For details concerning the 2SLS estimator see Wooldridge (2010).

[27] Using only one instrumental variable for a single endogenous variable, this means that the t-value for the instrument should be larger than 3.2 or the corresponding p-value smaller than 0.0016.

[28] There is theoretical and empirical evidence that 2SLS estimation using weak instruments may perform even poorer than OLS (Stock & Yogo, 2002).

[29] Overidentified means that we have more instruments than endogenous variables ($L > K$).

The two first-stage regressions corresponding to equations (11a) and (11b) are

$$\begin{aligned} \log\ p_i^E &= \theta_0 + \theta_1 \log\ (\text{ElCom price}) + \theta_2 \log\ (\text{Average neighbouring price of Watt}) \\ &\quad + \text{other explanatory variables} + \epsilon_i \end{aligned} \tag{17a}$$

and

$$\begin{aligned} \log\ K_i &= \theta_0' + \theta_1' \log\ (\text{ElCom price}) + \theta_2' \log\ (\text{Average Neighbouring Price of Watt}) \\ &\quad + \text{other explanatory variables} + \epsilon_i, \end{aligned} \tag{17b}$$

where the instruments for the endogenous variables, average electricity price and appliance stock index, are the ElCom price[30] and the average price (per Watt) of capital in neighbouring households. Depending on whether we are estimating the electricity demand with only socio-demographic variables, equation (11b), or a combination of energy services and some socio-demographic variables, equation (11a), we include those in the term "other explanatory variables".

We also estimate four sets of long-run models for electricity demand. All four models are estimated using instrumental variables. Two models have only one endogenous variable (the average price of electricity), while two models have two endogenous variables (the average price of electricity and the price of household appliances). The first-stage regression for the models with only one endogenous variable is

$$\log\ p_i^E = \phi_0 + \phi_1 \log\ (\text{ElCom price}) + \text{other explanatory variables} + \epsilon_i \tag{18}$$

where the term "other explanatory variables" includes next to the the appliance user costs either only socio-demographic variables or a combination of energy services and some socio-demographic variables depending on the model we are estimating. The first-stage regressions for the models with two endogenous variables, the average price of electricity and the price of household appliances, are, respectively

$$\begin{aligned} \log\ p_i^E &= \eta_0 + \eta_1 \log\ (\text{ElCom price}) + \eta_2 \log\ (\text{Average neighboring price of Watt}) \\ &\quad + \text{other explanatory variables} + \epsilon_i \end{aligned} \tag{19a}$$

and

$$\begin{aligned} \log\ p_i^K &= \eta_0' + \eta_1' \log\ (\text{ElCom price}) + \eta_2' \log\ (\text{Average neighboring price of Watt}) \\ &\quad + \text{other explanatory variables} + \epsilon_i. \end{aligned} \tag{19b}$$

As before, the term "other explanatory variables" includes either only socio-demographic variables or a combination of energy services and some socio-demographic variables depending on the model we are estimating, i.e. equation (10b) or (10a), respectively.

[30] In section 1.4.4 we use also two other instruments for average electricity price.

In addition, we also estimate four long-run models for appliance stock demand. Two models are estimated using instrumental variables with the price of household appliances being endogenous. It is also possible that the average price of electricity could be endogenous in the appliance stock demand. We estimated a model with the average price of electricity as an endogenous variable. However the test for the endogeneity of the average electricity price showed that the null hypothesis of the average price being exogenous may not be rejected. Therefore, we estimate two of the four models using OLS. The first-stage regression for the models with one endogenous variable, the price of household appliances, is

$$\log p_i^K = \eta_0' + \eta_1' \log \text{ (Average electricity price)} + \eta_2' \log \text{ (Average neighboring price of Watt)} \\ + \text{other explanatory variables} + \epsilon_i. \qquad (20)$$

As before, the term "other explanatory variables" includes next to the average electricity price either only socio-demographic variables or a combination of energy services and some socio-demographic variables depending on the model we are estimating, i.e. equation (10c) or (10d), respectively.[31]

1.4.2 Short-Run Results

The results of the electricity demand estimation in the short run using the appliance index from equation (12) are shown in Table 1.11. In columns (1) and (2) we assume that the average electricity price and appliance stock are exogenous. The price elasticity for electricity is between −0.8 and −0.9. We test for the potential endogeneity of the average electricity price and the appliance index and find that the null hypothesis of these two regressors being exogenous may be rejected.[32] Therefore, we focus on columns (3) and (4) where both the average electricity price and the appliance index are assumed to be endogenous. The instruments we use are the ElCom prices for the own utility and the average price per installed capacity, by the single family housing status, of other households within the same utility. Since we have two endogenous variables the relevant statistic to test for weak instruments is the Cragg-Donald statistic (Cragg & Donald, 1993). Stock & Yogo (2002) calculate the critical value of the Cragg-Donald statistic for a model with two endogenous variables and two instruments and find it to be 7.03 at the 10% level of significance.[33] The Cragg-Donald statistic values reported in Table 1.11 exceed the critical value and we can, therefore, conclude that the instruments do not appear to be weak.

[31] In the long-run, since we estimate a system of demand for electricity and appliance stock that may be considered to be inputs for producing energy services as output we could consider using a seemingly unrelated regression (SUR) model. The errors in an SUR model are correlated across equations for a given individual but are uncorrelated across individuals. However, as we use the same explanatory variables in estimating both the demand for electricity and the demand for appliance stock, OLS/IV regression for the two separate demand equations is algebraically equivalent to an SUR model and there is no efficiency gain from the joint estimation.

[32] We use the `endog()` option in Stata's `ivreg2` (Baum et al., 2010) command. If all endogenous regressors are included in the `endog()` option, then the test is equivalent to a Hausman test comparing IV and OLS estimates.

[33] The first stage results are reported in Table A.1 in the appendix. All the instruments are significant and have the expected signs.

The difference between the two columns is that in column (3) we use equation (6b) where the household characteristics and socio-demographic variables are used to determine the electricity demand while in column (4) we use equation (6a) where energy services are used along with some socio-demographic and residential characteristics. We include certain residential characteristics in column (4), e.g. if the household lives in a single family house, if it resides in an urban area, and if it is a tenant in the residence since these characteristics may not be captured by energy services. We also include the number of rooms as a residential characteristic since our energy services variables do not include the effect of lighting on electricity consumption. We include an indicator for whether a household is a customer of utility 1 in year 2011 since the electricity consumption in that particular utility is quite different to the rest of the utilities in the survey. We also have an indicator for the year in which the survey was carried out as well as an indicator for a household having a time-of-use tariff structure.

The price elasticities are negative, as expected, and statistically significant. Instrumenting for the potential endogeneity bias of the average price and the appliance stock, we obtain a price elasticity of between -0.4 and -0.5. The coefficient for appliance stock is positive and significant across the two models and indicates that installing 10% more capacity (in Watt) will lead to a 7-8% increase in electricity consumption.

The coefficients for the midpoint income are significant and negative in column (1) and (3). This may be due to the income effect being captured by certain residential and household characteristics like the number of rooms and household size.[34]

Table 1.10 shows the expected sign of the coefficients related to the characteristics of households. Most coefficients of household characteristics, as presented in column (3) of Table 1.11, are significant and show the expected sign. Household size, number of rooms, single family housing status and dummy for children increase the electricity demand, as expected. Households residing in an urban area, households with a retired person and those with a higher share of women reduce the estimated electricity demand, as expected. Results also indicate that households with a time-of-use (TOU) pricing scheme tend to use less electricity. However, the estimated coefficient is not statistically significant. The TOU tariff system is designed to shift some of the peak period consumption to the off-peak period. The part of peak period consumption that can not be shifted to the off-peak period is consumed in the peak price period and therefore less electricity is consumed in the peak period due to the higher price. A higher share of women in a household may reduce the consumption of electricity because there are either unobserved wealth effects (Brounen et al., 2012) or because women are more conscious towards environmental and energy related topics (Gaspar & Antunes, 2011). Tenants also tend to use less electricity. The strong statistical significance in household characteristics indicates a large degree of heterogeneity among households which indicates the advantage of using disaggregated data.

[34] The models have been estimated with only the price of electricity and income and the results, not presented here, show that the effect of the income is positive and significant. We have also performed a multicollinearity check after estimating the full model and find that the highest variance inflation factor is below 3. This indicates that multicollinearity is not an issue in our full model.

Table 1.10: Household characteristics and their expected sign on electricity demand

Variable	Sign	Reference
Number of rooms	$+$	Baker et al. (1989)
Household size	$+$	Baker et al. (1989)
Single family housing dummy	$+$	Brounen et al. (2012)
Tenant dummy	$+/-$	
Children dummy	$+$	Baker et al. (1989)
Retired dummy	$-$	Brounen et al. (2012)
Share of females	$-$	Brounen et al. (2012)
Time of use dummy	$+/-$	
Urban dummy	$-$	Leahy & Lyons (2010)
Income	$+$	Economic theory in general

The results of the estimation in column (4) of Table 1.11 indicate the change in electricity demand due to a change in certain energy services. A unit increase in cooking a meal at home per day leads to an increase in electricity consumption by 3% while an hour more of entertainment per day increases electricity consumption by 1%. Using one more hot water service per day increases electricity consumption by 3% while one more washing service per week increases electricity consumption by less than 1%, though this coefficient is not statistically significant.

Table 1.11: Regression of short-run log electricity demand

	(1)	(2)	(3)	(4)
(Log) Average price	-0.87[a]	-0.83[a]	-0.47[a]	-0.42[a]
	(0.08)	(0.08)	(0.08)	(0.08)
(Log) Appliance stock (in Watt)	0.29[a]	0.22[a]	0.76[a]	0.69[a]
	(0.03)	(0.03)	(0.19)	(0.19)
(Log) Midpoint income	-0.06[b]		-0.13[a]	
	(0.02)		(0.04)	
(Log) Household size	0.32[a]		0.23[a]	
	(0.04)		(0.06)	
Children dummy	0.10[b]		0.08	
	(0.04)		(0.05)	
Retired dummy	-0.06[b]		-0.06[c]	
	(0.03)		(0.03)	
Share of females	-0.14[a]		-0.15[a]	
	(0.05)		(0.05)	
No. of meals per day		0.04[a]		0.03[b]
		(0.01)		(0.01)
Hours of entertainment per day		0.01[a]		0.01[a]
		(0.00)		(0.00)
No. of hot water services per day		0.06[a]		0.03[c]
		(0.01)		(0.02)
No. of washing services per week		0.02[a]		0.01
		(0.00)		(0.01)
(Log) No. of rooms		0.32[a]		0.13[c]
		(0.04)		(0.08)
Single family housing dummy	0.28[a]	0.21[a]	0.35[a]	0.34[a]
	(0.03)	(0.04)	(0.04)	(0.04)
Urban dummy	-0.23[a]	-0.23[a]	-0.09[b]	-0.10[a]
	(0.03)	(0.03)	(0.04)	(0.04)
Tenant dummy	-0.18[a]	-0.12[a]	-0.04	0.00
	(0.03)	(0.03)	(0.06)	(0.05)
Utility 1 dummy	0.21[a]	0.17[a]	0.22[a]	0.20[a]
	(0.03)	(0.03)	(0.03)	(0.03)
Time-of-use dummy	-0.12[a]	-0.12[a]	0.01	0.02
	(0.04)	(0.04)	(0.05)	(0.05)
Year 2011 dummy	0.04[c]	0.09[a]	0.12[a]	0.13[a]
	(0.02)	(0.03)	(0.03)	(0.03)
Intercept	8.47[a]	7.91[a]	3.75[a]	2.73[c]
	(0.41)	(0.38)	(1.45)	(1.61)
Observations	1,944	1,944	1,844	1,844
Adjusted R^2	0.53	0.53	0.46	0.46
F-statistic of first stage			19.20	20.54
Cragg-Donald F-statistic			21.63	24.19
p-value of Endogeneity test			0.00	0.00

Heteroscedasticity-robust standard errors in parentheses.
[a], [b], [c]: Significant at the 1%, 5% and 10% levels, respectively.

1.4.3 Long-Run Results

The long-run estimates of electricity demand are shown in Tables 1.12 and 1.13. These models include the rental price of appliances. Columns (1) and (3) use the individual rental prices of the appliances whereas columns (2) and (4) use the price index of the appliances as calculated in equation (16). As in the short-run estimation we use household characteristics and socio-demographic variables in columns (1) and (2) while in columns (3) and (4) we use energy services and some socio-demographic variables. The only difference between the long-run and short-run models is that the appliance index in the short-run model is replaced by either the price of an aggregate measure of appliance stock or by the prices of individual appliances in the long-run model.

The price elasticities of residential electricity demand are negative, as expected, and statistically significant and range from a low of -0.45 to a high of -0.68. Using the rental prices of capital stock in columns (2) and (4), we find that an increase of 1% in the price per watt leads to a decrease in electricity consumption by around 1.1%.[35] The effect of income, as measured by the midpoint income, is statistically insignificant. The share of females in a household, the abundance of a retired person, being located in an urban area and being a tenant have negative effects on the electricity consumption. Increasing the household size, number of rooms and having children have positive on the electricity consumption. Most coefficient estimates are statistically significant and very similar across the different models.

As in the case with the short-run estimation we test for the potential endogeneity of the average electricity price in columns (1) and (3) and the potential endogeneity of the average electricity price as well as the price of capital stock in columns (2) and (4). We find that the null hypothesis of the average electricity price being exogenous can be rejected. We also find that the null hypothesis of the average electricity price and the price of capital stock being exogenous can be rejected.[36] Since we have two endogenous variables the relevant statistic to test for weak instruments is the Cragg-Donald statistic (Cragg & Donald, 1993). The critical value of the Cragg-Donald statistic for a model with two endogenous variables and two instruments is 7.03 at the 10% level (Stock & Yogo, 2002). Our calculated statistic is statistically significant at the 10% level in both columns, (2) and (4).[37]

The results of the estimation in columns (3) and (4) of Table 1.12 using energy services instead of the usual household characteristics indicate the change in electricity demand due to a change in certain energy services. The results from the long-run estimation are very similar to the estimates obtained in the short-run electricity demand estimation. An increase in cooking a meal at home by one per day leads to an increase in electricity consumption by around 2%, though it is not statistically significant, while an hour more of entertainment per day increases electricity consumption by 1-2%.

[35] We do not report the coefficients of the prices for individual appliances in the table. If we consider the rental prices of individual appliance only those of freezers and electric stoves are negative and significant. The rental price of personal computers is positive and significant in both models.

[36] As before, we use the `endog()` option in Stata's `ivreg2` (Baum et al., 2010) command.

[37] The first-stage results are reported in Table A.2 in the appendix. The instruments are significant and have the expected, positive, signs.

Using one more hot water service per day increases electricity consumption from 4-5% while one more washing service per week increases electricity consumption by 2%.

We estimate the appliance stock demand in Table 1.13. Columns (1) and (3) use the individual rental prices of the appliances whereas columns (2) and (4) use the price index of the appliance stock. We assume that the price index of the appliance stock is endogenous.[38,39] We also use the neighbouring average price per installed capacity as an instrumental variable. We test for the potential endogeneity of the price index of the appliance stock and find that the null hypothesis of this variable being exogenous may be rejected. Since the F-statistics of the first stages reported in Table 1.13 exceed the critical value we conclude that the instruments do not appear to be weak.

We find that the appliance stock index is highly dependent on its own price and income of the household. The coefficient of the price is negative as expected, while the coefficient of the midpoint income has a positive sign as we would also expect since higher income households tend to possess a larger appliance stock. The own-price elasticity is estimated to be between -1.4 and -1.6. However, the cross-price elasticity of electricity price on appliance stock is very small and while it is significant in column (2), it is statistically insignificant in column (4).

[38] The individual rental prices of the appliances might be endogenous as well, but we would need as many instruments as appliances. Since the solution is practically infeasible we assume these prices to be exogenous.

[39] As previously mentioned, we also estimated a model with the average price of electricity as an endogenous variable. However, the test for the potential endogeneity of the average electricity price showed that the null hypothesis of the average price being exogenous may not be rejected.

Table 1.12: Regression of long-run log electricity demand

	(1)	(2)	(3)	(4)
(Log) Average price	-0.69[a]	-0.53[a]	-0.60[a]	-0.45[a]
	(0.07)	(0.08)	(0.07)	(0.08)
(Log) Price of capital stock		-1.09[a]		-1.13[a]
		(0.32)		(0.37)
(Log) Midpoint income	-0.01	0.02		
	(0.03)	(0.03)		
(Log) Household size	0.39[a]	0.40[a]		
	(0.15)	(0.05)		
Children dummy	0.08[c]	0.07		
	(0.04)	(0.05)		
Retired dummy	-0.05[c]	-0.20[a]		
	(0.03)	(0.06)		
Share of females	-0.15[a]	-0.17[a]		
	(0.05)	(0.06)		
No. of meals per day			0.02	0.02
			(0.01)	(0.02)
Hours of entertainment per day			0.01[a]	0.02[a]
			(0.00)	(0.00)
No. of hot water services per day			0.04[b]	0.05[a]
			(0.01)	(0.02)
No. of washing services per week			0.02[a]	0.02[a]
			(0.00)	(0.00)
(Log) No. of rooms			0.22[a]	0.39[a]
			(0.04)	(0.06)
Single family housing dummy	0.38[a]	0.41[a]	0.29[a]	0.36[a]
	(0.04)	(0.04)	(0.04)	(0.05)
Urban dummy	-0.18[a]	-0.08[c]	-0.17[a]	-0.08[c]
	(0.03)	(0.05)	(0.03)	(0.05)
Tenant dummy	-0.18[a]	-0.11[b]	-0.13[a]	-0.02
	(0.03)	(0.05)	(0.03)	(0.06)
Utility 1 dummy	0.22[a]	0.26[a]	0.19[a]	0.20[a]
	(0.03)	(0.04)	(0.03)	(0.04)
Time-of-use dummy	-0.09[c]	-0.00	-0.06	0.02
	(0.05)	(0.05)	(0.05)	(0.05)
Year 2011 dummy	0.69[a]	0.10[a]	0.55[b]	0.12[a]
	(0.24)	(0.03)	(0.24)	(0.04)
Intercept	-14.92	7.98[a]	-8.91	7.15[a]
	(9.73)	(0.57)	(9.64)	(0.56)
Observations	1,844	1,844	1,844	1,844
Adjusted R^2	0.52	0.29	0.54	0.24
F-statistic of first stage	2166.98	12.35	2237.89	9.73
Cragg-Donald F-statistic	3164.20	13.15	3196.60	10.68
p-value of Endogeneity test	0.00	0.00	0.00	0.00

Heteroscedasticity-robust standard errors in parentheses.
[a], [b], [c]: Significant at the 1%, 5% and 10% levels, respectively.

Table 1.13: Regression of long-run log capital demand

	(1)	(2)	(3)	(4)
(Log) Average price	-0.16^a	-0.07^c	-0.14^a	-0.05
	(0.04)	(0.04)	(0.04)	(0.05)
(Log) Price of capital stock		-1.44^a		-1.59^a
		(0.19)		(0.25)
(Log) Midpoint income	0.11^a	0.19^a		
	(0.02)	(0.02)		
(Log) Household size	0.02	0.23^a		
	(0.10)	(0.03)		
Children dummy	-0.01	-0.01		
	(0.03)	(0.03)		
Retired dummy	0.03	-0.19^a		
	(0.02)	(0.03)		
Share of females	0.02	-0.04		
	(0.04)	(0.03)		
No. of meals per day			0.01	-0.02^c
			(0.01)	(0.01)
Hours of entertainment per day			0.00	0.01^a
			(0.00)	(0.00)
No. of hot water services per day			0.04^a	0.03^a
			(0.01)	(0.01)
No. of washing services per week			0.02^a	0.01^a
			(0.00)	(0.00)
(Log) No. of rooms			0.24^a	0.38^a
			(0.04)	(0.04)
Single family housing dummy	0.06^a	0.08^a	-0.04	0.01
	(0.02)	(0.02)	(0.02)	(0.03)
Urban dummy	-0.13^a	0.02	-0.09^a	0.05
	(0.02)	(0.03)	(0.02)	(0.03)
Tenant dummy	-0.13^a	-0.10^a	-0.11^a	-0.05
	(0.02)	(0.03)	(0.02)	(0.04)
Utility 1 dummy	0.01	0.06^b	-0.02	-0.00
	(0.02)	(0.02)	(0.02)	(0.03)
Time-of-use dummy	-0.05	-0.01	-0.04	-0.00
	(0.03)	(0.03)	(0.03)	(0.03)
Year 2011 dummy	-0.09	-0.03^c	-0.17	-0.02
	(0.16)	(0.02)	(0.16)	(0.03)
Intercept	7.33	5.55^a	13.21^b	6.45^a
	(6.50)	(0.35)	(6.35)	(0.38)
Observations	1,944	1,944	1,944	1,944
Adjusted R^2	0.38	0.49	0.42	0.32
F-statistic of first stage		25.19		20.15
Cragg-Donald F-statistic		27.13		22.37
p-value of Endogeneity test		0.00		0.00

Heteroscedasticity-robust standard errors in parentheses.
^{a}, ^{b}, ^{c}: Significant at the 1%, 5% and 10% levels, respectively.

1.4.4 Alternative instruments for price of electricity

In order to check for the robustness of at least one of the instruments we estimate the short- and long-run estimations using two different variations of the instrument for the average electricity price. Firstly, the neighbouring ElCom price and secondly, the grouped means of the average price. The ElCom price of neighbouring utilities is a natural choice as an instrument as it is very likely that the electricity price of a utility will be highly correlated with that of neighbouring utilities but the electricity consumption of a household in that particular utility will not be correlated with the price in a neighbouring utility. Using the mean value of the endogenous variable at a more aggregated level is another strategy to find an appropriate instrument. A more detailed description of these two alternative instruments can be found in section 1.3.2.

In Tables 1.14 and 1.16 we use the neighbouring Elcom price as an instrument for the average electricity price while in Tables 1.15 and 1.17 we use the grouped mean of the average price as an instrument.[40]

Generally, the resulting price elasticities for electricity demand are higher using the alternative instruments throughout all specifications. Using the neighbouring approach, we estimate price elasticities that are $0.1 - 0.15$ higher in absolute terms than with the ElCom price. With the grouped mean approach the difference is generally smaller than 0.1. The price elasticities are summarised in Table 1.21.

[40]The first-stage results are reported in Table A.4, A.5, A.6 and A.7 in the Appendix

Table 1.14: Regression of short-run log electricity demand using alternative instruments

	(1)	(2)	(3)	(4)
(Log) Average price	-0.87[a]	-0.83[a]	-0.57[a]	-0.52[a]
	(0.08)	(0.08)	(0.09)	(0.09)
(Log) Appliance stock (in Watt)	0.29[a]	0.22[a]	0.65[a]	0.58[a]
	(0.03)	(0.03)	(0.20)	(0.19)
(Log) Midpoint income	-0.06[b]		-0.11[b]	
	(0.02)		(0.04)	
(Log) Household size	0.32[a]		0.25[a]	
	(0.04)		(0.06)	
Children dummy	0.10[b]		0.08[c]	
	(0.04)		(0.04)	
Retired dummy	-0.06[b]		-0.06[b]	
	(0.03)		(0.03)	
Share of females	-0.14[a]		-0.14[a]	
	(0.05)		(0.05)	
No. of meals per day		0.04[a]		0.03[b]
		(0.01)		(0.01)
Hours of entertainment per day		0.01[a]		0.01[a]
		(0.00)		(0.00)
No. of hot water services per day		0.06[a]		0.04[b]
		(0.01)		(0.02)
No. of washing services per week		0.02[a]		0.01
		(0.00)		(0.01)
(Log) No. of rooms		0.32[a]		0.17[b]
		(0.04)		(0.08)
Single family housing dummy	0.28[a]	0.21[a]	0.34[a]	0.33[a]
	(0.03)	(0.04)	(0.04)	(0.04)
Urban dummy	-0.23[a]	-0.23[a]	-0.10[a]	-0.12[a]
	(0.03)	(0.03)	(0.04)	(0.03)
Tenant dummy	-0.18[a]	-0.12[a]	-0.06	-0.02
	(0.03)	(0.03)	(0.06)	(0.05)
Utility 1 dummy	0.21[a]	0.17[a]	0.22[a]	0.20[a]
	(0.03)	(0.03)	(0.03)	(0.03)
Time-of-use dummy	-0.12[a]	-0.12[a]	-0.02	-0.01
	(0.04)	(0.04)	(0.05)	(0.05)
Year 2011 dummy	0.04[c]	0.09[a]	0.10[a]	0.13[a]
	(0.02)	(0.03)	(0.03)	(0.03)
Intercept	8.47[a]	7.91[a]	4.87[a]	4.00[b]
	(0.41)	(0.38)	(1.41)	(1.57)
Observations	1,944	1,944	1,858	1,858
Adjusted R^2	0.53	0.53	0.49	0.49
F-statistic of first stage			17.49	19.39
Cragg-Donald F-statistic			19.15	22.16
p-value of Endogeneity test			0.00	0.00

Heteroscedasticity-robust standard errors in parentheses.
[a], [b], [c]: Significant at the 1%, 5% and 10% levels, respectively.
Neighbouring ElCom price used as IV for average electricity price.

Table 1.15: Regression of short-run log electricity demand using alternative instruments

	(1)	(2)	(3)	(4)
(Log) Average price	-0.87[a]	-0.83[a]	-0.50[a]	-0.45[a]
	(0.08)	(0.08)	(0.07)	(0.07)
(Log) Appliance stock (in Watt)	0.29[a]	0.22[a]	0.76[a]	0.68[a]
	(0.03)	(0.03)	(0.19)	(0.19)
(Log) Midpoint income	-0.06[b]		-0.13[a]	
	(0.02)		(0.04)	
(Log) Household size	0.32[a]		0.25[a]	
	(0.04)		(0.06)	
Children dummy	0.10[b]		0.10[b]	
	(0.04)		(0.05)	
Retired dummy	-0.06[b]		-0.06[c]	
	(0.03)		(0.03)	
Share of females	-0.14[a]		-0.15[a]	
	(0.05)		(0.05)	
No. of meals per day		0.04[a]		0.03[b]
		(0.01)		(0.01)
Hours of entertainment per day		0.01[a]		0.01[a]
		(0.00)		(0.00)
No. of hot water services per day		0.06[a]		0.04[b]
		(0.01)		(0.02)
No. of washing services per week		0.02[a]		0.01
		(0.00)		(0.01)
(Log) No. of rooms		0.32[a]		0.17[b]
		(0.04)		(0.08)
Single family housing dummy	0.28[a]	0.21[a]	0.27[a]	0.26[a]
	(0.03)	(0.04)	(0.04)	(0.04)
Urban dummy	-0.23[a]	-0.23[a]	-0.13[a]	-0.15[a]
	(0.03)	(0.03)	(0.04)	(0.03)
Tenant dummy	-0.18[a]	-0.12[a]	-0.05	-0.01
	(0.03)	(0.03)	(0.06)	(0.05)
Utility 1 dummy	0.21[a]	0.17[a]	0.19[a]	0.17[a]
	(0.03)	(0.03)	(0.03)	(0.03)
Time-of-use dummy	-0.12[a]	-0.12[a]	0.02	0.03
	(0.04)	(0.04)	(0.04)	(0.04)
Year 2011 dummy	0.04[c]	0.09[a]	0.07[b]	0.09[a]
	(0.02)	(0.03)	(0.03)	(0.03)
Intercept	8.47[a]	7.91[a]	3.86[a]	2.99[c]
	(0.41)	(0.38)	(1.45)	(1.61)
Observations	1,944	1,944	1,944	1,944
Adjusted R^2	0.53	0.53	0.45	0.45
F-statistic of first stage			19.51	20.35
Cragg-Donald F-statistic			21.99	24.05
p-value of Endogeneity test			0.00	0.00

Heteroscedasticity-robust standard errors in parentheses.
[a], [b], [c]: Significant at the 1%, 5% and 10% levels, respectively.
Grouped means of average price used as IV for average electricity price.

Table 1.16: Regression of long-run log electricity demand using alternative instruments

	(1)	(2)	(3)	(4)
(Log) Average price	-0.68[a]	-0.67[a]	-0.61[a]	-0.60[a]
	(0.10)	(0.11)	(0.10)	(0.10)
(Log) Price of capital stock		-0.92[a]		-0.91[a]
		(0.32)		(0.35)
(Log) Midpoint income	-0.01	0.01		
	(0.03)	(0.03)		
(Log) Household size	0.38[a]	0.40[a]		
	(0.14)	(0.05)		
Children dummy	0.09[b]	0.08		
	(0.04)	(0.05)		
Retired dummy	-0.05[c]	-0.18[a]		
	(0.03)	(0.05)		
Share of females	-0.14[a]	-0.16[a]		
	(0.05)	(0.05)		
No. of meals per day			0.02	0.02
			(0.01)	(0.02)
Hours of entertainment per day			0.01[a]	0.02[a]
			(0.00)	(0.00)
No. of hot water services per day			0.04[a]	0.06[a]
			(0.01)	(0.02)
No. of washing services per week			0.02[a]	0.02[a]
			(0.00)	(0.00)
(Log) No. of rooms			0.21[a]	0.38[a]
			(0.05)	(0.06)
Single family housing dummy	0.38[a]	0.40[a]	0.28[a]	0.34[a]
	(0.04)	(0.04)	(0.04)	(0.05)
Urban dummy	-0.17[a]	-0.10[b]	-0.16[a]	-0.10[b]
	(0.03)	(0.04)	(0.03)	(0.04)
Tenant dummy	-0.17[a]	-0.13[a]	-0.13[a]	-0.04
	(0.03)	(0.05)	(0.03)	(0.05)
Utility 1 dummy	0.22[a]	0.25[a]	0.19[a]	0.19[a]
	(0.03)	(0.04)	(0.03)	(0.04)
Time-of-use dummy	-0.08	-0.05	-0.06	-0.03
	(0.06)	(0.06)	(0.06)	(0.06)
Year 2011 dummy	0.74[a]	0.08[b]	0.63[b]	0.12[a]
	(0.26)	(0.03)	(0.26)	(0.04)
Intercept	-17.64[c]	8.66[a]	-12.16	7.85[a]
	(10.28)	(0.50)	(10.22)	(0.46)
Observations	1,858	1,858	1,858	1,858
Adjusted R^2	0.52	0.37	0.54	0.34
F-statistic of first stage	827.13	11.59	832.20	9.58
Cragg-Donald F-statistic	1096.67	12.04	1108.63	10.32
p-value of Endogeneity test	0.00	0.00	0.00	0.00

Heteroscedasticity-robust standard errors in parentheses.

[a], [b], [c]: Significant at the 1%, 5% and 10% levels, respectively.

Neighbouring ElCom price used as IV for average electricity price.

Table 1.17: Regression of long-run log electricity demand using alternative instruments

	(1)	(2)	(3)	(4)
(Log) Average price	-0.66[a]	-0.59[a]	-0.55[a]	-0.51[a]
	(0.07)	(0.07)	(0.07)	(0.07)
(Log) Price of capital stock		-1.11[a]		-1.08[a]
		(0.33)		(0.37)
(Log) Midpoint income	-0.01	0.02		
	(0.03)	(0.03)		
(Log) Household size	0.43[a]	0.42[a]		
	(0.14)	(0.05)		
Children dummy	0.10[b]	0.09[c]		
	(0.04)	(0.05)		
Retired dummy	-0.05	-0.21[a]		
	(0.03)	(0.06)		
Share of females	-0.14[a]	-0.17[a]		
	(0.05)	(0.06)		
No. of meals per day			0.02	0.02
			(0.01)	(0.02)
Hours of entertainment per day			0.01[a]	0.02[a]
			(0.00)	(0.00)
No. of hot water services per day			0.04[a]	0.06[a]
			(0.01)	(0.02)
No. of washing services per week			0.02[a]	0.02[a]
			(0.00)	(0.00)
(Log) No. of rooms			0.24[a]	0.43[a]
			(0.05)	(0.06)
Single family housing dummy	0.30[a]	0.33[a]	0.20[a]	0.26[a]
	(0.04)	(0.04)	(0.04)	(0.05)
Urban dummy	-0.22[a]	-0.12[a]	-0.20[a]	-0.12[a]
	(0.03)	(0.04)	(0.03)	(0.04)
Tenant dummy	-0.19[a]	-0.13[a]	-0.14[a]	-0.05
	(0.03)	(0.05)	(0.03)	(0.05)
Utility 1 dummy	0.19[a]	0.23[a]	0.17[a]	0.17[a]
	(0.04)	(0.04)	(0.03)	(0.04)
Time-of-use dummy	-0.05	-0.00	-0.01	0.02
	(0.05)	(0.05)	(0.05)	(0.05)
Year 2011 dummy	0.57[b]	0.05	0.40[c]	0.08[b]
	(0.24)	(0.03)	(0.24)	(0.04)
Intercept	-12.44	8.22[a]	-4.81	7.42[a]
	(9.54)	(0.54)	(9.43)	(0.50)
Observations	1,944	1,944	1,944	1,944
Adjusted R^2	0.50	0.28	0.52	0.26
F-statistic of first stage	2707.65	12.26	2831.83	9.85
Cragg-Donald F-statistic	5099.11	13.18	5134.14	10.94
p-value of Endogeneity test	0.00	0.00	0.00	0.00

Heteroscedasticity-robust standard errors in parentheses.
[a], [b], [c]: Significant at the 1%, 5% and 10% levels, respectively.
Grouped means of average price used as IV for average electricity price.

1.4.5 Interaction of income and electricity price

One possible extension of our models is to exploit different price elasticities for different household types and, while there are several options, we restrict our analysis to studying the price elasticities of different income levels. Table 1.18 shows studies that deal with the question of whether households with different incomes react differently to electricity price changes. The direction of the effect of income on price elasticity of electricity demand is mixed. While Nesbakken (1999), Jamasb & Meier (2010), Shi et al. (2012) estimate high income households to be more price elastic, Reiss & White (2005) and Alberini et al. (2011) estimate the opposite effect.

Table 1.18: Selected income and price elasticities of electricity demand in the literature

Source	**Method**	**Finding**
Nesbakken (1999)	Split sample regression for income higher and lower than the average	High income households are more elastic
Reiss & White (2005)	Calculate demand elasticities separately for each of the households in the sample, and then average using the survey sampling weights	Households with higher incomes are less elastic
Jamasb & Meier (2010)	Expenditure regression	Households on low incomes are less sensitive to electricity price changes
Alberini et al. (2011)	Allow responsiveness to energy prices to vary with the quartile of the income distribution	Higher income households are less elastic.
Shi et al. (2012)	Interaction term of rich dummy with price. Rich is above median income.	High income group is more price elastic than the low income group

We want to investigate this issue using interaction terms in the electricity demand regression. We use an interaction of two continuous variables using the midpoint income estimator and the electricity price variable. Therefore, we estimate equation (21b) and (21a) using 2SLS:

$$\log E_i^{LR} = \alpha'_{E0} + \alpha'_{E1}\log p_i^E + \alpha'_{E2}\log p_i^E \cdot M_i + \alpha'_{E3}\log p_i^K + \alpha'_{E4}M_i + Z_i\gamma^{E,LR} + \epsilon_i \quad (21a)$$

$$\log E_i^{SR} = \beta'_{E0} + \beta'_{E1}\log p_i^E + \beta'_{E2}\log p_i^E \cdot M_i + \beta'_{E3}\log K_i + \beta'_{E4}M_i + Z_i\gamma^{E,SR} + \epsilon_i \quad (21b)$$

The average electricity price and the appliance stock and its price can be instrumented as before. However, the interaction term may be endogenous as well. Wooldridge (2002) uses the interaction of the instrumental variable with the exogenous part of the interaction term as a natural instrumental variable for the interaction term.[41] On the other hand, Bun & Harrison (2014) show that under some conditions the interaction term may be exogenous. For the identification of the full marginal effect they still recommend to use IV regression with the same instruments as proposed in Wooldridge (2002). Therefore, we use the interaction of ElCom price and income as instrument for the interaction term of average electricity price with income.

Table 1.19 shows the results of the interaction of the two continuous variables. Column (1) uses

[41]See Wooldridge (2002) on page 122.

Equation (21b), whereas column (2) uses Equation (21a). The coefficients of the interactions are both negative and significant. We test for the potential endogeneity of the average electricity price, the interaction term and appliance stock in column (1) and the average electricity price, the interaction term and appliance price in column (2). The null hypothesis of these variables being exogenous can be rejected in both cases.[42] In order to calculate the marginal effects of the electricity price on electricity demand we use the formula: $\beta'_{E1} + \beta'_{E2} \cdot M$. The calculated marginal effects at different points of income are in Table 1.20. We find that the sensitivity to electricity price increases with income. However, since these results come from an IV estimation using three endogenous variables they should be used with some caution (Angrist, 2010).

As a first robustness check we estimate the same regression using the categorical variable of income instead of the continuous variable of income. The results show also an increasing sensitivity with increasing income groups. This confirms the effect found in the continuous case above. However, we observe a small decrease in the price responsiveness in group 4. In addition, as a second robustness check, we use split sample regressions as in Nesbakken (1999) and split the sample in two. The first sample is composed of income groups 1, 2 and 3, while the second sample uses observations from income groups 4, 5 and 6. The number of observations in each group are tabulated in Table 1.9 and we see that the sample sizes of these two split samples are similar. Using these two samples to estimate the original models as described in Section 1.2.2 we can observe that the price elasticities for the sample with higher income groups are larger in both, the short- and long-run regression. Therefore, our conclusion that the sensitivity to electricity price increases with income is supported also using split sample regression.

[42]The first stages are shown in Table A.8 in the Appendix.

Table 1.19: Regression of log electricity demand using price and income interaction

	(Short-run)	(Long-run)
(Log) Average price	2.02^b	1.68^c
	(0.79)	(0.87)
(Log) Midpoint income	0.67^a	0.72^a
	(0.25)	(0.28)
(Log) Midpoint income x (Log) Average price	-0.28^a	-0.25^b
	(0.09)	(0.10)
(Log) Appliance stock (in Watt)	0.71^a	
	(0.18)	
(Log) Price of capital stock		-1.04^a
		(0.31)
Single family housing dummy	0.35^a	0.42^a
	(0.04)	(0.04)
Urban dummy	-0.08^b	-0.08^c
	(0.04)	(0.04)
Tenant dummy	-0.04	-0.11^b
	(0.06)	(0.05)
Utility 1 dummy	0.22^a	0.25^a
	(0.03)	(0.04)
Time-of-use dummy	0.02	0.00
	(0.05)	(0.05)
Year 2011 dummy	0.11^a	0.09^a
	(0.03)	(0.03)
(Log) Household size	0.25^a	0.41^a
	(0.05)	(0.05)
Children dummy	0.07	0.07
	(0.05)	(0.05)
Retired dummy	-0.06^c	-0.19^a
	(0.03)	(0.05)
Share of females	-0.15^a	-0.16^a
	(0.05)	(0.06)
Intercept	-2.89	1.88
	(2.80)	(2.50)
Observations	1,844	1,844
Adjusted R^2	0.47	0.32
F-statistic of first stage	13.14	8.34
Cragg-Donald F-statistic	14.91	8.95
p-value of Endogeneity test	0.00	0.00

Heteroscedasticity-robust standard errors in parentheses.
^{a}, ^{b}, ^{c}: Significant at the 1%, 5% and 10% levels, respectively.

Table 1.20: Price elasticities calculated at different incomes using results from Table 1.19.

Income (CHF)	**Marginal Effects**	**Std. Err.**	***t*-statistic**	***p*-value**	[95% Conf.	Interval]
Short-run						
1'808	−0.119	0.139	−0.85	0.393	−0.390	0.153
2'981	−0.261	0.104	−2.51	0.012	−0.465	−0.057
4'915	−0.403	0.080	−5.01	0.000	−0.561	−0.245
8'103	−0.545	0.078	−6.95	0.000	−0.699	−0.392
13'360	−0.688	0.099	−6.92	0.000	−0.883	−0.493
22'026	−0.830	0.133	−6.25	0.000	−1.090	−0.570
Long-run						
1'808	−0.221	0.148	−1.49	0.136	−0.511	0.070
2'981	−0.347	0.110	−3.16	0.002	−0.562	−0.132
4'915	−0.473	0.084	−5.64	0.000	−0.638	−0.309
8'103	−0.600	0.083	−7.21	0.000	−0.763	−0.437
13'360	−0.726	0.108	−6.71	0.000	−0.938	−0.514
22'026	−0.852	0.146	−5.84	0.000	−1.139	−0.566

1.4.6 Discussion

If we compare the models with exogenous and endogenous average price we see that instrumenting for average price reduces the short-run elasticity from around -0.9 to around -0.5. This indicates that not correcting for the endogeneity of average price overestimates the price elasticity.[43] This appears consistent with Vaage (2000) who mentions that ignoring the simultaneity of the appliance choice and use may lead to an upward bias (in absolute terms) in the price elasticities of electricity demand.

If we compare the different ways of incorporating appliances into the electricity demand estimation then using an appliance index is a superior approach to using individual appliance dummy variables since it avoids the problem of finding enough instruments in an instrumental variable approach. It is very difficult to find instruments for multiple endogenous variables due to the possibility of weak instruments that will produce inconsistent estimates. We can also distinguish vintage and size among other characteristics of the appliances with the index. This makes our approach using an appliance index unique and more accurate than the traditional way of using a set of individual appliance dummies. Our results also indicate that using the appliance stock index produces very stable results. Additionally, the appliance stock index allows us to estimate the corresponding long-run appliance stock demand in a single regression.

A household's appliance stock is not fixed in the long run and therefore we expect the long-run electricity price elasticities to be higher than the short-run price elasticities. While in the short-run only the utilisation rate of the existing capital stock can be chosen, in the long run the level of capital stock can also be optimised. In some studies, elasticity estimates from cross-sectional studies are interpreted as being long-run values (Baltagi & Griffin, 1984). The assumption is that the majority of households in a cross-section are well adapted to their financial circumstances and the cross-section will represent a steady-state. Therefore, the estimated elasticities will represent long-run circumstances (Thomas, 1987). However, the long-run elasticities in this study are only slightly higher than the short-run estimates. This is possibly because the long-term estimates may be considered to be more medium-term due to the cross-sectional nature of the data and we do not directly observe any adjustment decisions. Halvorsen & Larsen (2001) use pooled cross-section data (five years) from the Norwegian Survey of Consumer Expenditure and also find negligible differences between estimated short- and long-run Cournot elasticities. They attribute this result to the fact that there is no substitute for electricity in the use of household appliances in Norway.

[43] We also correct for the possible endogeneity of the appliance index by using an instrument and find that the price elasticity increases very slightly. The results are not reported in this thesis but can be obtained upon request.

1.5 Conclusion

In this chapter we estimate the price elasticity of residential electricity consumption in Switzerland using a unique household survey conducted in 2005 and 2011. The future direction of Swiss climate and energy policies has been the subject of much political debate. It is, therefore, important to obtain a measure of the responsiveness of Swiss households to changes in the price of electricity. This will enable policy makers and electric utility companies to design appropriate pricing policies to modify consumer behaviour. The previous estimate of price elasticity with household data in Switzerland was done in 1998 and this study is a much-needed update of this measure. Moreover, this study improves upon the previous studies by using an instrumental variables approach to correct for potential endogeneity concerns as well as using an aggregate measure of a household's stock of appliances.

We estimate the effect of the stock of household appliances on the consumption of electricity. Previous studies have not always considered household appliances and when they have, not always accounted for the possibility that the choice of appliances may be endogenous. We construct an appliance stock index to capture a household's stock of major appliances. This is a single index that avoids the problem of choosing multiple instruments that may lead to a problem of weak instruments. It also has the advantage of being a more accurate measure of the appliance stock than using appliance indicator variables. It also allows us to estimate a long-run appliance stock demand. We find that the appliance stock is highly dependent on its own price and the income of households. The own-price elasticity is estimated to be between -1.4 and -1.6. We also estimate models of electricity demand based on household production theory that use energy services as explanatory variables. We find that the difference in the price elasticity of demand for electricity if we use energy services or if the usual method of approximating energy services with household and socio-demographic characteristics, is not very high and, therefore, using household and socio-demographic information are good measures of energy services.

In our analysis we calculate the long- and short-run price elasticities using an instrumental variables approach to account for the fact that the price of electricity and the appliance stock may lead to simultaneous causality and, therefore, be endogenous. The price of electricity is endogenous since we use the average price obtained by multiplying the electricity consumption with the marginal price of electricity and adding the fixed fee component, if applicable. The stock of appliances may be endogenous since the choice of appliances may depend on the amount of electricity consumed.

We find that, after correcting for endogeneity, the long-run price elasticity of residential electricity consumption is generally higher than -0.5 while the short-run estimate is lower than -0.5, when we consider the absolute value of price elasticity. In order to check for the robustness of at least one of the instruments used, we employ models using alternative instruments for average electricity price. Generally, the resulting price elasticities for electricity demand are higher using the alternative instruments throughout all specifications. We conclude that the choice of instrument does have an impact on estimates, however as in our case the differences are not too large. Table 1.21 provides a summary of the estimated price elasticities using the different instrumental variables models.

Table 1.21: Estimated price elasticities

	ElCom Price	Alternative instruments: Neighbouring ElCom Price	Alternative instruments: Grouped Mean Average Price
Short-Run			
Socio-demographics	−0.47	−0.57	−0.50
Energy services	−0.42	−0.52	−0.45
Long-Run			
Socio-demographics	−0.53	−0.67	−0.59
Energy services	−0.45	−0.60	−0.51

However, our observation of short- and long-run price elasticities is in line with existing economic theory that the long-run elasticity should be more elastic than the short-run elasticity because households take into account the decision to adjust their stock of appliances. Therefore, they are more sensitive to price changes in the long-run. The price elasticity estimates for Switzerland fall within the range of other studies made for other countries as well as previous studies for Switzerland that use disaggregated data and show that the response of Swiss households to electricity prices is inelastic. Our estimates indicate that, from the point of view of policy makers, pricing policy may have a small impact on households' electricity consumption in the short run. However, since the estimate of the long-run price elasticity of electricity consumption is higher this indicates that households will be influenced by pricing policy even though the impact may not be as substantial as needed. It may be the fact that electricity is priced very low and since the fraction of a household's budget allocated to electricity expense is small, there is not much impact observed in the responsiveness of consumption to electricity price. Policy makers concerned about reducing electricity consumption may need to discuss the possibility of using a combination of policies, including pricing policy, to effectively reduce or, at least, stabilize the per customer electricity consumption in Switzerland.

In terms of other implications for policy, the estimates provide policy makers and utility companies with estimates needed for forecasting electricity demand and enable them to plan for generation, transmission and distribution capacities. These estimates are also a much-needed update for Switzerland and will provide future researchers, especially researchers working with computable general equilibrium models, to model various aspects of the Swiss and European Union electricity systems, with better values of price elasticities. For example, researchers can study the welfare analysis of the introduction of an energy/electricity tax by using our estimates. In addition, using this extensive disaggregate dataset it might be interesting to exploit different price elasticities for different household types. Such values might as well be interesting to be used as input values for computable general equilibrium models for Switzerland. We limit ourselves to the income dependence on price elasticity. In the literature this effect was estimated to go in both directions. We investigate this issue using interaction terms in the electricity demand regression. We find that the sensitivity to electricity price increases with income. However, note that these results come from an IV estimation using three endogenous variables. Therefore, they should be used with some caution.

2 Demand-Side Management by Electric Utilities in Switzerland: Analysing its Impact on Residential Electricity Demand[44]

2.1 Introduction

Energy efficiency policies have been promoted since the oil crises of the 1970s. However, in recent years with the global discussion on climate change, increasing energy efficiency has been a part of the strategy of several industrialized nations in order to reduce the emissions of CO_2 and other greenhouse gases. Indeed, the large potential of CO_2 reductions from increased end-use energy efficiency was highlighted by the World Energy Outlook 2009 (IEA, 2009). As a side effect, energy efficiency policies also reduce air pollution from pollutants such as nitrogen oxides, sulphur dioxide and particulate matter. Apart from its impact on pollutant emissions, the literature on energy efficiency also argues that promoting energy efficiency costs less than building new power plants. Increasing energy efficiency would therefore prevent the need for constructing new and expensive power plants. Further, reducing electricity demand also might help to improve energy security and to reduce the need to extend the transmission and distribution network lines. Lastly, reducing energy demand combined with reducing peak demand can lead to improved grid reliability. Therefore, energy efficiency policy instruments play an important role.

However, a well-known problem is the slow diffusion of energy efficiency technologies. Energy-efficient technologies often have a positive net present value and are therefore cost-effective. However, consumers fail to adopt these energy-efficient technologies. This gap between the observed level of energy efficiency and the higher level of efficiency that is economically attractive or cost-effective is referred to as the *energy efficiency gap* (Jaffe & Stavins, 1994). Different researchers have tried to study these barriers that hinder the full diffusion of energy efficient technologies.

According to Gillingham & Palmer (2014), who have written a literature review on the energy efficiency gap, there are two possible explanations for the under-investment in energy efficient technology: Market failures and behavioural failures. The main market failures are imperfect information and credit constraints. In rented apartments there might exist an additional issue: the principal-agent problem, where the landlord decides on the technology, but the renter pays the energy bills. There are many behavioural failures related to the energy efficiency gap. They include loss aversion, choice overload, suboptimal decision heuristics, default option and herd behaviour. State intervention through policy instruments can target such market and behavioural failures and promote energy efficiency. For example, imperfect information may be targeted using information campaigns and labelling while credit constraints may be mitigated using rebate schemes.

[44]This essay is based on chapter 4 in the report "*An Evaluation of the Impact of Energy Efficiency Policies on Residential Electricity Demand in Switzerland*" (Boogen et al., 2015). Nina Boogen is the primary author of this essay in all regards.

Promoting energy efficiency is also part of demand-side management efforts that are often undertaken by utilities and the government. Demand-side management (DSM) refers to the *"planning, implementing, and monitoring activities of electric utilities that are designed to encourage consumers to modify patterns of electricity usage, including the timing and level of electricity demand"* (EIA, 1999). Utility DSM programmes began in the late 1970s as a response to the energy crises primarily by utilities on the west coast of the USA before gradually spreading to the east coast, north central and other regions of the USA, as well as to British Columbia, Ontario and other provinces in Canada. In recent years DSM has spread to Australia and several countries in Europe, Latin America and Asia, although DSM efforts outside of North America until the 1990s have been limited (Nadel & Geller, 1996).

The original intention of DSM programmes was to change the pattern of electricity demand so as to modify the load faced by a utility. It was subsequently modified to take into account the programmes undertaken by utilities to promote energy efficiency. DSM, therefore, incorporates energy efficiency, energy conservation, and load management (Carley, 2012). There are various ways in which utilities and federal and local governments have carried out these objectives. They include, among other things, policies like appliance standards, financial incentive programmes, information campaigns and voluntary programmes (Gillingham et al., 2006).[45] Table 2.1 provides an overview of some market and non-market instruments for demand-side management, both for load management and reducing energy demand.

Table 2.1: Demand-side management instruments

	Load management	**Energy efficiency**
Market instruments	1. Time-of-use tariff 2. Critical peak pricing 3. Critical peak rebates 4. Real-time pricing 5. Interruptible load tariff	1. Efficiency bonus 2. Rebate systems 3. Energy tax
Non-market instruments	1. Ripple control 2. Smart metering	1. Information campaign 2. Voluntary agreements on efficiency goals 3. Appliance standards 4. Labelling

The World Energy Outlook (IEA, 2009) emphasises the huge potential of energy efficiency measures. These measures are viewed by many as "low-hanging fruit" due to their low marginal cost. It is, therefore, important to analyse the impact of various energy efficiency measures since there is a lack of a systematic analysis of DSM efforts in Switzerland. This includes a qualitative analysis of DSM programmes as well as a rigorous econometric analysis of the effectiveness of such programmes on Swiss residential electricity demand. This essay contributes to the public policy debate about the degree to which DSM programmes can reduce the demand for electricity in the residential sector as well as influence the adoption of energy efficiency measures. While we correlate changes in electricity consumption with changes in spending in DSM programmes or with the presence of DSM programmes, we can only infer that energy efficiency measures were adopted

[45] For a detailed description of the history of utility-sponsored DSM programmes in the US please refer to Eto (1996), Nadel & Geller (1996), and Nadel (2000).

by households through the impact on the household's electricity consumption. A second major contribution of this paper is that, to our knowledge, this is the first econometric estimation of aggregate DSM efforts in a European country. Another contribution is that we construct a scorecard to measure the energy efficiency activities of individual utilities and correlate changes in the scorecard to to changes in the residential electricity consumption. Our scorecard is similar to the state energy efficiency scorecard published by the American Council for an Energy-Efficient Economy that measures the commitment of states to promote energy efficiency. In this essay we consider energy efficiency measures but not load management programmes for our econometric estimation since we are unable to identify their impact on load. However, we consider both energy efficiency measures as well as load management programmes for our descriptive analysis.

The structure of this chapter is as follows. In the rest of this section we provide a brief overview of energy policy and DSM efforts in Switzerland as well as review of previous research on DSM in Switzerland. In section 2.2 we provide a description of our survey performed on some Swiss utilities. Section 2.3 describes the utilities in our survey and their DSM activities as well as the construction of an energy efficiency score. The following section on policy evaluation, section 2.4, describes the existing literature on evaluating DSM activities. The variables used in our model and their sources are also described in section 2.4. Our identification strategy and estimating equation of the impact of energy efficiency programmes on residential electricity demand are described while the results of the econometric estimation are also provided in section 2.4. Section 2.4 also has several robustness checks. The final section, section 2.5 has concluding remarks.

2.1.1 Energy Policy and DSM in Switzerland

Switzerland is a federal state consisting of 26 cantons. The responsibilities are divided between the federal government, cantonal governments and municipalities. In this institutional context, Swiss energy policy is defined and implemented at all the three levels, federal, cantonal, and municipal. Moreover, local utilities also play an important role especially for the definition of the implementation of energy efficiency instruments. It was only in 1990 that the energy policy was embedded into the Federal constitution. Swiss residents voted for the energy article in September 1990, giving the federal government a mandate to promote the economical and efficient use of energy and renewable energy (SFOE, 2007). Following that, in January 1999, the Energy Act (EnG) and Energy Regulation (EnV) came into force (Swiss Confederation, 2014). Their goal is to ensure an economic and sustainable provision of energy and the promotion of local and renewable energy sources. Federal Councillor Adolf Ogi started a programme called "*Energie 2000*" that ran between 1990 and 2000. This programme was relaunched as "*EnergieSchweiz*" in 2001 by Federal Councillor Moritz Leuenberger. The activities of *EnergieSchweiz* aim at raising awareness, information and education, networking and promotion of projects in the fields of renewable energies and energy efficiency. The programme works in partnership with the cantons, communities and partners from industry, environmental and consumer organizations, and private sector agencies (SFOE, 2014).

Other energy efficiency measures introduced by the national government include appliance standards (SFOE, 2014) and energy labels (Sammer, 2007). For the industry, the government introduced two measures: voluntary targets (EnAW, 2010) and competitive tenders (SFOE, 2012).

The Electricity Supply Act (StromVG) brought forward the relatively late start of liberalising the electricity market in Switzerland, which is planned in two phases. In the first phase, customers with a yearly consumption over 100 MWh can choose to go to the free market. In the second phase, which has not started yet, it is planned that all other small consumers can also choose their electricity supplier. The first experiences showed that the goals of liberalisation where not reached completely. Therefore, the government started a process for the revision of the Electricity Supply Act. These activities had to be stopped in March 2011, because of the urgent need to draw up a new energy concept for 2050 (SFOE, 2013c).

Following the decision of the Swiss Federal Council to phase out nuclear energy after the Fukushima Daiichi incident, the Swiss Federal Office of Energy (SFOE) developed the *Energy Strategy 2050*. This sees the utilities as key players for reducing electricity consumption because they have direct contact with end-customers. With this in mind the Federal Council proposed, within the initial package of measures, mandatory efficiency goals on a national level for the utilities that sell more than 30 GWh as one way to reduce electricity consumption. The mandatory efficiency goals could be complemented with a white certificates scheme.[46]

Given the mandatory efficiency goals for large utilities it is important for utilities to take a leading role in implementing DSM measures for improving energy efficiency. As mentioned previously, DSM instruments are mostly defined and implemented at the local level. There is no policy framework on utility-centred DSM at the national level. In Switzerland, 681 utility companies (as of May 2014) are involved in the production, distribution and supply of electricity.[47] These utilities are of different sizes ranging from small municipal utilities supplying single communities to international operating companies. In contrast to other European countries, there are two DSM measures that Swiss utilities have applied for several decades: ripple control and time-of-use pricing (TOU). Ripple control is a traditional instrument to control loads in order to keep the electricity network stable. It is a superimposed higher-frequency signal that is put on the standard power signal (50 Hz). Loads can be switched off and on in this way, e.g. for public street lamps, electric boilers and heaters (SFOE, 2009). In addition, ripple control is used to switch from peak to off-peak hours in the traditional metering system. Most Swiss utilities apply a TOU pricing for residential customers, where prices vary according to the time of the day with higher prices during the day as compared to the night. The difference between peak and off-peak prices faced by residential consumers vary between 50 and 100% (SFOE, 2009). There are also utilities that price differently in winter and summer. However, this approach has been losing popularity in recent years.

In 1989, residents of Zürich voted for a more rational use of energy. Subsequently, the public utility installed a fund that promotes measures energy saving measures and green investments (ewz,

[46] A white certificates scheme works like a CO_2 emission trading scheme. To meet the reduction target a firm or utility can either perform its own reduction measures or buy certificates on the market. If the utility reduces by more than its efficiency goal, it can sell white certificates on the market. This policy ensures that the measures are performed where the marginal cost of reduction is the lowest. Until now, Denmark, France, Great Britain, Italy and the Flemish part of Belgium have introduced mandatory efficiency goals for the utilities, however only France and Italy also have an additional white certificates trading system (SFOE, 2012).

[47] http://www.elcom.admin.ch/themen/00002/00097/index.html

2003). In 1998, the parliament in the canton of Basel-Stadt voted for a new energy law that was pioneering. It allowed the canton to raise a tax on electricity, that would be redistributed equally among the residents and companies (SFOE, 2003). Zürich and Basel are two early examples of DSM measures introduced by utilities in Switzerland. In recent years, several utilities introduced energy efficiency measures such as rental of smart meters, awareness campaigns and funding help for efficient appliances. However, as mentioned above, there has been no policy framework on utility-centred DSM at the national level until now.

2.1.2 Previous Work

While there is a substantial literature on the development of DSM in the US and its impact on electricity demand, little is known about DSM efforts in Switzerland and its effectiveness.[48] The diversity of utility companies in Switzerland does not help to gain a broad overview. In 2011, two environmental organisations, the World Wide Fund for Nature (WWF) and Pro Natura, developed a rating system for the ecological comparison of Swiss utilities. Vettori et al. (2011) compare 12 utilities on five criteria, namely, composition of the electricity mix, ecological efforts in hydro power production, electricity products and services, efforts in promoting energy efficiency and strategic orientation with respect to ecology. They use a multi-criteria analysis to rate the utilities. This evaluation method transforms ratings of different scales in performance levels and thus allows comparison across different ranges. For each criterion, a score between 0 and 4 is assigned. Each criterion has a specific weighting. The scores are multiplied by the weighting, resulting in the score per criterion. This scores per criterion are then summed up to a total score. The maximum possible score is achieved when each criterion is fully met. In their report, Vettori et al. (2011) use publicly available information on the utilities in a first draft. In a second step, the utilities could add information left out in the first draft.

Similarly, Vettori et al. (2014) assess the extent to which the utilities promote energy efficiency and renewable energy using data on 24 utilities. They compare them based on their strategic orientation, role model effect, renewables (production, water protection and supply), energy efficiency services, funding programmes and tariff measures. They use a multi-criteria analysis and the aim of this benchmarking was to trigger a reaction in utilities, the target group, which contributes to the energy transition and the goals of the *Energy Strategy 2050*. A prerequisite is that the benchmarking concept should be widely accepted by the utilities. In developing the conceptual framework Vettori et al. (2014) have laid great emphasis on a participatory approach, which integrated the utilities and other involved organizations as a "sounding board". Further, the process was split into two parts, a pilot survey after which the benchmarking was improved and an additional survey afterwards.

Blumer et al. (2014) use cross-sectional data on 114 utilities and a two-step cluster analysis to identify three different clusters of Swiss utilities based on their activity in implementing DSM programmes. In addition they use an analysis of variance (ANOVA) to find that the clusters differ significantly on utility characteristics such as size.[49]

[48] See section 2.4.1 for an overview of the impact of DSM in the US.
[49] Further information on this paper can be found in section 2.3.

2.2 Survey

In order to perform a qualitative analysis of utility DSM efforts in Switzerland as well as an empirical analysis on the impact of DSM on electricity consumption we collected data on the measures introduced by Swiss electric utilities using a survey. For this purpose, we sent out questionnaires by e-mail to 105 utilities in Switzerland between April and November, 2013.[50] We mailed a questionnaire to the 50 largest utilities and to a random sample of 55 mid-sized utilities. The objective of the survey was to gather information on the electricity delivered to residential customers as well as to quantify any efforts made by utilities on demand-side measures to reduce electricity consumption. To achieve this objective we split the questionnaire into two parts. The first part covered questions about the consumption of residential customers, number of customers, electricity tariffs and utility characteristics. In the second part of the questionnaire we asked questions on DSM activities.

Table 2.2 shows the response rate of the survey, differentiating between the three major language areas in Switzerland.[51] The overall response rate of our survey was almost 42%. While the overall response rate was quite high, taking into account sufficiently completed answers resulted in a lower response rate of close to 30%. However, these 30 utilities account for almost half of the electricity delivered to households with around 45% of residential electricity sold in 2011. Most of the utilities, around 80%, are located in the German-speaking part of Switzerland while the rest of the utilities are divided almost equally between the French-speaking and Italian-speaking parts, 10% and a little over 10%, respectively.

Table 2.2: Survey response rates

Region	Surveys sent	Responses with data	Responses without data	Overall response rate	Useable response rate
German	81	23	9	39.51%	28.40%
French	14	3	5	57.14%	21.43%
Italian	10	4	0	40.00%	40.00%
Total	**105**	**30**	**14**	**41.90%**	**28.57%**

The utilities surveyed were asked to fill in the respective data for 2006 until 2012. This means that we have a panel data set. The main advantage of using panel data is that we can control for unobserved heterogeneity of the utilities. However, we have an unbalanced panel dataset since some of the utilities were unable to provide information for the first few years. For our primary variable of interest, electricity consumption, there are 184 observations in total for the 30 utilities over seven years.

In Switzerland, electricity utilities are quite diverse in terms of their organization and ownership, size and field of activity. There are different ways to measure the size of a utility. Different proxies

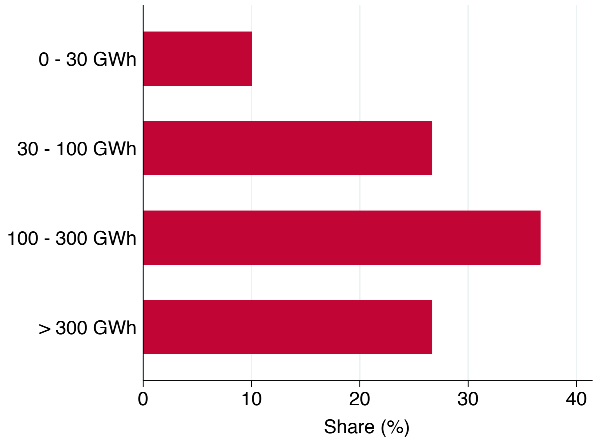
[50] While there are over 600 utilities in Switzerland, we restricted our survey due to constraints on time and resources.

[51] For simplicity, we consider utilities located in the Romansh-speaking areas to be part of the German-speaking region.

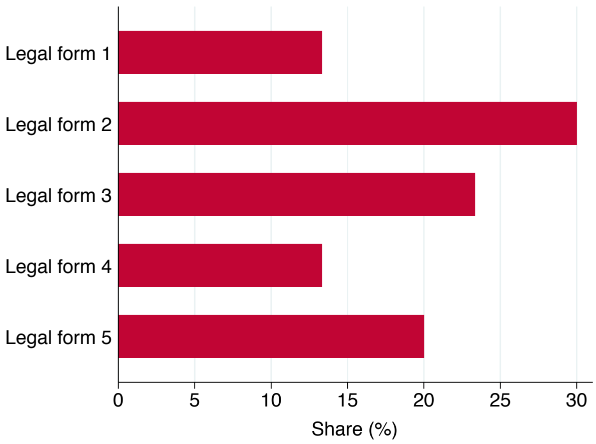
for the size of a utility could be, e.g., the sales revenue, the number of employees or the quantity of electricity delivered. Figure 2.1a presents four groups according to the utilities' supply of electricity to their residential customers in 2012. The graph shows that the majority of utilities supply between 100 and 300 gigawatt hours (GWh).

Another feature of Swiss electricity utilities is its legal form. We distinguish between five legal forms: (1) dependent public institution, (2) independent public institution, (3) publicly owned stock company, (4) stock company with a majority of public ownership and, (5) stock company with a minority of public ownership. Figure 2.1b shows the distribution of our surveyed utilities across the different legal forms. The graph shows that a third of the utilities are independent public institutions. Together with dependent public institutions they constitute about 45% of the sampled utilities. The other three categories are stock companies with different degrees of public ownership.

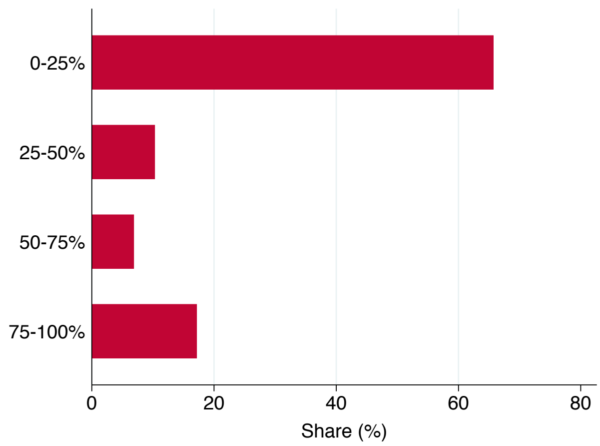
Utilities can be active in production, transmission and distribution of electricity. As we focus on utilities with residential end-use consumers, the utilities in the sample are mostly distribution companies. Nonetheless, some of the utilities also generate their own electricity. Figure 2.1c shows the shares of electricity produced by a utility itself. The graph shows that more than 60% of the utilities in the survey produce less than 25% of their electricity sold. This indicates that the utilities in the sample are more focused on the distribution side. Only a minority, close to 20%, produces more than three quarters of their supply to residential customers.



(a) Share of utilities by electricity supplied to residential customers in 2012



(b) Share of utilities by legal form



(c) Share of utilities by own production

Figure 2.1: Utility characteristics

2.3 Descriptive Analysis of DSM in Swiss Utilities

In this section we provide a detailed descriptive overview on the activities of the sampled utilities in the field of DSM. We have data on 30 utilities[52] for seven years from 2006 to 2012. Since not all utilities could provide information for all seven years, we do not have all the observations (210 from 30 utilities for seven years) for our analyses.

In the previous section, we discussed that Swiss electric utilities are quite diverse in the sense of their organisation and ownership, size and field of activity. Blumer et al. (2014) state that even if the size of utilities is not sufficient to explain the variance in the programme activities, a certain size could be a necessary condition for a utility to adopt and run an energy efficiency programme. They measure size of a utility as the number of employees to capture the organisational capacity, and hypothesise that if there is a lack of human resources, utilities will not be able to implement DSM. The authors also use the legal form as an explanation for measuring the activity of a Swiss utility in promoting energy efficiency measures. They argue that stock companies should have more interest in energy efficiency promotion, as they need to position themselves in the changing Swiss electricity market. However, there is also an argument for an opposite effect. Public utilities may be required by law to introduce measures for energy efficiency. Such a public mandate for energy efficiency might be introduced due to a referendum or an governmental initiative, either at the city or cantonal level. For example, in 1989, the inhabitants of Zürich voted for the "Stromsparbeschluss". This included the establishment of a fund to promote the rational electricity use and the use renewable energy sources. Similarly, the canton of Basel-Land has a public mandate for information and advice on the rational use of electricity. It is financed by the municipalities and the canton with each municipality and the canton paying CHF 0.25 each per inhabitant per year. Feiock et al. (2012) find that municipality-owned utilities that have their own generation capacities are more likely to implement energy efficiency programmes. Utilities with their own capacities are interested in DSM since, it is argued, it might be less expensive to implement conservation measures than to build new power plant capacity, especially peak power plants, as they are only used for a few hours a year.

Table 2.3 provides the summary statistics of the various DSM initiatives or strategies by Swiss utilities for the promotion of energy efficiency. A fifth of the utilities surveyed also have a corporate strategy for promoting energy efficiency. In addition, around a fifth has a public mandate to promote energy efficiency.[53] As mentioned previously, a public mandate obliges a utility to implement energy efficiency measures by law. While only 7% of the utilities have quantified goals to do this, 14% have a fund to which a fixed amount of the revenue is dedicated to DSM or renewable projects. Another 7% have a voluntary fund, where the customers can choose an electricity product that transfers also a fixed amount of the electricity price to such a fund. Figure 2.2 shows the development of the characteristics listed in Table 2.3 from 2006 to 2012. In the beginning, the number of utilities that have specific DSM initiatives seems to be quite stable. However, after 2009, there appears to be an increase in the number of utilities having such DSM initiatives. Still the share of utilities

[52] Note that in this study the term "utility" makes no distinction between grid operators and energy suppliers.
[53] There are few utilities that have both a corporate strategy and public mandate.

with, for example, a corporate energy efficiency strategy, is very low. In 2012, there are only eight utilities out of the 30 in our sample that have a corporate energy efficiency strategy. This may reflect the fact that there is no coherent policy framework at a national level for Swiss electricity utilities. We first evaluate tariff design characteristics in the next section. In the second, third, and fourth parts of this section we describe the utilities' activities in three DSM areas; energy efficiency consulting, replacement of appliances and funding activities. The last part reports the calculation and description of an energy efficiency score for utilities.

Table 2.3: Summary statistics of utility DSM initiatives

Variable	Mean	Std. Dev.	Min.	Max.	N
Dummy for public energy efficiency mandate (Leistungsauftrag)	0.19	0.39	0	1	210
Dummy for corporate energy efficiency strategy	0.20	0.40	0	1	210
Dummy for quantified energy efficiency goals	0.07	0.26	0	1	210
Dummy for energy efficiency fund	0.14	0.35	0	1	210
Dummy for voluntary energy efficiency fund	0.07	0.25	0	1	210

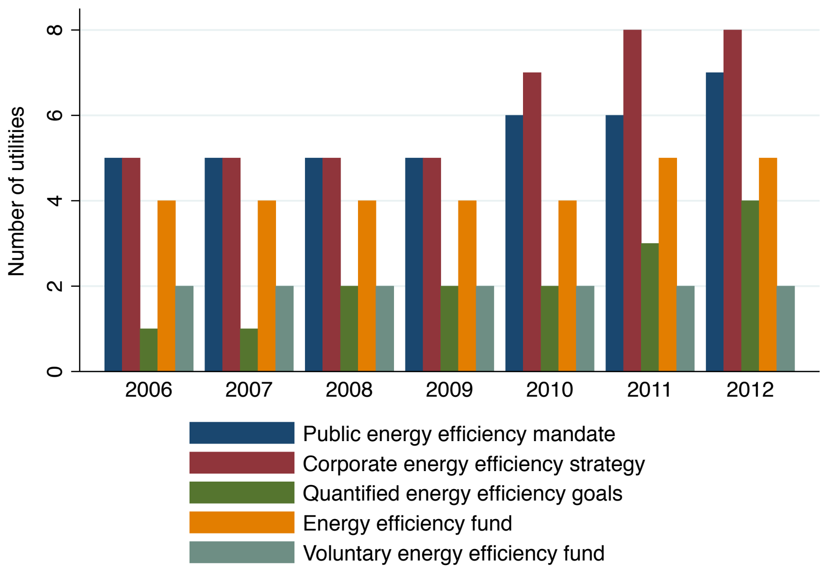


Figure 2.2: Utility energy efficiency measures (2006–2012)

2.3.1 Tariff Design

Designing a tariff system is also a way to promote energy efficiency by providing incentives to the consumer to reduce their electricity consumption. For example, a fixed fee combined with an increasing block pricing scheme can provide incentives to consumers for high electricity savings. Since the introduction of the Swiss Electricity Supply Law (StromVG) in 2007, Swiss utilities are obliged to report their electricity prices for customers in the basic supply[54] to the regulator, ElCom,

[54]Customers in the basic supply (Grundversorgung) are not on the free market.

by the 31st of August each year. ElCom then publishes the average prices for different household (or industry) types.[55] Generally, the electricity price in Switzerland has three components: a price for grid utilisation, a price for the electricity itself, and federal and municipal duties. Table 1.6 shows a breakdown of the price components.

With regard to the electricity tariff structure, Figure 2.3 shows that most of the utilities surveyed have a fixed fee and time-of-use pricing policy (FF+P/OP in Figure 2.3) for their residential customers. There are also a number of utilities in our sample that have a fixed fee and single tariff scheme (FF+Single in Figure 2.3). There are only 3 utilities in our sample that do not have a fixed fee (P/OP in Figure 2.3). There are also a few utilities that have either a fixed fee and a progressive tariff scheme (FF+PT in Figure 2.3) or a fixed fee and a regressive tariff scheme (FF+RT in Figure 2.3).

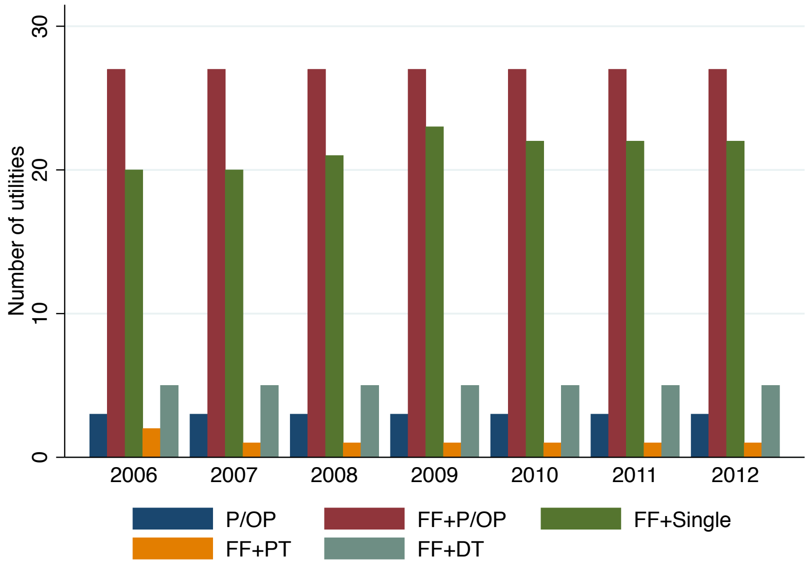


Figure 2.3: Utility tariff structure (2006–2012)

In our survey we also asked for tariff measures that the utilities introduced to promote energy efficiency. The utilities reported several such measures including a progressive tariff, a bonus for energy efficiency, and a tax on electricity (see Figure 2.4). More than half of the utilities surveyed also have a special tariff for interruptible loads.[56]

[55] http://www.strompreis.elcom.admin.ch, website accessed 15. October 2014.

[56] In the survey we asked utilities if they have an option for customers using appliances with heavy loads, e.g. electric boilers and heat pumps, to choose a special tariff scheme where they are charged lower electricity prices but where utilities have the option to regulate electricity supply depending on the total load faced by the utility.

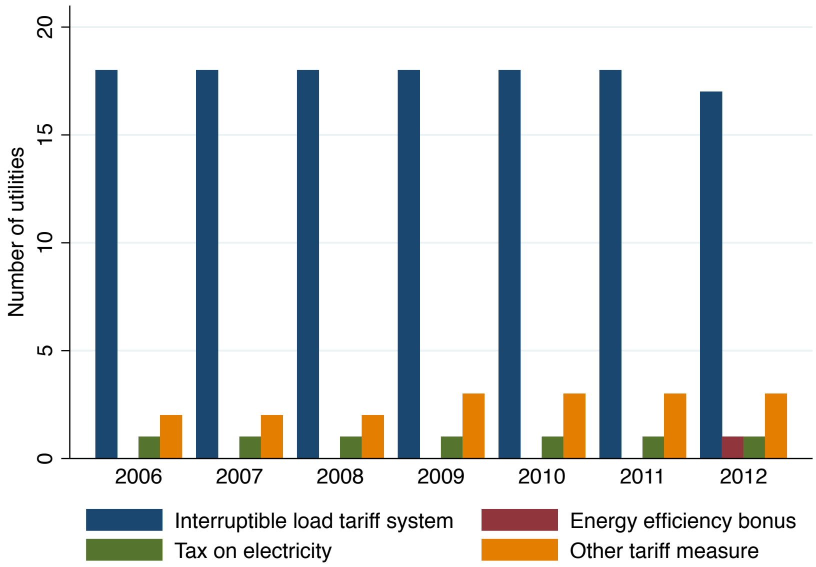


Figure 2.4: Utility tariff measures (2006–2012)

2.3.2 Consulting Activities

Despite the lack of a coherent national policy to promote energy efficiency, one of the areas in which utilities in Switzerland are quite active is in energy efficiency consulting. Consulting in this case includes various forms of information programmes in order for the consumer to gain knowledge on either his consumption or on means and ways to save energy. We group these measures into six different fields. They include information programmes on the internet and leaflets, public relation events, smart meter rentals, energy efficiency information on the electricity bill, energy advice centres and energy audits. Table 2.4 shows the summary statistics of the popularity of these programmes. The table shows that, on average, a utility runs at least three of these measures. The most abundant form is giving the customers information on the utility's respective webpage. Three quarters of the utilities use this form of consultancy. However, only a third of the utilities run an energy advice centre, as this is a more expensive measure to introduce.

Table 2.4: Summary statistics - Consulting activities

Variable	Mean	Std. Dev.	Min.	Max.	N
Information on Web, leaflets etc.	0.76	0.43	0	1	210
Public relation, fairs etc.	0.61	0.49	0	1	210
Rental of smart meters	0.55	0.50	0	1	210
Energy efficiency information on bill	0.46	0.50	0	1	210
Energy Advice Centre	0.28	0.45	0	1	210
Energy Audits	0.53	0.50	0	1	210
All Consulting (Sum of measures)	3.19	1.89	0	6	210

Figure 2.5 plots the number of utilities that implemented the respective measure as a function of time. The graph shows that, in general, the number of utilities active in consulting is growing for all six measures during our study period. This is even more pronounced from 2009 onwards, except

for the rental of smart meters, whose numbers declined in 2012. Rental of smart meters used to be a rather popular measure in the beginning of the study period but it was overtaken by most of the other measures in 2012.

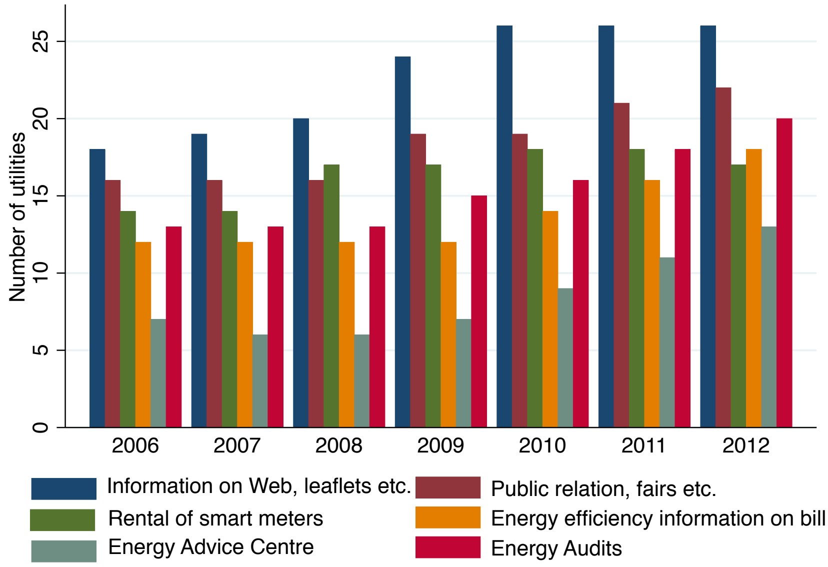


Figure 2.5: Utility consulting measures (2006–2012)

2.3.3 Replacement of Appliances

Another option for the utilities to promote energy efficiency is through helping their customers to replace old and inefficient home appliances and (electric) heating systems. This can be carried out by providing them with information on new and energy efficient appliances or even with financial help. Table 2.5 provides a snapshot of appliance and heating system measures in 2012 and provide a breakdown of our surveyed utilities that provide consulting, funding or both for home appliances as well as heating systems. While most utilities provide one or the other, there are 7 utilities that provided both for home appliances and 10 utilities that provided both to consumers interested in buying heating systems.

Table 2.5: Appliance and heating system measures in 2012

	Consulting	Funding	Both
Home appliances	16	7	7
Heating system	18	10	10

Figure 2.6, meanwhile, shows the number of utilities that have DSM measures concerning consulting and funding of home appliances and heating systems from 2006 to 2012. While 41% of the utilities consult their residential customers on home appliances by giving them information and advice on energy efficient home appliances, only 20% help their clients with the funding of such energy efficiency investments. The same applies for heating systems with 44% providing consulting while

30% of the utilities help with funding. Figure 2.6 shows that the number of utilities providing consulting activities has increased since 2009.

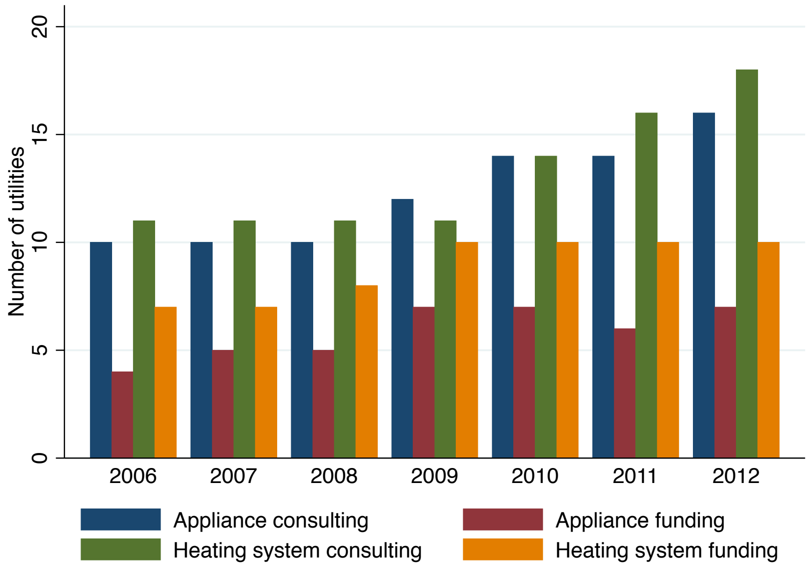


Figure 2.6: Utility measures for replacement of appliances (2006–2012)

2.3.4 Funding Activities

In order to measure the utilities' activity in DSM a popular method is to use the monetary effort for their programmes. We summarize the DSM expenditures between 2006 and 2012 for the 30 surveyed utilities in Table 2.6. DSM expenditure is measured as the annual expenditure on all energy efficiency measures directed at residential customers. A utility spent, on average, CHF 2.86 per residential customer during the survey period. The variation between the utilities is large as shown by the range and standard deviation. There are 14 utilities that have DSM in all the years, from 2006 to 2012. There are 11 further utilities that changed from having no DSM to having some DSM spending over the seven year period. There are 5 utilities that did not report any DSM spending in our study period. The maximum amount spent is almost 31 CHF per customer in a year. This variation can also be seen in Figure 2.7, where we plot electricity consumption per customer against DSM expenditure per customer. Note that Figure 2.7 includes all the surveyed 30 utilities and not only utilities with positive spending. We can see that there is a clear bunching around zero DSM expenditure and only a few utilities spend a large amount, per customer, on DSM measures.[57] Figure 2.8 provides a detailed analysis where the spending by individual utility is plotted separately. Apart from observing the evolution of individual utility DSM spending over time, the graphs show that we can exploit the variation in DSM activities within utilities and across utilities over time to make an econometric estimation of the impact of DSM activities on electricity consumption.

[57]We have also estimated robust regression models that are variants on linear regression models that downplays the influence of outliers. The results suggest that outliers do not cause a problem and the coefficients from the robust regression models are, in general, very similar to our standard regression models.

In any case, we need to note that DSM expenditure may be measured with measurement error. Because of accounting purposes it is not possible for some utilities to tell the exact amount spent on such activities. Therefore, some utilities have only provide rough estimates of this variable. For this reason, we create two indicator variables that, we think, measure the funding activities in a more robust way. Firstly, we use a binary variable for positive spending where the cut-off for the switch from zero to one is spending greater than zero. Secondly, we use a similar dummy with a cut-off at the first quartile of DSM expenditure per customer. Figure 2.9 shows a box-plot of the positive spending binary variable against the consumption per customer from 2006 to 2012, whereas Figure 2.10 displays the same for the second binary variable. As before, the graphs show us that we can exploit the variation in the binary DSM variable within utilities and across utilities over time to make an econometric estimation of the impact of DSM activities on electricity consumption.

Table 2.6: Summary statistics - Funding activities

Variable	Mean	Std. Dev.	Min.	Max.	N
Expenditure on all DSM measures	313129	1048719	0	5900000	210
Expenditure on Funding	98089	336516	0	2951717	210
Expenditure on all DSM measures per customer	2.86	6.13	0	30.83	201
Expenditure on all DSM measures per MWh	0.97	2.56	0	15.22	184
Expenditure on Funding per customer	1.28	3.49	0	30.14	185
Expenditure on Funding per MWh	0.32	0.82	0	5.33	184

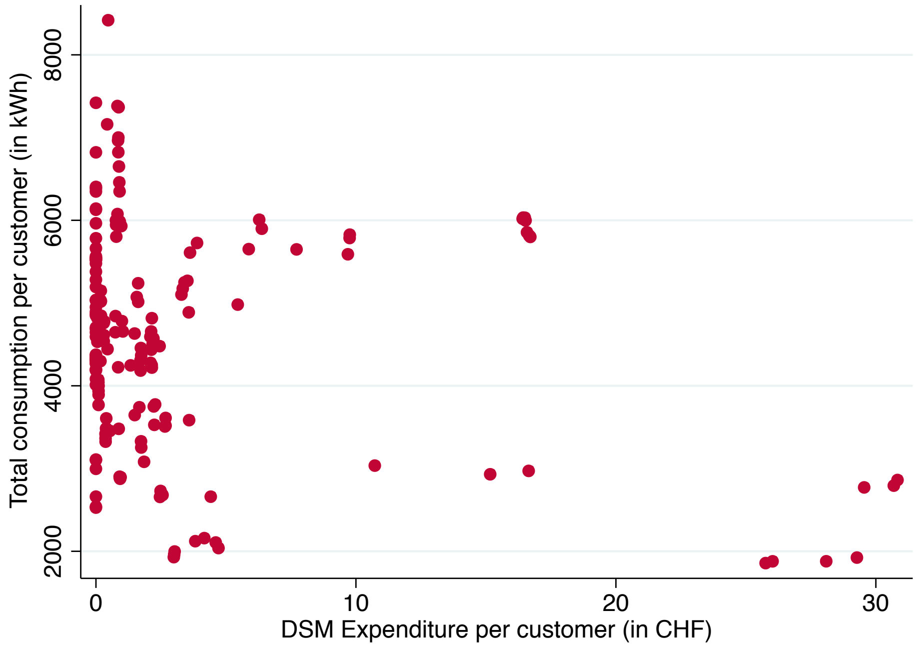


Figure 2.7: Electricity consumption per customer versus DSM Expenditure per customer

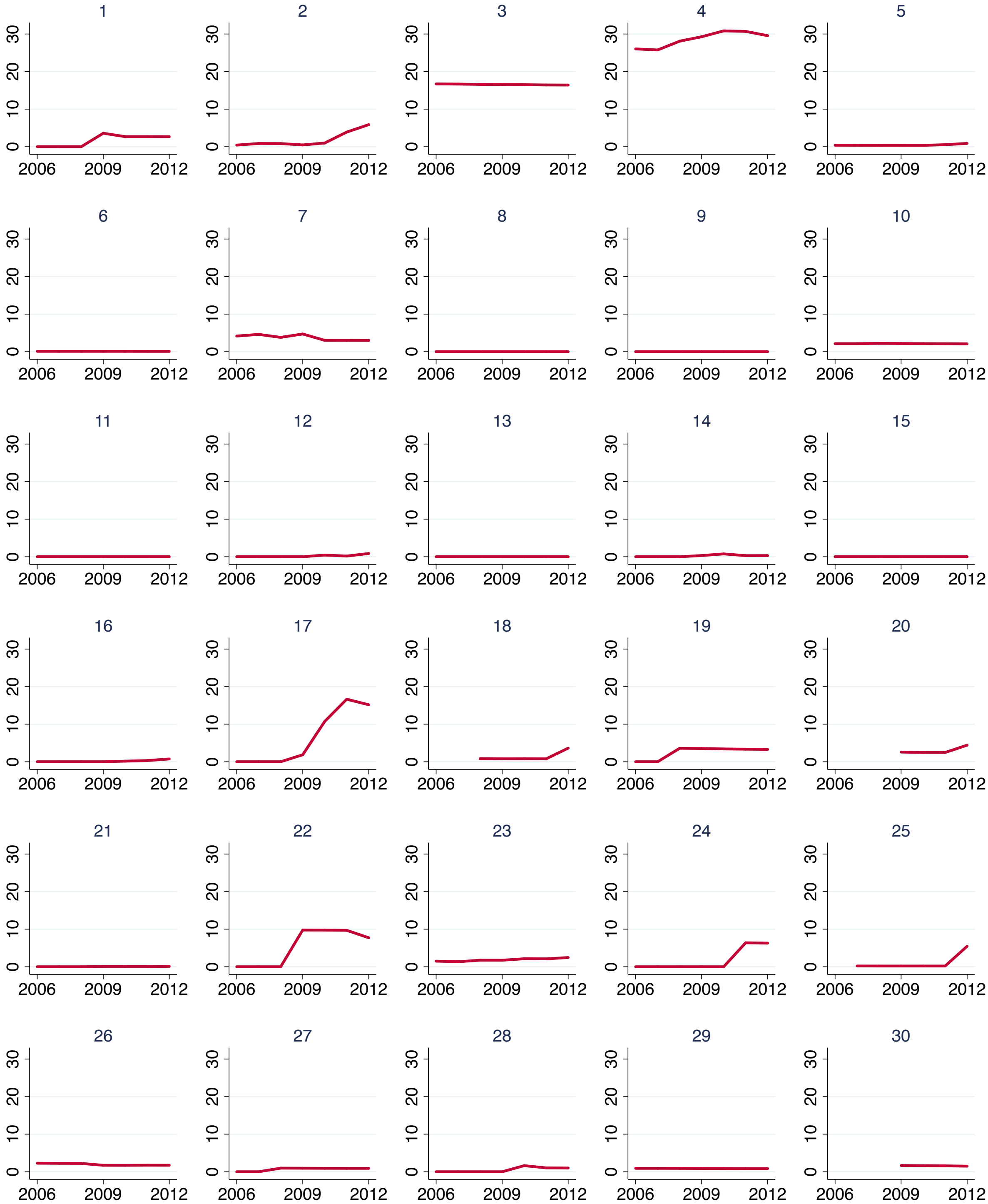


Figure 2.8: DSM Expenditure per customer for utilities in our sample (2006–2012)

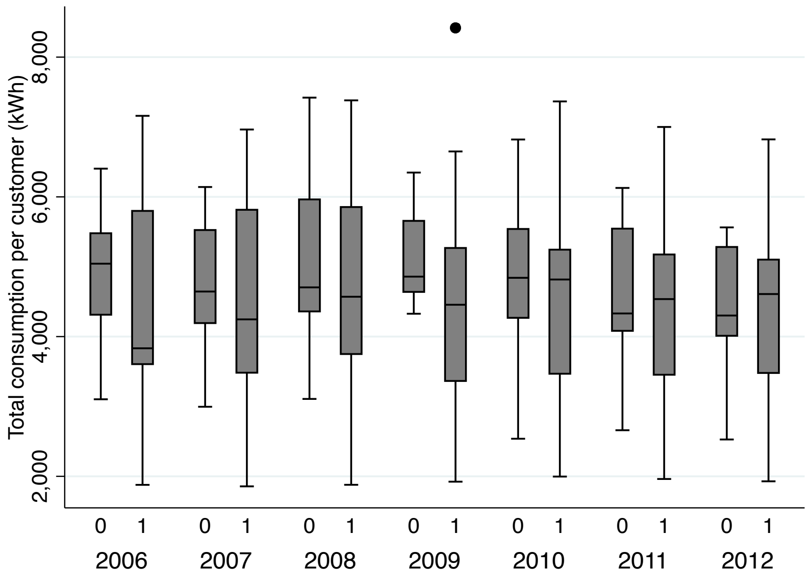


Figure 2.9: Electricity consumption per customer versus positive DSM spending

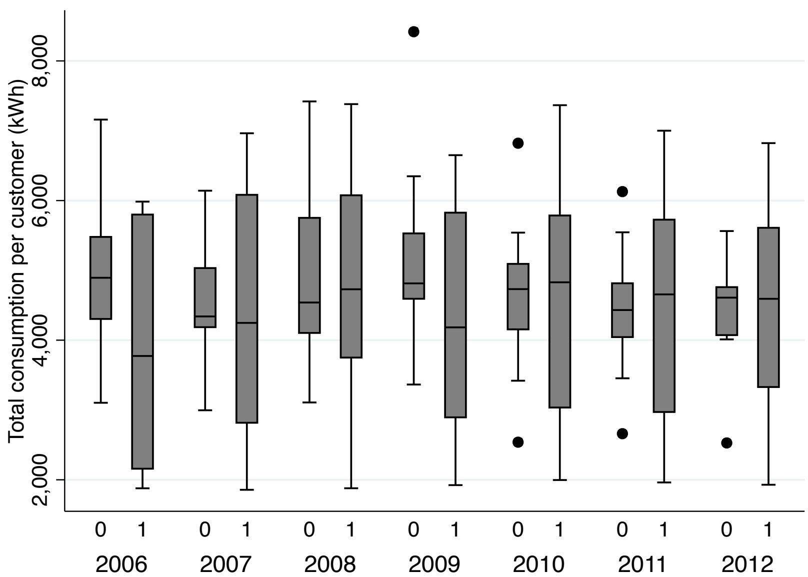


Figure 2.10: Electricity consumption per customer versus 1st Quartile positive DSM spending

2.3.5 Energy Efficiency Score

It is possible to aggregate all the different DSM activities performed by utilities and represent them in an index. For example, Berry (2008) and Carley (2012) use the ACEEE state scorecard to evaluate the effectiveness of DSM in the US. The ACEEE state scorecard is an energy efficiency index that the American Council for an Energy-Efficient Economy (ACEEE) calculated for the first time in 2006. It has now become an annual benchmark of the progress of US state energy efficiency policies and programmes. It considers six policy areas, one of which is utility and public benefits programmes and policies. Within this sub-score programme budget and savings, energy efficiency resource standard and regulation type are considered as the measures (ACEEE, 2014). Table 2.7 list the policy categories used in the ACEEE state scorecard, whereas the measure of utility and public benefits programmes and policies is the most important one as a state could reach a maximum points of 20 out of total 50 points.

Table 2.7: ACEEE state scorecard – Policy areas and points distribution

Policy category	**Maximum points**	**% of total points**
Utility and public benefits programmes and policies	20	40%
Transportation policies	9	18%
Building energy codes	7	14%
Combined heat and power	5	10%
State government initiatives	7	14 %
Appliance and equipment efficiency standards	2	4%
Total	50	100%

We develop a scorecard in a similar way. However, we focus on the DSM utility programmes aimed at only residential customers. The advantage of using such an index or score is that it incorporates the various DSM activities into one measure. Therefore, we get a measure of the utility's commitment to promote energy efficiency. This may be more robust than a monetary measure since the score may have less measurement error. We use information from the second part of the survey in order to develop an energy efficiency score that measures a utility's commitment to promote energy efficiency among their residential customers. For this purpose, we use the reports from Vettori et al. (2011, 2014) as a basis. In contrast to those studies, we consider only the energy efficiency policies that are directed only at residential customers and do not consider the commercial and industrial customers. However, we can calculate the energy efficiency score for all years between 2006 and 2012 and also analyse the dynamics of our score. We cover five fields of action: utility's strategy, tariff design, consulting offers, replacement of appliances and spending on financial programmes. We assign an equal weight of 20% to each of these energy efficiency strategies.

The **first field of action** deals with the strategy of the utilities and asks whether the utility has either a public mandate for promoting energy efficiency or a corporate strategy. If it has either of these, we ask whether there are defined efficiency goals or an energy efficiency fund. Some utilities transfer a fixed amount of their revenues or a fixed amount of the electricity price to a fund. From this fund they finance energy efficiency measures, research or renewable projects. The **second field**

of action, tariff design, covers four sub-criteria: presence of a fixed fee, tariff linearity, interruptible load tariff, and tariff measures. Ito (2014) states that if households respond to average electricity prices rather than to marginal prices the monthly fixed fee removes the incentive to households to save electricity. This is because a decreasing average price reduces the incentive to save electricity. There is evidence in the literature that shows that residential consumers are more concerned about the average price (e.g., Shin (1985) and Borenstein (2009)). Utilities may also have different tariffs for smaller and larger customers or block tariffs. This results in increasing (progressive), linear or decreasing (regressive) tariff structures. California and Italy introduced progressive tariffs for their residential customers in the 1970s (Dehmel, 2011; Tews, 2011). In Switzerland, on the other hand, many utilities have an interruptible load tariff in order to switch off large users during peak hours.[58] This helps to shift the peak demand to off-peak demand hours. We are not considering the traditional time-of-use tariff scheme since all the utilities in our sample offer this scheme to, at least, some of their customers. Tariff measures may take the form of an efficiency bonus that rewards customers with rebates for reaching saving goals, or a tax that gets refunded to the households in equal parts.

The **third field of action** covered by our score is consulting offers by a utility. We aggregate the various offers into six categories of measures: information (leaflets, webpages, etc.); public relations (fairs, etc.); rental of smart meters; information on the bill; energy advice centres; and energy audits. Since some utilities in Switzerland help their customers with the replacement of old and inefficient electricity heating systems and home appliances, we analyse this in the **fourth field of action** of the score. These programmes for efficient appliances can either provide customers with information or financial means. The **fifth, and last, field of action** deals with actual spending on such measures. We use spending for financial programmes per MWh sold to residential customers as an indicator.

Figure 2.11 shows how the energy efficiency score was calculated using the different criteria and their corresponding weights. The overall score ranges from 0 to 4, with 0 being the worst, in terms of energy efficiency efforts, and 4 being the best. Table 2.8 presents the summary statistics of the score, with utilities obtaining an average score of 1.21 out of a maximum of 4. The maximum energy efficiency score reached by one of the surveyed utilities is 3.5. Figure 2.12 shows the development of the energy efficiency score of the six years of the study period. We can see a slight improvement throughout the years, especially after 2008.

To obtain a better picture of the relation between the energy efficiency score and spending on DSM measures, we present Figure 2.13 in which the logarithm of DSM expenditure is plotted against the energy efficiency score. The graph shows that there is a positive correlation between DSM expenditure and the energy efficiency score with higher DSM expenditure being reflected, on average, with a higher energy efficiency score.

Figure 2.14 plots the logarithm of the electricity consumption per customer against the energy efficiency score. The energy efficiency score for each utility is averaged over two periods, one from 2006 to 2009 (indicated by the blue dots), and another from 2010 to 2012 (indicated by the red

[58]See Footnote 56

	Criteria	0	1	2	3	4	Weights
1	**Strategy**						**20%**
	Does the utility have a strategy/ public mandate and defined goals for energy efficiency?	None		yes, but not quantified	yes, quantified	yes with fund	20%
2	**Tariff design**						**20%**
	Fixed tariff	yes, fixed fee				No fixed fee	5%
	Electricity purchased by regressive, linear or progressive rate	regressive rate		linear rate		progressive rate	5%
	Tariff for interruptable appliances for residential loads: Demand Shift	No				Yes	5%
	Tariff measures to decrease the consumption	None		for part of the customers (e.g. efficiency bonus)		incentive tax	5%
3	**Consulting**						**20%**
	Information supply and supply of consulting for residential customers	None	1 measure	2 - 3 measures	4 - 5 measures	6 measures	20%
4	**Programs for efficient appliances and equipment**						**20%**
	Does the utility promote the conversion of existing electric storage heaters and electric water heaters to energy efficient technologies?	None, no information		consulting, no financial measures		consulting, and financial measures	10%
	Incentives for the replacement of inefficient appliances. Does the utility support the purchase of energy efficient appliances?	None, no information		consulting, no financial measures		consulting, and financial measures	10%
5	**Spending on programs**						**20%**
	What was the expenditure (in CHF) for financial support, as measured by the electricity sales in utility area?	no financial support	>0-0,5 Fr/MWh per year	0,5-0,75 Fr/MWh per year	0,75-1 Fr/MWh per year	>1 Fr/MWh per year	20%

Figure 2.11: Calculation of energy efficiency score

dots). The general picture shows a negative correlation between electricity consumption and the energy efficiency score, meaning that higher energy efficiency scores seem to be associated with utilities that have lower electricity consumption.

In addition, we also provide a rough idea on the relative evolution of the utilities with regard to their energy efficiency scores. We do this to see if utilities have, relative to each other, remained stable with regard to energy efficiency measures. The results of this exercise are provided in Table 2.9. In this table we provide a list of all the 30 (anonymous) surveyed utilities. We then calculate the average energy efficiency score for each utility between, firstly, 2006 and 2009 and, secondly, 2010 and 2012. We then rank these scores for both periods to get an idea of how the ranking has changed over the two periods. For example, utility 1 was ranked 21st for the average energy efficiency score between 2006 and 2009 and ranked 14th between 2010 and 2012. While a glance at the rankings seems to indicate that there is a high correlation between the rankings in the two periods. This is confirmed with the Spearman's rank correlation coefficient. The correlation coefficient for the two rankings is calculated to be 0.82, which indicates a high degree of correlation. Therefore, we conclude that the ranking of utilities, in terms of their energy efficiency score, has remained fairly stable over our study period. We also provide this graphically in Figure 2.15 where we plot the

Table 2.8: Summary statistics - Energy efficiency score

Variable	Mean	Std. Dev.	Min.	Max.	N
Energy efficiency score	1.21	0.88	0	3.5	210

energy efficiency score ranking in 2006-2009 against the ranking in 2010-2012.

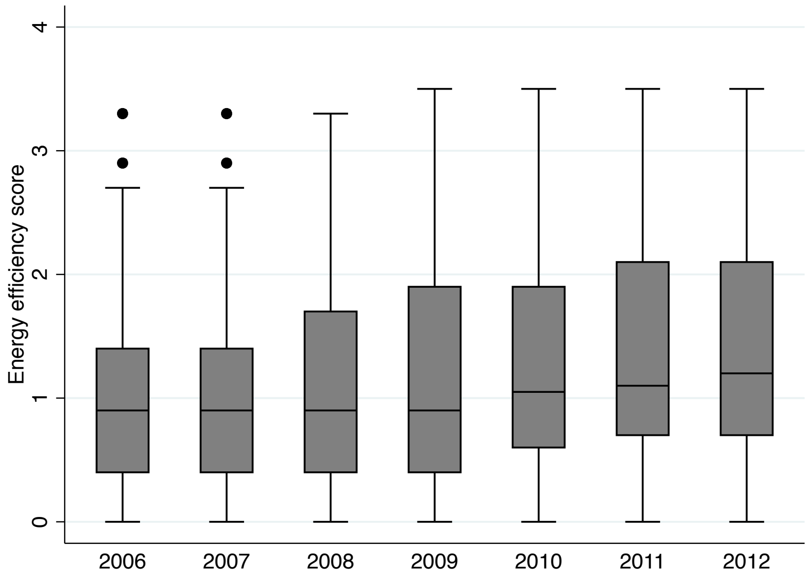


Figure 2.12: Energy efficiency score over the study period (2006–2012).

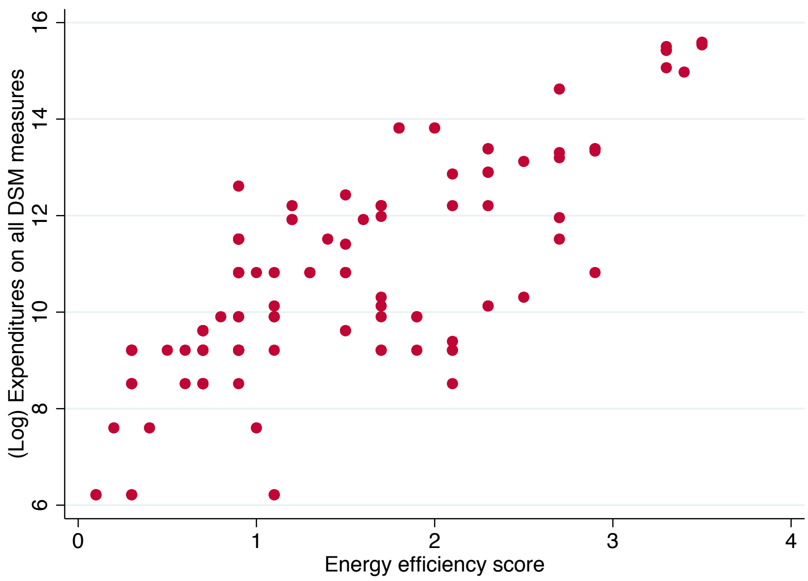


Figure 2.13: (Log) Expenditure on DSM versus energy efficiency score

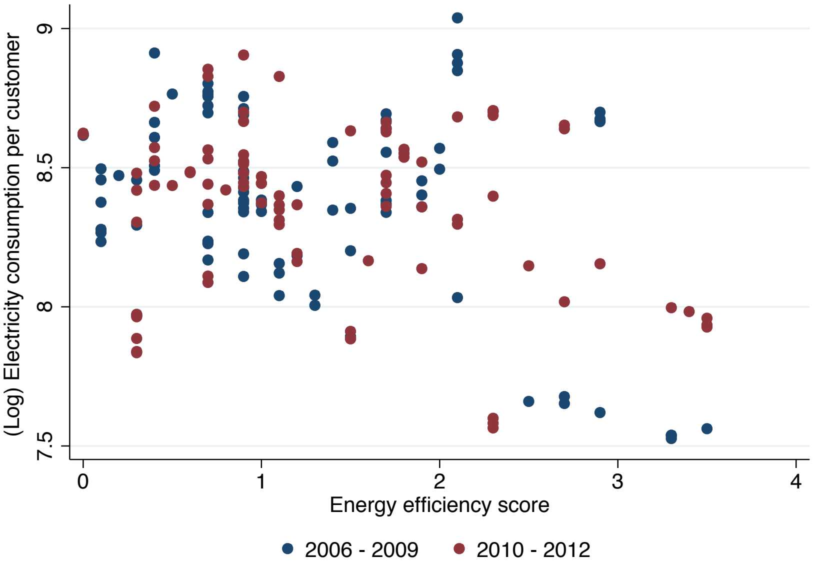


Figure 2.14: Energy efficiency spending versus energy efficiency score

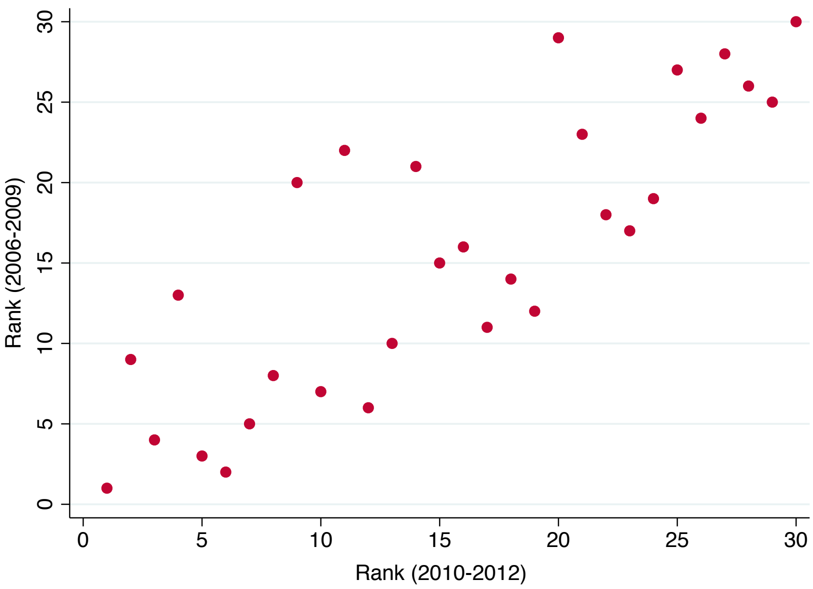


Figure 2.15: Relative energy efficiency score ranking

Table 2.9: Ranking of the utilities according to the energy efficiency score

Utility ID	Rank (2006-2009)	Rank (2010-2012)
1	21	14
2	4	3
3	2	6
4	1	1
5	13	4
6	29	20
7	3	5
8	11	17
9	24	26
10	12	19
11	30	30
12	16	16
13	25	29
14	27	25
15	5	7
16	23	21
17	9	2
18	15	15
19	7	10
20	10	13
21	28	27
22	6	12
23	8	8
24	20	9
25	14	18
26	19	24
27	26	28
28	22	11
29	18	22
30	17	23

2.4 Policy Evaluation

In this section we perform an econometric estimation of the effectiveness of DSM programmes in Switzerland using the information from our survey. First, we provide a review of the current literature on DSM effectiveness, based mostly on the US. In the second section, we provide a brief description of the additional data that we use to supplement our survey data. Thirdly, we describe our empirical strategy which is based on a difference-in-differences framework. We then provide results of our econometric estimation and, in the final section, present results of robustness checks.

2.4.1 Previous Work

The empirical literature on the effectiveness of demand side management (DSM) programmes in the US is extensive. Table 2.10 provides an overview of the empirical analyses of DSM, almost exclusively in the US. Early analyses concentrated on estimating its cost-effectiveness measured in terms of the cost of kWh saved compared to the cost of producing it. For example, Joskow & Marron (1992) and Eto et al. (1996) find that these programmes were both cost-effective and also effective in reducing energy consumption. There are also several other qualitative studies that show that DSM programmes are cost-effective (Eto et al., 2000; Nadel, 1992; Nadel & Geller, 1996). The first empirical analyses attempt to measure the accuracy of self-reported DSM savings of the utilities and draw conclusions on the effectiveness of DSM programmes.

Parfomak & Lave (1996) analyse the aggregate industrial and commercial conservation impacts, which were reported by 39 utilities in the north-east U.S. and California between 1970 and 1993. They estimate the effect of the reported conservation on electricity demand while controlling for average electricity price, other fuel prices, economic activity, and weather by estimating a regression equation in first differences and a weighted-least-squares (WLS) estimator. They conclude that 99.4% of the self-reported conservation is statistically observable.

Further, Loughran & Kulick (2004) analyse the electricity sales of 324 utilities in the US from 1989 to 1998. They use a subsample of 119 utilities that had positive DSM expenditures throughout the whole study period and estimate the electricity sales as a function of DSM expenditures, utility-level controls (concentration in residential, commercial, industrial sales) and state-level controls (weather, energy prices, gross state product) by using a first differences regression. They conclude that DSM expenditures lower electricity sales significantly, by 0.3% to 0.4% for the total sample and by 0.6% to 1.2% for the sub-sample, but the effect is smaller than those reported by the utilities. As an explanation, they suggest that utilities do not completely control for selection bias.

In a follow-up to the Loughran & Kulick (2004) study, Auffhammer et al. (2008) use the same data and econometric models as in Loughran & Kulick (2004) but use an alternative, sales-weighted, test statistic and non-parametric bootstrapped confidence intervals to improve the analysis. Their results show that the reported electricity savings from utility DSM programmes may not be as inaccurate as reported by Loughran & Kulick (2004). This supports the earlier conclusions reached by Parfomak & Lave (1996).

Table 2.10: Estimated DSM effects in the literature

Source	DSM Policy Variable	Effect	Model
Parfomak & Lave (1996)	Reported Conservation (GWh)	99.4% of the reported conservation impacts are statistically observable in system level sales after accounting for economic and weather effects.	Weighted least squares (WLS) estimators
Loughran & Kulick (2004)	1. Dummy if utility has positive DSM expenditure 2. DSM expenditure	DSM expenditures lowered mean electricity sales by 0.3 to 0.4 percent. Larger effect for a sample of utilities reporting positive DSM expenditures in every year (0.6 to 1.2 percent). Utilities themselves estimated effect between 1.8 and 2.3 percent. Authors think the difference is because utilities generally do not fully control for selection bias.	First difference fixed effects approach
Dulleck & Kaufmann (2004)	Information programme value (0-1)	Providing customers with information reduced overall electricity demand by roughly 7%	Monthly time series
Horowitz (2004)	DSM savings per dollar state gross commercial product (which are endogenous) therefore instruments: 1. DSM instrument with non-declining DSM savings by replacing with the latest higher values 2. DSM instrument is estimated with a Tobit model using population and supply costs as explaining variables	Electric utility demand side management programmes were responsible for reducing commercial sector electricity intensity in 2001 by 1.9% relative to the 1989 level.	Dynamic GLS-FE model
Horowitz (2007)	Reported accumulated (1992-2003) electricity savings attributable to DSM programmes to categorize utilities in four different quartiles of different commitment to energy efficiency policies.	Those states that have moderate to strong commitment to energy efficiency programmes reduce electricity intensity relative to what it would have been with weak programme commitment; in the residential sector by 4.4%	Difference-in-differences approach
Auffhammer et al. (2008)	DSM expenditure	Reported utility DSM savings may be more accurate than Loughran & Kulick (2004) claim. Supports Parfomak & Lave (1996).	Loughran & Kulick (2004) model and data plus better test statistic and non-parametric bootstrap confidence intervals

Continued on next page

Table 2.10 – continued from previous page

Source	**DSM Policy Variable**	**Effect**	**Model**
Berry (2008)	1. ACEEE efficiency programme score 2. Utility efficiency programme spending score and 3. Other efficiency programme score	The higher the utility efficiency programme expenditures per capita and the greater the range of other efficiency programmes offered, the greater is the reduction in the growth of electricity sales. A one-point increase in the efficiency programme score is associated with about a 3.2% decrease in the growth of electricity sales over the 5-year study period.	OLS regression of difference
Rivers & Jaccard (2011)	DSM expenditure per capita	DSM expenditures by Canadian electric utilities have had only a marginal effect on electricity sales	Partial adjustment model (to correct for the inertia) with bias corrected estimators (by Kiviet (1995))
Arimura et al. (2012)	DSM spending per customer, lagged DSM spending (as well as their polynomials) as instruments.	They found that DSM expenditures have resulted in an annual average of 0.9 percent electricity savings at an average cost of 5 cents per kWh of electricity savings.	Basic approach of Loughran & Kulick (2004) plus address possible endogeneity in spending (by using a nonlinear GMM approach)
Carley (2012)	1. DSM policy effort (ACEEE score) 2. Public benefit funds spendings 3. Dummy for the state having an energy efficiency portfolio standard 4. Dummy for the state offering a performance incentive	State-run DSM efforts contribute to electricity savings across the country. Public benefit funds coupled with performance incentives are found to encourage utility participation in DSM programmes. Energy efficiency portfolio standards and performance incentives effectively promote electricity savings, but public benefit funds without the support of other DSM policies are not significant drivers of either DSM programme participation or total DSM electricity savings.	Two-step Heckman method

A second wave of empirical studies modelled electricity policy trends more generally. Horowitz (2004) concludes that "market transformation" programmes might affect conservation as well. Therefore, if this is not taken into account in the model, the model will produce biased estimates. Therefore, Horowitz (2004) explicitly separates market effects from DSM programme effects. He uses panel data set from 42 states between 1989 and 2001 but only from the commercial sector. Using a dynamic generalised least squares-fixed effects model, Horowitz (2004) finds that electricity intensity in the commercial sector is reduced by about 2% through DSM programmes.

Horowitz (2007) uses a difference-in-differences approach to analyse whether changes in electricity demand and electricity intensity from the pre-1992 period (1977–1992) to the post-1992 period (1992–2003) for the residential, commercial, and industrial sectors were related to the intensity of commitment to DSM programmes. He measures the intensity of commitment as the quartile groups of accumulated electricity savings reported by the utility between 1992 and 2003. He finds that US states that are in the upper three quartiles reduce electricity intensity relative to the lowest quartile in the residential sector by 4.4%.

Berry (2008) analyses the relationship between state-level efficiency programme effort, obtained from the efficiency programme scorecard published by the American Council for an Energy-Efficient Economy (ACEEE), and growth in electricity sales between 2001 and 2006 using data of 47 US states. He uses an OLS regression on the differences between 2001 and 2006 electricity sales, controlling for efficiency programme score, differences in GDP, price changes and weather. He shows that the higher the utility efficiency programme expenditures per capita and the greater the range of other efficiency programmes offered, the greater the reduction in the growth of electricity sales. A one-point increase in the efficiency programme score was associated with about a 3.2% decrease in the growth of electricity sales over the 5-year study period.

Recently, Arimura et al. (2012) use the basic approach of Loughran & Kulick (2004) to estimate the cost-effectiveness of DSM programmes. However, they adapt it by explicitly addressing possible endogeneity in spending, by using a nonlinear GMM approach, and an extended study period till 2006. Following Auffhammer et al. (2008), they calculate confidence intervals for the estimates of percentage savings and cost effectiveness. Arimura et al. (2012) conclude that DSM expenditures were responsible for annual average electricity savings of 0.9%.

Finally, Carley (2012) analyses the effect of four different DSM policy variables on electricity savings using cross-sectional data of 3090 utilities in 48 US states from 2007. She uses a two-step Heckman model to help minimise the selection bias of the policy variables. The DSM policy variables she uses are: (1) DSM policy effort (from the ACEEE scorecard), (2) public benefit funds spending, (3) a dummy for the presence of energy efficiency portfolio standard in a state, and (4) a dummy for the presence of performance incentives in a state. She finds a significant impact of state-run DSM programmes in increasing electricity savings.

The literature on evaluation of DMS programmes outside of the US and especially the empirical estimation of the effectiveness of DSM measures is very scarce. Dulleck & Kaufmann (2004) focus on information programmes in Ireland and find that while the short-run demand behavior does not change significantly, the long-run demand changes by a great amount.[59] They conclude that information programmes reduce electricity demand by around 7%. Another DSM study has been done for Canada by Rivers & Jaccard (2011). Rivers & Jaccard (2011) apply a partial adjustment model with bias-corrected estimators, based on Kiviet (1995), and conclude that DSM expenditure has only a marginal effect on electricity consumption in Canada.

To the best of our knowledge, these are the only two empirical studies conducted outside of the US. This leaves a major gap in research on the effectiveness of European energy efficiency measures in the residential electricity sector. Moreover, all of the above-mentioned studies, except for Carley (2012) and Horowitz (2004), treat the policy variable as exogenous. This may bias results since unobserved factors that influence the residential electricity demand may also influence the state's decision on whether or not to introduce a policy leading to a simultaneity problem. We try to overcome this problem by using an instrumental variables (IV) approach. In addition, similar to Carley (2012), we use different versions of policy variables: DSM expenditure per customer, two different versions of a dummy for positive DSM spending and a score that measures the DSM effort of a utility. We can then verify the robustness of our estimates.

While there is substantial literature on the development of DSM in the US and its impact on electricity demand, little is known about DSM efforts in Switzerland and its effectiveness. There is no policy framework on utility-centred energy efficiency at a national level. In 2011, two environmental organizations, the World Wide Fund for Nature (WWF) and Pro Natura, developed a rating system for the ecological comparison of Swiss utilities. Vettori et al. (2014) assess the extent to which the utilities promote energy efficiency and renewable energy using data on 24 utilities. Blumer et al. (2014) use data on 114 utilities and a two-step cluster analysis to identify three different clusters of Swiss utilities regarding their activity in implementing DSM programmes. In addition they use analysis of variance (ANOVA) to find that the clusters differ significantly on utility characteristics such as size, share of production, number of large clients, and the level of activity in implementing DSM programmes.

2.4.2 Data

There are three main sources of data. The first source is our survey from which we obtain utility characteristics, electricity consumption and price data as well as the DSM measures. Demographic data like income and political variables are from the Bundesamt für Statistik (BFS). The final source is MeteoSchweiz from where we obtain information on heating and cooling degree days.

Table 2.11 shows the summary statistics of all the variables used and their source. Most Swiss utilities have two kinds of tariffs for customers with a time-of-use scheme and a single tariff scheme. Customers with a time-of-use scheme pay a different price for electricity depending on the time of day with a higher rate during the day and a lower rate at night. Customers with a single tariff scheme pay a single price for electricity regardless of the time of day. To take this into account we weight the average price by using the number of customers in each tariff scheme. Based on the

[59] While this study is also European, our analysis is based on an aggregate DSM measure as opposed to the specific nature of DSM programme, i.e. information programmes, studied by Dulleck & Kaufmann (2004)

information from residential electricity tariffs, we calculate a weighted average electricity price for each utility and year.[60]

Demographic data is from the BFS. We use the average taxable income (per taxpayer) as a measure of the income of a household. Electricity demand also depends on the household size and we calculate this by dividing the population of the area served by a utility by the number of customers serviced by that particular utility to get an average size of a household in the area serviced by the utility. We also use heating and cooling degree days, collected from MeteoSchweiz, as a measure of the effect of weather variables on the demand for electricity. We also report the summary statistics of the five legal forms and the share of own production, as these variables are used as an instrument as part of the robustness checks described in section 2.4.5.

The primary independent variable of interest is a measure of demand-side management programmes. We calculate this in several ways. The first way is through an indicator variable that takes the value 1 if the utility has had any DSM spending in the year and zero, otherwise. The second way is also by using an indicator variable. However, in this case, we assign a value 1 to the DSM variable if the DSM spending lies at or above the first quartile of positive DSM spending. The third measure is by using the reported DSM spending by a utility. The last measure uses the energy efficiency score calculated in section 2.3.5.

All these measures have their respective advantages over each other. The advantage of the first binary measures over the continuous measure is that it does not suffer from measurement error as the DSM expenditure are self-reported.[61] Some utilities cannot accurately observe the amount spent on DSM activities because of the different quality of accounting systems. These utilities have only provided rough estimates on the expenditure. The advantage of the continuous measures over the binary measures is that they provide a measure of the intensity of DSM activities and not just an indication of whether a utility engages in DSM or not. However, we should note that we assume that each CHF spent has the same effect regardless on what measure it was spent. For example, we can not distinguish a CHF spent on an energy advice centre and a CHF spent on financial incentives. The advantage of the energy efficiency score is that we get a measure of a utility's commitment to promote energy efficiency which may be more robust than a monetary measure since the score may have less mismeasurement. The score captures, in one index, the various DSM activities. However, the disadvantage is that it cannot distinguish between the effectiveness of different DSM activities and can not be expressed in monetary terms.

[60] Details are provided in equation (37) in the Appendix.

[61] The second dummy variable (1. quartile dummy) does suffer from measurement error as well.

Table 2.11: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N	Source
Total consumption per customer (kWh)	4547.52	1311.02	1856.77	8418.08	182	Survey
Average price	20.91	3.75	13.16	28.96	182	Survey
Average taxable income (per taxpayers)	69127.31	9894.18	56006	104537.19	210	BFS
Household size: population/customer	1.86	0.55	0.76	4.24	185	Survey & BFS
Heating degree days	3567.52	904.93	2130.16	6452.90	210	MeteoSchweiz
Cooling degree days	137.99	90.15	0	442.12	210	MeteoSchweiz
Positive DSM expenditure dummy	0.66	0.47	0	1	210	Survey
DSM expenditure: 1. quartile dummy	0.51	0.50	0	1	210	Survey
DSM expenditures per customer	2.86	6.13	0	30.83	201	Survey
DSM expenditures per customer†	4.42	7.17	0.06	30.83	130	Survey
Energy efficiency score	1.21	0.88	0	3.50	210	Survey
Dependent public institution	0.14	0.34	0	1	204	Survey
Independent public institution	0.29	0.46	0	1	204	Survey
Stock company: 100% publicly owned	0.23	0.42	0	1	204	Survey
Stock company: majority publicly owned	0.14	0.34	0	1	204	Survey
Stock company: minority publicly owned	0.21	0.41	0	1	204	Survey
Share own production: 0-25%	0.66	0.48	0	1	204	Survey
Share own production: 25-50%	0.1	0.3	0	1	204	Survey
Share own production: 50-75%	0.07	0.25	0	1	204	Survey
Share own production: 75-100%	0.17	0.38	0	1	204	Survey

†: Conditional on DSM spending greater than zero.

2.4.3 Empirical Strategy

Our primary identification strategy to estimate the effectiveness of DSM efforts in Swiss utilities is to use the variation in DSM measures within utilities over time and across utilities. In effect, we are using the method of difference-in-differences to obtain this estimate. Difference-in-differences (DD) is a method used to determine causal relationships and its basic idea is to identify a policy intervention or treatment by comparing the difference in the outcomes before and after the intervention for the treated groups with the difference for the untreated groups. It is, therefore, crucial to have observations from the treated and untreated units both before and after the policy intervention. The policy intervention is assumed to be a quasi-experiment with units that receive the policy intervention, or treatment, and units that do not receive the policy intervention, called the control.

In our analysis, we consider utilities that have implemented DSM as the treated units. There are 14 utilities that have DSM in all the years, from 2006 to 2012, and are considered to be in the treatment group. There are 11 further utilities that changed from having no DSM to having some DSM spending over the seven year period. On the other hand, there are 5 utilities that did not report any DSM spending in our study period. Due to the fact some utilities are changing from having no DSM to having DSM the number of utilities that belong to the treatment group is changing over time. Figure 2.16 shows the evolution over time. Note that there is no utility that changes back from having DSM to having no DSM.

The simplest version of a difference-in-differences (DD) estimator consists of two groups: a treated group (N) and a non-treated group (A) over two time periods, before and after the treatment. This is illustrated in Table 2.12 and Figure 2.17. The treatment on N occurs between the time periods

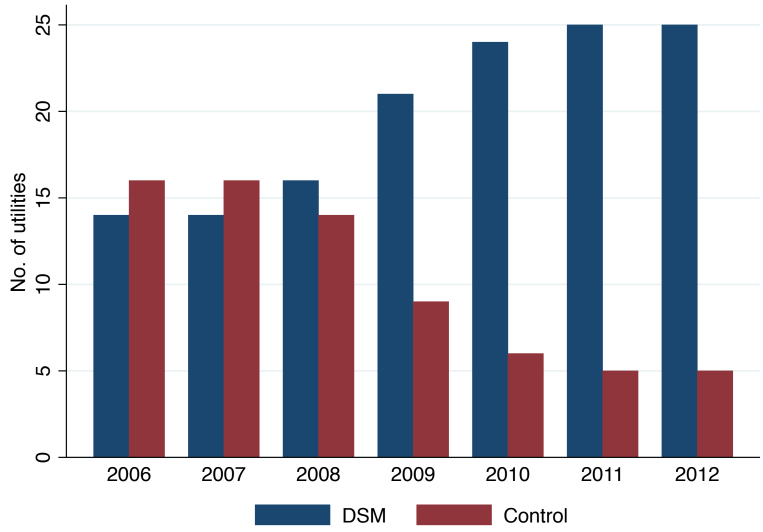


Figure 2.16: Treated and non treated utilities over the study period (2006–2012).

$t = 0$ and $t = 1$, where N_N^* is observed after the treatment and N_N is the counterfactual. The average treatment effect on the treated is the change in the outcome variable introduced through the treatment and can be estimated by calculating the difference of the difference in the outcomes of the treated group and the difference of the control group:

$$DD = (\mathrm{N}_\mathrm{N}^* - \mathrm{N}_\mathrm{V}) - (\mathrm{A}_\mathrm{N} - \mathrm{A}_\mathrm{V}) \tag{22}$$

Table 2.12: DD method and the subgroups

	Treated group	**Control group**
Before treatment (t=0)	N_V	A_V
After treatment (t=1)	N_N^*	A_N

Here, we use the sample means of the four outcomes. Alternatively, the same estimator is also possible in a regression framework:

$$Y_i = \mu + \gamma \cdot D_i + \delta \cdot T_i + \alpha \cdot (D_i \cdot T_i) + \varepsilon_i \tag{23}$$

where Y_i is the outcome variable, μ is the intercept common to all observations, D_i indicates whether the individual unit belongs to the treated group or not, T_i is the time dummy for before and after the treatment and ε_i is the usual idiosyncratic error term. In a further step we can introduce covariates X_i' that control for observed heterogeneity:

$$Y_i = \mu + \gamma \cdot D_i + \delta \cdot T_i + \alpha \cdot (D_i \cdot T_i) + X_i'\beta + \varepsilon_i \tag{24}$$

Equations (23) and (24) can be used either with repeated cross-sectional data or with panel data for two years.[62] Using panel data over several years, it is also possible to control for unobserved heterogeneity. In a case with panel data with multiple groups and time periods we can use a fixed effects regression:

$$Y_{it} = \mu + \gamma i + \delta_t + \alpha D_{it} + X_i'\beta + \varepsilon_{it} \tag{25}$$

where γi and δ_t are the individual and time fixed effects, respectively.

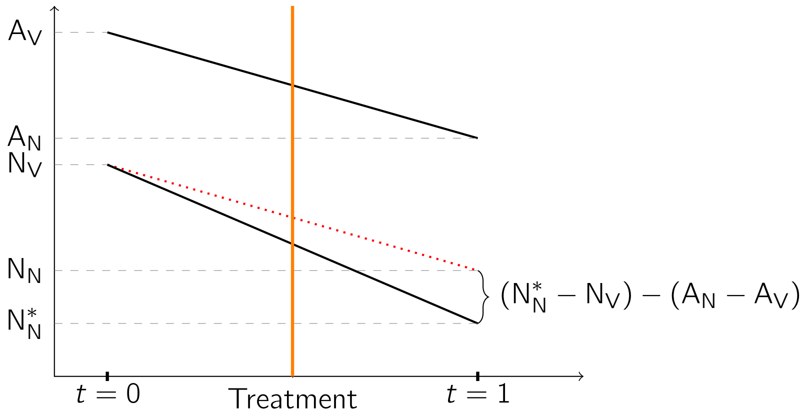


Figure 2.17: Graphical illustration of the DD method

In our specific case, the treatment is the implementation of DSM initiatives at the utility level. The outcome that we want to test is the effectiveness of such incentives in Switzerland with respect to a reduction in electricity consumption. We consider the utilities that have spent money on DSM as the treated utilities while those utilities without any DSM spending belong to the control group.

The multi-group multi-period formulation in our framework is

$$\log E_{it} = \beta_0 + \beta_1 DSM_{it} + \lambda_i + \delta_t + \epsilon_{it}, \tag{26}$$

where the subscripts i and t are the indices for an individual utility and time, respectively, E_{it} is the electricity consumption per customer (in kWh), DSM_{it} is the DSM policy variable of utility i in year t, λ_i is the utility fixed effect to control for any unobserved heterogeneity, δ_t is a year fixed effect common to all utilities, and ϵ_{it} is the usual idiosyncratic error term. Our coefficient of interest is β_1 since it captures the effect of the DSM measures on electricity consumption. In addition to this basic model, we can extend it to further include other observable characteristics that can be used to control for any other factors that might influence the electricity consumption per customer. We can, therefore, reformulate equation (26) as

$$\log E_{it} = \beta_0 + \beta_1 DSM_{it} + \beta_2 p_{it}^E + \beta_3 Y_{it} + \beta_4 HS_{it} + \beta_5 HDD_{it} + \beta_6 CDD_{it} + \lambda_i + \delta_t + \epsilon_{it}, \tag{27}$$

where the additional variables p_{it}^E, Y_{it}, HS_{it}, HDD_{it}, and CDD_{it} refer to the electricity price,

[62]Further details and an example can be found, for example, in Wooldridge (2010) and Angrist & Pischke (2008). Obviously, using repeated cross-sectional data, the sample must be representative.

average taxable income per taxpayer, average household size calculated as the population divided by the number of customers, heating degree days, and cooling degree days, respectively for the area serviced by utility i in year t.[63] Our specification, equation (27), is in semi-log form since the continuous DSM measure contains zeros and the logarithm of zero is undefined.[64] There exists a variant of equation (27) where the DSM_{it} variable may include DSM effort lagged by one or more time periods. Several studies have explored this possibility, including Loughran & Kulick (2004), Rivers & Jaccard (2011) and Arimura et al. (2012). We considered this extension in our model but did not obtain any effect of the lagged DSM variable on the electricity consumption in the current period. However, the short time span of our data (seven years), could be an issue and it may be an avenue worth pursuing in the future with richer time-series data.

In equations (26) and (27) we incorporate utility fixed effects (λ_i) to control for any unobserved heterogeneity and year fixed effects (δ_t) which are common to all utilities. This is the typical set-up for difference-in-differences estimation using panel data. We allow the individual-specific effect (λ_i) to be correlated with the explanatory variables, i.e. $E(x_{it}\lambda_i) \neq 0$. However, we still assume that the explanatory variables are uncorrelated with the error term, i.e. $E(x_{it}\varepsilon_{it}) = 0$. The fixed effects estimation uses dummy variables for each utility and is, therefore, also called the *least squared dummy variables* (LSDV) approach.[65]

Fixed effects estimation, or panel data estimation in general, have a great advantage when we suspect that the outcome variable (Y_i) depends on explanatory variables which are not observable but correlated with the observed explanatory variables (unobserved heterogeneity). If such omitted variables are constant over time, the fixed effects estimator allows us to consistently estimate the effect of the observed explanatory variables. One drawback of the fixed effects estimator is that we cannot include any time-invariant variables as they cannot be identified from the fixed effects.

There are two key identification assumptions in the DD approach. The first is that the trend in the outcome variable are similar for both the treatment and control groups in the absence of treatment, referred to as the parallel (or common) trend assumption. The violation of this assumption means that we cannot attribute the effect of the outcome solely to the policy intervention (Angrist & Pischke, 2008). The second assumption is that the assignment of a unit to the treatment group is exogenous. This may be violated if there is selection based on unobservable characteristics of the units or if the policy intervention is affected by the outcome. In section 2.4.5 we perform various robustness checks to ensure that we do not need to be concerned with regard to these issues.

2.4.4 Results

The results of estimating equation (27) are in Table 2.13. Columns (1) and (2) are the results from estimating equation (27) with indicator variables for DSM_{it}. In column (1), the indicator variable takes the value 1 when a utility has spending on energy efficiency greater than zero and

[63] Income and heating and cooling degree days have been scaled to ensure that the results are easier to read.

[64] We have also performed the regressions by using a linear transformation of the DSM variable to ensure that the logarithm is defined and using a log-log model. The results are similar.

[65] For econometric details please refer to Wooldridge (2010).

takes the value 0, otherwise. In column (2), the indicator variable takes the value 1 when a utility has spending on energy efficiency greater than the first quartile of DSM expenditure and takes the value 0, otherwise. Column (3) estimates equation (27) with a continuous measure of DSM spending, the DSM expenditure per customer. Column (4) estimates equation (27) using the energy efficiency score.

Our results from columns (1) and (2) indicate that spending on DSM programmes has a statistically significant effect on the electricity consumption per customer. Positive DSM spending reduces electricity consumption per customer by around 5% in column (1) and by around 6% in column (2).[66] Our estimates from column (3) indicate that when we use the continuous measure of DSM spending the results confirm the negative and statistically significant impact. Increasing per customer DSM spending by CHF 1 in column (3) leads to a reduction in electricity consumption by around 0.5%. Assuming that a household, on average, consumes 4600 kWh of electricity per year, one additional Swiss franc of DSM spending causes a reduction in electricity consumption of 0.5%, which is around 23 kWh per year. Therefore, the cost of saving one kilowatt hour is on average around CHF 0.04.[67] In other words, increasing per customer spending on DSM in column (3) by 10% leads to a reduction in electricity consumption by around 0.14% when evaluated at the mean of DSM spending.[68,69]

The results with the energy efficiency score also indicate a statistically significant impact of utility DSM efforts on reducing per customer electricity demand. Column (4) in Table 2.13 shows that an increase in the energy efficiency score by one point leads to a reduction in electricity consumption by around 3%. Evaluating the elasticity at the mean energy efficiency score, we find that a 1% increase in the energy efficiency score reduces per customer residential electricity consumption by around 0.04%.

The coefficients of several other explanatory variables in Table 2.13 are statistically insignificant. The only variables that show consistent significance statistically are electricity price and household size. The price elasticity of electricity, evaluated at the mean of the average price, is around -0.38 for all models so the results are quite stable. The estimates obtained in this chapter are based on a static model of electricity consumption. The elasticity for household size is around 0.11 which implies that increasing the household size by 1% increases electricity consumption by around 0.11%. The coefficients for the other explanatory variables are statistically insignificant probably due to the lack of within-variation of those variables. Since our panel is relatively short in terms of the number of years, we expect these socio-demographic and weather variables not to exhibit much variation and, therefore, is captured by the utility fixed effects. Several explanatory variables are not statistically significant but that is not a problem since we are more interested in the coefficient

[66] The percentage change is calculated by using $100[e^{\beta_1} - 1]$ where β_1 is the coefficient of the DSM measure in equation (27).

[67] This is obtained by dividing the cost, CHF 1, with the electricity saved, 23 kWh.

[68] We should note that the estimated impact of the DSM programmes obtained in the model with the binary DSM measure and in the model with the continuous DSM measure cannot be directly compared due to the discrete nature of the former measure and the continuous nature of the latter measure.

[69] Elasticity for a semi-log equation, $\log Y = \beta x$, is calculated as follows: Taking derivatives of both sides we get $\frac{dy}{y} = \beta \frac{dx}{x} x$. The elasticity is then, usually, calculated at the mean value of x. Therefore, the elasticity is $\beta \bar{x}$ where $\bar{x}$ is the mean value of x.

of the policy intervention variable, DSM, in our DD model.

Table 2.13: FE Models of (Log) Per Customer Residential Electricity Demand

	(1)	(2)	(3)	(4)
Positive DSM expenditure	-0.047^a			
	(0.017)			
DSM expenditure: 1.quartile		-0.058^b		
		(0.025)		
DSM expenditure per customer			-0.005^b	
			(0.002)	
EE score				-0.030^b
				(0.014)
Average price	-0.018^a	-0.016^a	-0.018^a	-0.018^a
	(0.006)	(0.006)	(0.006)	(0.006)
Taxable income: Taxpayers	0.004	0.003	0.005	0.003
	(0.005)	(0.005)	(0.005)	(0.005)
Household size	0.066^c	0.063^c	0.064^c	0.062
	(0.039)	(0.035)	(0.037)	(0.038)
Heating degree days	-0.009	-0.010	-0.008	-0.008
	(0.009)	(0.009)	(0.009)	(0.009)
Cooling degree days	-0.020	-0.038	-0.038	-0.027
	(0.031)	(0.031)	(0.031)	(0.030)
Utility fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	182	182	182	182
Adjusted R^2	0.954	0.955	0.954	0.954

Robust standard errors in parentheses.
^{a}, ^{b}, ^{c}: Significant at the 1%, 5% and 10% levels, respectively.
Income and heating and cooling degree days have been scaled.

2.4.5 Robustness

The advantage of DD estimation is that both group-specific and time-specific effects are accounted for by taking the time changes in the means of the outcome variable for both the treatment and control groups. However, as with any methodology, we need to be careful in implementing this method. The DD identification, as mentioned previously, depends on the assumption that the treatment and control groups exhibit parallel trends and to test this we perform some robustness checks.

To check for the parallel trends assumption we perform some placebo tests.[70] These are done in several ways. In all the placebo tests we exclude utilities that had DSM programmes throughout the time period in our survey. The only issue in our placebo tests is the low number of observations in our regressions and we should be careful in interpreting our results. However, considering the relatively small initial dataset we cannot perform the robustness checks without this caveat. First, we consider utilities that did not have DSM spending in years 1, 2 and 3 but positive spending in

[70]See Waldinger (2012) for a more detailed discussion and Stata code on placebo tests.

years 4, 5, 6 and 7.[71] We assign a value 1 to the DSM indicator variable to those utilities in year 3. The results from this regression are presented in Table 2.14. We also perform a similar regression for the continuous DSM spending variable.[72] The results from this regression are in column (2) of Table 2.14. If the parallel trends assumption would be violated we would expect our coefficients of interest, the "Pseudo" variables to be significant. However, they are statistically insignificant in both columns.

Second, as in the previous case, we again consider utilities that did not have DSM spending in years 1, 2 and 3 but positive spending in years 4, 5, 6 and 7. However, this time we assign a value 1 to the DSM indicator variable to those utilities in years 2 and 3. The results from this regression are presented in Table 2.15. We also carry out a similar regression for the continuous DSM spending variables. The results from this regression are in column (2) of Table 2.15. If the parallel trends assumption would be violated we would expect our coefficients of interest, the "Pseudo" variables to be significant. However, they are statistically insignificant in both columns.

Third, we consider utilities that did not have DSM spending in years 1, 2, 3 and 4 but positive spending in years 5, 6 and 7. We assign a value 1 to the DSM indicator variable to those utilities in year 4. The results from this regression are presented in Table 2.16. We also carry out a similar regression for the continuous DSM spending variables. The results from this regression are in column (2) of Table 2.16. If the parallel trends assumption would be violated we would expect our coefficients of interest, the "Pseudo" variables to be significant. However, they are statistically insignificant in both columns.

In the fourth, and final, placebo test we again consider utilities that did not have DSM spending in years 1, 2, 3 and 4 but positive spending in years 5, 6 and 7. This time we assign a value 1 to the DSM indicator variable to those utilities in years 3 and 4. The results from this regression are presented in Table 2.17. We also estimate a similar regression for the continuous DSM spending variables. The results from this regression are presented in column (2) of Table 2.17. If the parallel trends assumption would be violated we would expect our coefficients of interest, the "Pseudo" variables to be significant. However, they are statistically insignificant in both columns.

As mentioned before, due to the low number of observations in each placebo regression, we need to be careful in making any conclusions, but the lack of statistical significance for our relevant policy variables in the placebo tests indicates that the parallel trends assumption is not violated. Therefore, our original fixed effects results in Table 2.13 appear to be robust.

[71] We consider here, and in what follows, years 1, 2, 3, 4, 5, 6 and 7 to correspond to our surveyed years 2006, 2007, 2008, 2009, 2010, 2011 and 2012, respectively.

[72] In this regression, as well as in subsequent placebo tests for the continuous variable, we assign a random positive value to those utilities that had positive DSM spending in future years.

Table 2.14: Placebo Test 1

	(1)	(2)
Pseudo DSM dummy	-0.135	
	(0.090)	
Pseudo DSM expenditure per customer		-0.005
		(0.004)
Average price	0.063	0.045
	(0.049)	(0.053)
Taxable income: Taxpayers	0.004	0.009
	(0.010)	(0.014)
Household size	1.727	1.745
	(1.349)	(1.357)
Heating degree days	0.045	0.032
	(0.056)	(0.059)
Cooling degree days	-0.267	-0.224
	(0.169)	(0.184)
Utility fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	27	27
Adjusted R^2	0.905	0.894

Robust standard errors in parentheses.
^{a}, ^{b}, ^{c}: Significant at the 1%, 5% and 10% levels, respectively.
Income and heating and cooling degree days have been scaled.

Table 2.15: Placebo Test 2

	(1)	(2)
Pseudo DSM dummy	-0.124	
	(0.094)	
Pseudo DSM expenditure per customer		-0.002
		(0.003)
Average price	0.043	0.024
	(0.042)	(0.047)
Taxable income: Taxpayers	0.006	-0.004
	(0.010)	(0.009)
Household size	1.144	1.062
	(1.085)	(1.168)
Heating degree days	0.031	0.010
	(0.050)	(0.061)
Cooling degree days	-0.292	-0.162
	(0.195)	(0.171)
Utility fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	27	27
Adjusted R^2	0.895	0.872

Robust standard errors in parentheses.
^{a}, ^{b}, ^{c}: Significant at the 1%, 5% and 10% levels, respectively.
Income and heating and cooling degree days have been scaled.

Table 2.16: Placebo Test 3

	(1)	(2)
Pseudo DSM dummy	-0.097	
	(0.098)	
Pseudo DSM expenditure per customer		-0.005
		(0.005)
Average price	-0.006	0.003
	(0.019)	(0.011)
Taxable income: Taxpayers	-0.002	-0.002
	(0.012)	(0.012)
Household size	-0.008	-0.071
	(1.101)	(1.043)
Heating degree days	-0.002	0.001
	(0.055)	(0.055)
Cooling degree days	-0.145	-0.166
	(0.169)	(0.181)
Utility fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	26	26
Adjusted R^2	0.778	0.779

Robust standard errors in parentheses.
^{a}, ^{b}, ^{c}: Significant at the 1%, 5% and 10% levels, respectively.
Income and heating and cooling degree days have been scaled.

Table 2.17: Placebo Test 4

	(1)	(2)
Pseudo DSM dummy	-0.122	
	(0.099)	
Pseudo DSM expenditure per customer		-0.007
		(0.007)
Average price	-0.005	-0.013
	(0.018)	(0.023)
Taxable income: Taxpayers	0.004	0.010
	(0.011)	(0.016)
Household size	-0.182	-0.211
	(0.975)	(0.927)
Heating degree days	0.021	0.024
	(0.053)	(0.056)
Cooling degree days	-0.205	-0.206
	(0.168)	(0.179)
Utility fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	26	26
Adjusted R^2	0.810	0.807

Robust standard errors in parentheses.
^{a}, ^{b}, ^{c}: Significant at the 1%, 5% and 10% levels, respectively.
Income and heating and cooling degree days have been scaled.

In addition, DD estimation requires that the policy changes are not endogenous themselves. Our placebo tests showed that this may not be a major concern for us. However, we use the method of instrumental variables (IV) as another robustness check. An instrument should satisfy the conditions for relevance and exogeneity. It should, therefore, be correlated with the potentially endogenous DSM spending variables variable but not with the error term. A weakness of using an instrumental variables procedure is the difficulty of finding valid and convincing instruments. A potential solution is to use utility characteristics that may influence the decision to implement DSM programmes but will not directly affect the residential electricity consumption.

One of the problems with using instrumental variables in a fixed effects short-panel data framework is the potential low variation of those variables over time. This is especially true of utility characteristics that exhibit very little variation over time. The instrumental variables we consider are the legal form of a utility and a measure of the share of the total electricity sold by a utility that is produced by itself. These two variables satisfy the condition for instrument relevance since, as we argue below, both firm characteristics are possible determinants of DSM. They also satisfy the exogeneity condition since neither are possible direct determinants of residential electricity demand and the effect will be seen only indirectly through DSM.

The legal form of a utility is obtained from our survey with five different kinds of legal forms, as given by Figure 2.1b. The first instrument is constructed as a dummy variable with a utility being a stock company or not. It does not show any within-utility variation over our survey period and, therefore, a traditional fixed effects model with instrumental variables will not work. There is some evidence in the DSM literature that the ownership of a utility may be a factor in the implementation of DSM initiatives. However, there is conflicting evidence on the direction of DSM initiatives taken by utilities based on the ownership. Hopper et al. (2009) shows that the energy-saving goals of investor-owned utilities are higher while Carley (2012) finds that investor-owned and cooperative utilities are more likely to have DSM programmes than municipal utilities. On the other hand, Vojdani (2008) states that energy conservation is a low priority for investor-owned utilities in the US. Cabrera et al. (2012) argue that DSM programmes are used as tools to obtain certain political goals such as an energy reduction plan and that publicly owned utilities are more active in such a situation.

The own production share is also obtained from our survey, where we distinguish four cases as illustrated in Figure 2.1c. The share of electricity sold by a utility that is produced by itself may also have an impact on the implementation of DSM programmes. This can manifest itself through the cost of purchasing electricity with utilities that generate only a small share of their own electricity needing to purchase electricity at a higher cost to fulfil the demand of their customers. Therefore, these utilities may find it cheaper to engage in DSM activities than in purchasing electricity in the market. On the other hand, Blumer et al. (2014) reason that utilities that generate a substantial fraction of their own electricity may have an incentive to promote DSM since this increases the amount of electricity that they can sell to other utilities. Therefore, the second instrument is constructed as a dummy variable with a utility having an own production share of 0–25%. It also does not show any within-utility variation over our survey period and, therefore, a traditional fixed effects model with instrumental variables will not work.

The presence of a possible endogenous binary policy variable indicates a situation described in Heckman (1978). Therefore, we use a probit model to model the nonlinear binary policy variable. The instrumental variable is used in this probit stage along with the other explanatory variables. We then use the prediction of the policy variable from this stage as an instrument for the endogenous binary policy variable in a fixed effects instrumental variables regression model. This is a consistent estimation method that has been proposed by Amemiya (1978), Heckman (1978) and Lee (1979).[73] The instrumental variable is the excluded instrument in this model. We refer to this Heckman-type selection approach, in subsequent descriptions, as the "nonlinear" approach.[74] In our specification, we use two instrumental variables, namely the legal form of a utility and a measure of the share of the total electricity sold by a utility that is produced by itself, in the nonlinear probit first stage.

The results of the selection model, modelled as a probit, are provided in Table 2.18 where we observe that the probability of DSM decreases when a utility is a stock company while it increases as the own share of electricity production is low. The effects are statistically significant in both columns (1) and (2). The predicted probabilities from this stage are then used as instruments in a two-stage least squares (2SLS) model and the first-stage results of this estimation are provided in Table 2.19. While the coefficient for the predicted probability is statistically significant in column (1), it is not significant in column (2), which indicates that the instrument is very weak and we expect the second-stage results to be imprecisely estimated.

The second-stage results of these estimation procedures are provided in Table 2.20. Column (1) corresponds to instrumental variables estimation for column (1) in Table 2.13 with the non-linear approach. The potentially endogenous DSM binary variable is the positive DSM spending. Column (2) corresponds to the DSM binary variable where the cut-off for assigning a value of unity is the first quartile of DSM spending. Our results show that estimates for the effect of positive DSM spending on per customer residential electricity consumption is very high compared to the normal DD fixed effects results in Table 2.13. However, it is reassuring to observe that the effects are negative and significant, except in column (2). The estimate of the DSM coefficient in column (2) exhibits a very high standard error and the F-statistic from the first stage also indicate that the nonlinear procedure in this instance may have some issues, as we expected from the statistically insignificant coefficient of the predicted probability in Table 2.19. The F-statistic in column (1) also indicates that our instruments, while valid, may be weak since the value of the F-statistic is less than 10, the generally acceptable cut-off for the strength of instruments.

[73] Wooldridge (2002, p. 939) provides a description of this method.

[74] We also performed the estimations using the instrumental variables in a standard fixed effects framework but, as expected, we encountered a problem of weak instruments due to the low variability of the instruments that led to problems of identification.

Table 2.18: Probit stage of nonlinear estimation

	(1)	(2)
Average price	-0.053	0.006
	(0.034)	(0.033)
Taxable income per taxpayer	0.005	0.011
	(0.012)	(0.011)
Household size	-0.032	0.384^c
	(0.234)	(0.226)
Heating degree days	-0.016	-0.036
	(0.025)	(0.023)
Cooling degree days	-0.552^b	-0.907^a
	(0.228)	(0.251)
Dummy for stock company	-0.971^a	-1.346^a
	(0.256)	(0.249)
Dummy for share of own production: 0-25%	0.839^a	0.480^c
	(0.263)	(0.251)
Intercept	2.289	1.000
	(1.879)	(1.850)
Observations	182	182

Robust standard errors in parentheses.
^{a}, ^{b}, ^{c}: Significant at the 1%, 5% and 10% levels, respectively.

Table 2.19: First stage of IV/2SLS estimation

	(1)	(2)
Average price	-0.007	0.015
	(0.021)	(0.018)
Taxable income per taxpayer	-0.022	-0.043^b
	(0.018)	(0.020)
Household size	0.092^c	-0.006
	(0.052)	(0.157)
Heating degree days	-0.001	-0.029
	(0.026)	(0.026)
Cooling degree days	0.250^c	-0.183
	(0.136)	(0.168)
Probability(Positive DSM expenditure)	0.885^b	0.065
	(0.386)	(0.458)
Observations	182	182

Standard errors in parentheses.
^{a}, ^{b}, ^{c}: Significant at the 1%, 5% and 10% levels, respectively.
^{d} Used in the probit stage.
^{e} Estimated in the probit stage.

Table 2.20: FE Models of (log) residential electricity demand per customer

	(1)	(2)
Positive DSM expenditure	-0.171^{c}	
	(0.089)	
DSM expenditure: 1.Quartile		-1.900
		(12.645)
Average price	-0.021^{a}	0.011
	(0.006)	(0.197)
Taxable income per taxpayer	0.002	-0.076
	(0.005)	(0.547)
Household size	0.074^{c}	0.064
	(0.040)	(0.257)
Heating degree days	-0.010	-0.063
	(0.009)	(0.365)
Cooling degree days	-0.003	-0.405
	(0.037)	(2.555)
Utility Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Observations	182	182
First Stage F-statistic	5.253	0.020

Robust standard errors in parentheses.
^{a}, ^{b}, ^{c}: Significant at the 1%, 5% and 10% levels, respectively.

The previous part provides a description of a possible way to account for an endogenous binary policy variable. However, we also have continuous dependent variables, DSM expenditure and energy efficiency score, that may also be endogenous. A way to solve the problem of instruments with low within-variation for the continuous endogenous variables could be to use OLS, without individual fixed effects, in the first stage. This will reduce the problem of low within-variation of the instrumental variables. We are aware that this is not a standard procedure. In order to use this approach we estimate the IV manually by using the predicted values of the first stage in the second stage. However, this method produces incorrect standard errors (Wooldridge, 2012) and, therefore, we bootstrap the standard errors.[75]

The technique of bootstrapping is used to obtain a description of the sampling properties of empirical estimators (like standard errors or confidence intervals) using the sample data themselves, rather than broad theoretical results.[76] In short, the bootstrap takes the sample (the values of the independent and dependent variables) as the population and the estimates of the sample as true values. Instead of drawing from a specified distribution (such as the normal) by a random number generator, the bootstrap draws with replacement from the sample. It therefore takes the empirical

[75] In order to bootstrap the standard errors we use a unique procedure. We run both, a manual IV regression where a fixed effects regression is used both in the first and in the second stage and one where a OLS regression is used in the first stage but a fixed effect in the second stage, and randomly rearrange the predicted error terms. Through pooling these error terms we introduce variation that we would not have using IV where fixed effects regression is used in both the first and second stage. Then we recalculate the endogenous variable and the dependent variable. Afterwards we re-estimate the coefficients. This procedure we do 10,000 times (Heimsch, 2014).

[76] See Greene (2012) for theoretical details.

distribution function as true distribution function. The bootstrap is typically used for consistent but biased estimators as in our case.

The results of this manual 2SLS estimation using the bootstrapping procedure are displayed in Table 2.21. The results show that DSM expenditure per customer reduce residential electricity consumption and while the estimated coefficient is higher compared to our results in Table 2.13 the signs of the coefficients are the same. The comparison between Table 2.21 and Table 2.13 for the energy efficiency score shows that the impacts are the same with the expected negative sign but, as with the DSM expenditure per customer variable, magnitude of the impact reported in Table 2.21 is much higher than that reported in Table 2.13.

Table 2.21: Bootstrapped IV, First stage OLS, N=10,000

	Estimate	**Std. Err.**	**t-stat**	**p-value**
DSM expenditure per customer	-0.025	0.014	-1.836	0 .034
Energy efficiency score	-0.194	0.100	-1.944	0.027

Note: The estimate is the mean of the variable of interest from 10,000 replications.

A summary of the results for our variable of interest, the DSM variable in its various forms, are provided in Table 2.22. The table reproduces the results of all our estimation methods. Even though we have used various estimation methods we prefer to use the basic difference-in-differences method, column DD in Table 2.22, because the variant of the DD model using instrumental variables may suffer from biased estimates. This is likely to occur because our instruments do not exhibit a lot of variation over time and are relatively weak. Also, we perform these additional regressions to ensure that our DD results are robust and the estimates from the IV regressions confirm that DSM programmes reduce the consumption of electricity per customer.

Table 2.22: Summary of results for DSM variables

Variable	**DD**	**Nonlinear**	**Bootstrapped IV**
Positive DSM expenditure	-0.047	-0.171	
DSM expenditure: 1. Quartile	-0.058	-1.900	
DSM expenditure per customer	-0.005		-0.025
Energy efficiency score	-0.030		-0.194

2.4.6 Policy Implications

We now perform a simple counterfactual exercise, using the results of our econometric estimation of the impact of DSM initiatives from the continuous measure of DSM in column (3) in Table 2.13, to obtain a rough estimate of the cost of DSM programmes for a utility.[77] This is done to get an idea of the approximate range within which the costs of DSM may lie. To perform the counterfactual exercise we first estimate the electricity consumed per customer in the absence of any DSM programme. Using equation (27), we assign zero to the value of the DSM_{it} variable. Therefore, assuming that $DSM_{it} = 0$ we get

$$\widehat{\log E_{it}} = \beta_0 + \beta_2 p^E_{it} + \beta_3 Y_{it} + \beta_4 HS_{it} + \beta_5 \cdot HDD_{it} + \beta_6 CDD_{it} + \lambda_i + \delta_t, \tag{28}$$

where $\widehat{\log E_{it}}$ is the (log) electricity consumed per customer in the absence of DSM. We convert the logarithmic value to the level value $\widehat{E_{it}}$ hereafter.

Since the estimate of the "DSM expenditure per customer" coefficient is negative, an increase in this variable will lead to a reduction in the electricity consumed per customer. Therefore, the estimated electricity consumed in the presence of DSM, $\widetilde{E_{it}}$, will be lower than in the absence of DSM. The reduction in the electricity consumed may be attributed to the effectiveness of the DSM programmes. The per customer impact of the DSM programmes is, therefore

$$\Delta E_{it} = \widehat{E_{it}} - \widetilde{E_{it}} \tag{29}$$

for utility i in year t. Summing the ΔE_{it} for all utilities over all years and taking into account the number of customers, we obtain the total electricity saving from DSM programmes:

$$\text{Total } E \text{ Saved} = \sum_{it} (\Delta E_{it} * \text{No. of customers}_{it}). \tag{30}$$

The cost of the DSM programmes is obtained by multiplying the "DSM expenditure per customer" variable with the number of customers for utility i in year t and summing over all these values, i.e.

$$\text{Total } DSM \text{ Cost} = \sum_{it} (DSM_{it} * \text{No. of customers}_{it}). \tag{31}$$

Now, the only calculation remaining is to divide the total DSM cost, equation (31), by the total electricity saved due to the DSM programmes, equation (30), to get an estimate of the cost to utilities of reducing a unit of electricity by implementing DSM programmes:

$$\text{Cost of a kilowatt hour} = \frac{\text{Total } DSM \text{ Cost}}{\text{Total } E \text{ Saved}} \tag{32}$$

[77] A counterfactual exercise is a calculation performed to obtain a scenario of what may have happened in the absence of a policy. This is then compared with the estimated effect of having the policy in place to enable us to make a cost-benefit analysis.

We calculate the cost of saving a kilowatt hour by using the estimated coefficient of "DSM expenditure per customer" and find it to be around CHF 0.04. The average cost of producing and distributing electricity in Switzerland is around CHF 0.18 per kilowatt hour.[78] It should be noted that these costs from the VSE are based on current production and distribution capacities. It is very likely that these costs may be higher in the future with the construction of new capacity. We should recognise, however, that the cost of DSM programmes calculated are very rough estimates due to our small sample and the fact that the DSM efforts reported in our survey may suffer from measurement error. The range of estimated cost, based on one standard deviation away from the point estimate, is from a low of CHF 0.03 to a high of CHF 0.09. Another potential caveat is that we do not consider any possible positive external benefits from not having to produce an additional unit of electricity or any possible negative externalities from generating electricity. In case there are any positive external benefits from not producing electricity or any possible negative externalities from generating electricity, our costs that we have calculated will be overestimated.

2.5 Conclusion

In this chapter we use the results of a survey carried out on 30 Swiss utilities to, firstly, provide a description of current demand-side management practices in Switzerland and, secondly, carry out an econometric analysis of the impact of such practices on the demand for per customer residential electricity demand. We find that while a lot of utilities have some kind of DSM programmes in place, the intensity of such programmes is somewhat lacking when compared to a country like the US. The average DSM spending per customer in the US is around CHF 9 per customer while it is less than CHF 3 per customer for Switzerland.[79] The difference, in terms of the maximum per customer DSM spending, is also very large with CHF 190 in the US compared to CHF 31 in Switzerland. However, the amount of electricity generated in the US is substantially higher than in Switzerland while the consumption per capita and per household are also much higher, as shown in Table 1.1. Therefore, if we consider the expenditure on all DSM measures as well as energy efficiency funding per MWh consumed in Switzerland the value is almost CHF 1 for the former and around CHF 0.32 for the latter. This compares to CHF 1.8 on all DSM measures per MWh consumed and CHF 1.2 on energy efficiency spending per MWh consumed in the US. These figures indicate that utility efforts on DSM in the US are substantially higher than similar efforts in Switzerland.[80] We also find significant variation within Swiss utilities with some utilities having a very high spending. Another finding of our analysis is that Swiss utilities tend to focus more on communicating to its consumers about energy efficiency, with many utilities involved in providing information and having public relation campaigns as opposed to financial incentives and energy audits. There are, however, a few utilities that have invested much more in DSM. Using information from our survey, we also calculate an energy efficiency score for each of the surveyed

[78] VSE website, accessed 10 April, 2015.

[79] The figure for per customer DSM spending in the US is from Arimura et al. (2012). They report an average DSM spending per customer of US$ 9.41 between 1989 and 2006. We have converted the amount, and subsequent US dollar amounts, to Swiss Francs by using an exchange rate of US$ 1 = CHF 0.97.

[80] We should note, however, that the figures for the US are for total spending on DSM and energy efficiency. The figures for spending by the residential sector are not available.

utilities from 2006 to 2012. This has not been performed before for DSM measures on residential customers for Swiss utilities. We find that, while some utilities at the higher end of DSM efforts have a relatively high score, we believe that there is a lot of scope for improvement to increase DSM efforts.

The results of the econometric impact of DSM measures on residential electricity consumption indicate that, while the impact appears to be statistically significant, the size is small. There may be two possible hypotheses for this. The first is that the lack of intensity of DSM efforts may not have a large effect on electricity consumption. It may be effective for utilities to make more intensive efforts in energy efficiency programmes due to the low cost of energy efficiency (Goldman et al., 2014). The second explanation is that there may not be much scope for Swiss households to reduce their electricity consumption. The majority of Swiss households live in multi-family houses. Therefore, we may expect the presence of a principal-agent type of problem with the landlord or the tenant not investing in energy-efficient products because neither reaps the full benefits of that investment. Therefore, it may be more strategic for utilities and policy makers to target owners instead of tenants with energy efficiency programmes. However, these are merely hypotheses and it is important to test these possible explanations in future research.

Using the results of the econometric estimation we perform a simple counterfactual exercise to obtain an estimate of the cost of saving a unit of electricity that would have been produced in the absence of DSM programmes. We find that, on average, the cost of saving a kilowatt hour is around CHF 0.04. This is a rough estimate and should be treated with caution due to our relatively small sample of utilities and the possible measurement error of the DSM spending variable. The range of our estimate for this cost using the point estimate and one standard deviation above and below this point estimate is from a low of CHF 0.03 to a high of CHF 0.09 and compared to this the current cost of producing and distributing electricity in Switzerland (CHF 0.18/kWh) lies above this range. Our costs may be overestimated since there could be positive external benefits by not having to produce an additional unit of electricity. In comparison to US studies of DSM programmes that estimate the cost-effectiveness of such programmes to be between \$0.008−\$0.229/kWh saved, our point estimate lies in the lower part of that range. Given our findings, it appears that DSM programmes may be a valuable option for Switzerland to pursue its goals in *Energy Strategy 2050*.

Finally, our experience with the survey conducted on the Swiss utilities suggests that it would be useful for Swiss regulators, policy makers as well as researchers to have an easily available dataset with information on utilities and their DSM efforts, similar to the one that is provided in the EIA Form 861 by the US Energy Information Administration. US utilities of a certain size have to, by law, fill in the form and report on their DSM efforts. Having a similar system would be useful for analysing DSM efforts in Switzerland, especially due to the extremely high importance of the *Energy Strategy 2050*.

3 Estimating the potential for electricity savings in Swiss households

3.1 Introduction

A third of the total end-use electricity consumption in OECD countries originates from households (IEA, 2015). Therefore, the residential sector could be an important driver of energy efficiency saving. The actual potential of electricity saving in the residential sector is an important question. This is relevant for most industrialised nations as end-use energy conservation can significantly help to reduce CO_2 emissions (IEA, 2009).

McKinsey & Company (2009) have estimated the potential for energy savings for all end-uses, except transport, in the US. They apply an economic-engineering approach based on bottom-up models. As a foundation they use the National Energy Modeling System (NEMS) maintained by the Energy Information Administration (EIA) to produce reports for the Annual Energy Outlook. In the residential sector they identify different typical household types and calculate the potential savings for each energy-saving measure. They predict energy saving in 2020 in the residential sector to be 25-30%.

Prognos (2011) estimate the potential for energy saving in Switzerland similar to McKinsey & Company (2009). They find that the electricity consumption for households can be reduced by almost 15% by 2035 and 20% by 2050 compared to the reference scenario. In such economic-engineering models the researcher has to make assumptions on the future technology. This paper, on the other hand, follows a top-down approach using stochastic frontier analysis based on micro-economic production theory to measure the level of technical efficiency in the use of electricity in Swiss households. This approach uses a relative technology benchmark, which is given through the sample. As some households in the sample have newer appliances and technologies at home, we measure the potential of electricity saving using today's technology. In this way, we can estimate this potential independent of assumptions on future technologies.

It is important to note that energy demand is derived from the demand for energy services within the framework of household production theory. We assume that households purchase inputs such as energy and capital (household appliances) and combine them to produce outputs which are the desired energy services such as cooked food, washed clothes or hot water (Muth, 1966; Flaig, 1990). We can, therefore, attribute a production function to this process. Following the neoclassical production framework (Debreu, 1951; Farrell, 1957), we assume that households minimise the amount of inputs used in the production of a given amount of output and choose the input combination which minimises production costs. However, in practice, we observe that households may be producing energy services without minimising the use of all inputs or at least one of the inputs, thereby leading to possible inefficiency in the use of electricity. Since producing energy services can be considered to be the result of a production process we can measure how efficiently it is produced, referred to as the productive efficiency.

Productive efficiency in a microeconomics framework is traditionally measured in a radial way, meaning that the focus is on the efficiency of all inputs used in the production process. However, in this paper, we are only interested in the efficiency in the use of one of the inputs, namely electricity. In this context the concept of input-specific efficiency introduced by Kopp (1981) is useful. As we discuss later in more detail, there are several approaches within the production theory to measure input-specific efficiency. We follow an approach, similar to Zhou et al. (2012b), that estimates a sub-vector electricity distance frontier function using stochastic frontier analysis (SFA).

This paper has one major contribution to the existing literature. While the stochastic frontier approach has been used with aggregated energy data using either an energy input demand frontier function (e.g. Filippini & Hunt (2012); Filippini et al. (2014)) or a sub-vector distance function (Zhou et al. (2012b)[81]), we use disaggregated data since residential consumers are typically very heterogeneous and it can add more detail to the knowledge of consumer response. Weyman-Jones et al. (2015) are one of the first to estimate energy efficiency using SFA with disaggregated household survey data. They estimate an energy input demand frontier function originally proposed by Filippini & Hunt (2011) using a cross-sectional household dataset from a survey in Portugal. However, the model used by Weyman-Jones et al. (2015) is relatively simple with only a few explanatory variables. Alberini & Filippini (2015) use a similar energy demand frontier approach using a large panel dataset from US households to estimate the level of energy efficiency.[82] These studies estimate the level of technical as well as allocative efficiency. In this chapter we are interested in estimating the level of technical efficiency in the use of electricity.

We use a survey of residential electricity demand conducted on Swiss households in 2005 and 2011. The data include information on appliance stock as well as information on the amount of energy services consumed within a household such as the number of meals consumed, hot water, entertainment, lighting and washing. Therefore, we are able to estimate a sub-vector input distance function, similar to Zhou et al. (2012b), but using household survey data. Thus, to the best of our knowledge, this is the first study that includes energy services in the frontier model and adopts a distance function approach on a disaggregated level to estimate the level of technical efficiency in the use of electricity based on a microeconomic foundation.

The rest of the paper is organised as follows. In the next section, we introduce the concept of input-specific efficiency to familiarize the reader with the microeconomic foundation of energy efficiency measurement. We provide an overview of the existing literature on parametric energy efficiency measurement in section 3.3. In section 3.4 we develop a model for the estimation of the input-specific technical efficiency levels using disaggregated data. In Section 3.5 we describe the household survey data. The results of our different specifications we present in the penultimate section while in the final section we offer concluding remarks.

[81] Note that even Zhou et al. (2012b) use GDP as the output variable in the model instead of energy services.

[82] Using panel data Alberini & Filippini (2015) are able to distinguish and estimate the level of persistent and transient energy efficiency. In our study we do not have panel data and it is not possible to make this distinction. The concept of persistent and transient efficiency was introduced by Colombi et al. (2014) and Filippini & Greene (2015).

3.2 Input specific efficiency in the use of electricity

The residential demand for electricity is a derived demand from the demand for energy services like a warm meal, washed clothes or hot water. Therefore, the demand for residential electricity can be described using standard household production theory whereby households combine electricity and capital goods as inputs to provide services.[83] Since this is a production process we can attribute a production function to it. In this context, households are assumed to minimise the amount of inputs used to produce a given level of energy services and are also expected to choose the combination of inputs that minimise the costs to produce a predefined level of energy services. However, there may also be instances where households do not minimise the use of all or one of the inputs.[84] In this paper we are particularly interested in the efficiency in the use of electricity while producing energy services. Therefore, we compare the observed use of electricity with its optimal use.

Productive efficiency can be discussed using the microeconomic theory of production framework. In this context, the radial definition of technical, allocative and overall productive efficiency introduced by Farrell (1957) is an important concept. Based on Farrell (1957), Figure 3.1 shows an economic agent using capital (K) and energy (E) as inputs to produce a given level of output (y) that, in our case, is an energy service. If quantities of inputs defined by point $x1$ in Figure 3.1 are used, it is technically inefficient since the point lies above the isoquant. A technically efficient economic agent uses combinations of energy and capital that lie on the isoquant. The level of technical inefficiency of the economic agent is represented by the distance between points $x1$ and $\theta x1$ (marked in green), which is the amount by which all inputs could be proportionally reduced without a decrease in the level of production. Technical efficiency θ can be expressed as the ratio between the distance from the origin to technically efficient input vector $\theta x1$ and the distance from the origin to input vector $x1$. In a single-output case, the technical efficiency is measured with a production function. On the other hand, a distance function approach is taken within the framework of a multi-output production.

If the input price ratio, as represented by the slope of isocost line, is known, a cost efficient input combination can be identified. An economic agent that uses a cost-minimising input vector is shown by point x^*, where the isocost line is tangent to the isoquant. From Figure 3.1 the economic agent operating at $\theta x1$ is technically efficient but allocative inefficient since it operates with higher costs. The distance between $\alpha x1$ and $\theta x1$ (marked in red) measures the allocative inefficiency of the economic agent. The allocative efficiency is defined as the ratio between the distance from the origin to $\alpha x1$ and the distance from the origin to $\theta x1$. Thus, the overall productive efficiency α can be calculated as the ratio between the distance from the origin to $\alpha x1$ and the distance from the origin to $x1$ and includes both technical and allocative efficiency. We can improve the overall productive efficiency from $\theta x1$ to x^* by substituting energy with capital. For example, we can substitute single glazed windows with double glazed windows.

[83] See Deaton & Muellbauer (1980) for a description of household production theory and Flaig (1990) and Filippini (1999) for applications in the demand for electricity.

[84] These instances may be explained by the energy efficiency gap, behavioural failures and other barriers.

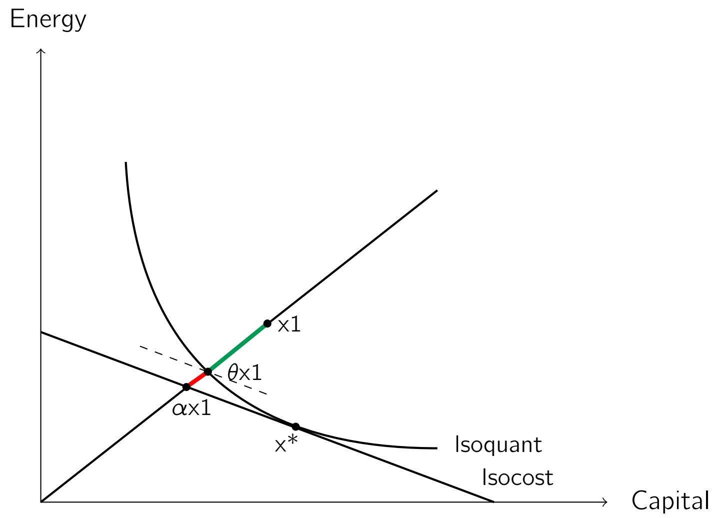


Figure 3.1: Productive efficiency using two inputs, energy and capital

Based on Farell's work, Kopp (1981) introduced the concept of an input-specific or single-factor technical efficiency measure. With the radial concept of technical efficiency all inputs can be proportionally decreased with an improvement in input use efficiency. However, in the non-radial measure of technical efficiency, where we consider only one specific input, only that input will be decreased with an improvement of efficiency, whereas the other inputs are kept constant.[85] In this paper we estimate the input-specific technical efficiency because, in comparison to previous studies, we have information on energy services and the appliance stock. Therefore, with this data on inputs and outputs it is possible to accurately estimate the level of technical efficiency. The level of overall energy efficiency as estimated in Weyman-Jones et al. (2015) and Alberini & Filippini (2015) is also a possibility. However, with our data we focus our analysis on the level of technical efficiency.

Figure 3.2 illustrates the difference between the radial and non-radial approaches. It shows an isoquant for a given amount of energy services produced with different amounts of energy and capital. Assuming that a household produces an energy service at x1, we can define the different concepts. The radial technical efficiency corresponds to the distance between x1 and $\theta x1$. In the case of the radial concept, we can clearly see that both inputs, capital and energy, will be equally decreased with an improvement in efficiency. However, we want to keep capital stock fixed and, given an improvement in efficiency, analyse how the quantity of energy used changes. The energy specific (or non radial) technical efficiency is displayed in Figure 3.2 as the distance between x1 and βx1 or as the ratio of E1 to E3.

There are three different approaches to estimate the input-specific technical efficiency (Filippini & Hunt, 2015). Firstly, Reinhard et al. (1999) estimate an indicator of input-specific technical efficiency from the estimation of a production frontier using a two-step procedure. Secondly, Kumbhakar & Hjalmarsson (1995) estimate an input requirement frontier function, which measures the minimum amount of an input, in this case labour input, that is needed to produce a given level

[85]For a more detailed discussion on the radial and non-radial concept in the framework of energy efficiency measurement see Filippini & Hunt (2015).

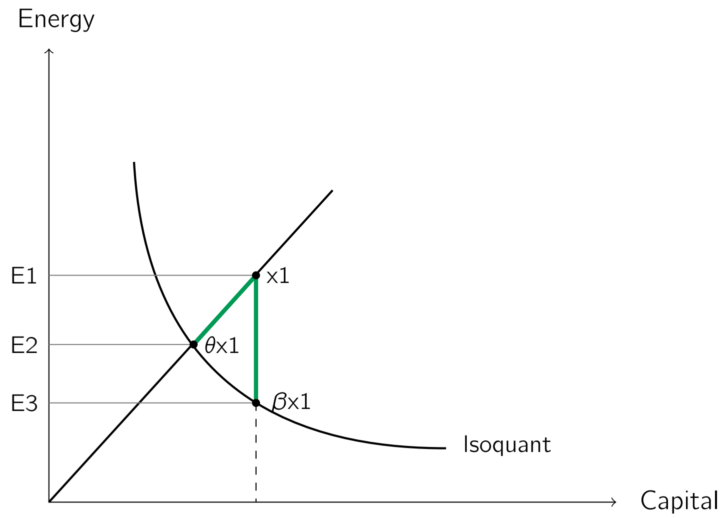


Figure 3.2: Input-specific efficiency: a non-radial measure

of output. Thirdly, Zhou et al. (2012b) propose the estimation of a sub-vector energy distance function which is based on the estimation of a particular input distance function.

As mentioned before, with the radial approach to efficiency measurement, all inputs are reduced or all outputs are expanded proportionally. In this case we would use an input distance function (reduce all inputs by the same factor) or an output distance function (expand all outputs by the same factor) to measure the technical efficiency. In the real world, there are often situations where some of the inputs are fixed or quasi-fixed i.e. in the short run. If we take some inputs as variable and some as fixed we can use a sub-vector input distance function.

Going one step further, we can even think of an approach that allows for varying degree of discretion, which is called directional distance function. This means that we allow for improvements in any direction in the input-output space (Bogetoft, 2013). Some studies use this approach in the framework of the joint production of goods and bads, allowing to expand in good outputs and reduce the bad outputs like pollution at the same time (Chung et al., 1997). In another case we can expand outputs and contract inputs at the same time. This special case is also called hyperbolic distance function (Fare et al., 1994). Both the input distance function and the sub-vector input distance function are special cases of the directional distance function family.

In case we also want to estimate the input-specific overall efficiency (allocative and technical), we can adapt the approach originally proposed by Filippini & Hunt (2011). They propose the estimation of this measure using an input demand frontier function.

In this paper we are interested in measuring the non-radial technical efficiency. However, we cannot use the approach adopted by Reinhard et al. (1999) since we are in a multi-output framework and it is not possible to estimate a production function. Moreover, the input requirement function was originally designed for a multiple output, single input firm framework. Other inputs, which are hold fixed, have also been included to estimate the input requirement function (Boyd, 2008; Guan et al., 2009). Hence, from a theoretical point of view, the sub-vector distance function is our preferred method in order to measure the electricity specific technical efficiency of Swiss households.

3.3 Previous work

The four approaches to measure the efficiency in the use of energy, as outlined in section 3.2, are relatively new. There are not many econometric applications in the area of the measurement of efficiency in the use of energy. Table 3.1 provides an overview of applications using SFA methods.

Diewert (1974a) introduced the concept of factor requirement functions in the 1970s. He defined the factor requirement function, $g(y)$, which gives the minimal amount of input, x, required to produce the vector of outputs, y. Originally the factor requirement function was estimated in a multiple output, single input firm framework.[86] Empirical examples that use input requirement function most often analyse labour use efficiency (Kumbhakar & Hjalmarsson, 1995; Battese et al., 2000; El-Gamal & Inanoglu, 2005) or excess capital (Guan et al., 2009). To the best of our knowledge, there are only two papers that apply the input requirement function to energy use efficiency. Firstly, Boyd (2008) estimates the efficient use of energy in the industrial sector using SFA. He uses a cross-sectional micro-dataset of wet corn milling plants in the US. Boyd (2008) develops a heuristic model, which he sees as an application to an energy factor requirement function. He explains the variation in energy use in different plants using inputs (corn), outputs (different products like modified starch, corn syrup, ethyl alcohol, etc.) and capacity utilization using a linear functional form and specifies the one-sided error term with a truncated normal distribution. The main effects in the model can be attributed to total corn processed, the mix of products, and capacity utilization. In addition, Boyd (2008) concludes that a great part of the variance of the model can be attributed to the inefficiency term. Secondly, Khayyat & Heshmati (2014) use an inverted factor demand model to estimate the efficiency in the use of energy in 25 Korean industrial sectors between 1970 and 2007. Apart from energy, they use information and communication technology (ICT) capital, non-ICT capital, material and labour as inputs to the production process. The variation in energy input is viewed as production risk for the Korean companies, as all the primary energy in Korea is imported. Khayyat & Heshmati (2014) find a broad variation in the inefficiency in the use of energy among industries and over time. They also find that an increase in ICT capital input reduces the production risk while all other inputs increase the variability of energy demand and therefore the production risk.

Following the theoretical work of Chambers et al. (1996, 1998) most applications of sub-vector distance function have been implemented with non-parametric data envelopment analysis (DEA) to deal with desirable and undesirable outputs (e.g. Chung et al. (1997); Watanabe & Tanaka (2007); Zhou et al. (2012a)). There are two important applications using the sub-vector distance function approach and stochastic frontier analysis. Firstly, Zhou et al. (2012b) employ a cross-sectional economy-wide sub-vector energy distance function for 21 OECD countries from 2001. Energy, capital stock and labour are the inputs while GDP is the output variable. The authors estimate the function using SFA as well as non-parametric estimators. They conclude that the parametric approach has higher discriminating power than the non-parametric approaches. Secondly, Lin &

[86] Kumbhakar & Hjalmarsson (1995); Coelli et al. (2005); Kumbhakar et al. (2002) and Gathon & Perelman (1992) use only one input as the dependent variable and various outputs as explanatory variables. However, some empirical papers introduced other inputs, that are hold fixed, in addition, e.g. see Boyd (2008); Guan et al. (2009).

Table 3.1: Applications using stochastic frontier analysis

Source	**Model**	**Topic**
Boyd (2008)	Input requirement function	Energy use in corn milling plants in the US
Khayyat & Heshmati (2014)	Input requirement function	Energy use in Korean industry
Zhou et al. (2012b)	Sub-vector distance function	Energy use in OECD countries
Lin & Du (2013)	Sub-vector distance function	Energy use in China
Buck & Young (2007)	Input demand function	Energy use in commercial buildings
Filippini & Hunt (2011)	Input demand function	Energy use in OECD countries
Filippini & Hunt (2012)	Input demand function	Energy use in the US
Filippini et al. (2014)	Input demand function	Energy use in the EU
Orea et al. (2015)	Input demand function	Energy use and rebound in the US
Weyman-Jones et al. (2015)	Input demand function	Electricity in Portuguese households
Alberini & Filippini (2015)	Input demand function	Energy use in US households

Du (2013) measure the energy efficiency of China's 30 administrative regions from 1997 to 2010 using a sub-vector energy distance function. They divide the regions in China into three groups to estimate a parametric metafrontier approach. Lin & Du (2013) use the same variables as Zhou et al. (2012b) and conclude that using pooled estimation underestimates the energy efficiency in China.

Filippini & Hunt (2011) are among the first to use an input demand frontier function to estimate energy efficiency for 29 OECD countries from 1978 to 2006 using SFA. A similar approach is used in Filippini & Hunt (2012) using US data from 1995 to 2007 and Filippini et al. (2014) for EU countries between 1996 and 2009. The latter adapts the model in order to evaluate policy measures. The inefficiency term is split into a systematic component, which is a vector of policy measures, and a random part.[87] Filippini et al. (2014) conclude that financial incentives and standards are important in promoting energy efficiency but information policies do not have a significant impact. Orea et al. (2015) use the Filippini & Hunt (2011) model to estimate the energy efficiency and rebound effect in the US.

Examples of the use of parametric frontier analysis to estimate the energy efficiency at the disaggregated level are rare. For example, Buck & Young (2007) measure the level of energy efficiency from a sample of Canadian commercial buildings from the Commercial and Institutional Building Energy Use Survey in 2001. They use a heteroskedastic frontier model and condition the inefficiency frontier on a vector of exogenous factors that influence efficiency of the building like building-owner characteristics, main activity in the building (e.g., office, retail, service, etc.) and stated incentives for doing conservation measures. Their results suggest that the main activity has an influence on the estimated inefficiency. Also, buildings owned by the government and non-profit organisations tend to be more inefficient than privately owned buildings.

Weyman-Jones et al. (2015) use a cross-sectional dataset from a survey conducted on around 3,500 Portuguese households in 2008. They follow the Filippini & Hunt (2011) approach and

[87] The inefficiency term, υ_i, can be written as $\upsilon_i = \gamma \cdot Z_i + \epsilon_i$, where Z_i is a systematic component and ϵ_i is a random part.

combine electricity demand modelling and frontier analysis to estimate residential electric efficiency in Portugal. In their model, electricity use is a function of the family income, the number of clients and dummies for different energy consumption bands. As exogenous influences on efficiency, they use electric heating and electric water heating ownership as Z-variables.[88] The model used by Weyman-Jones et al. (2015) is relatively simple and with few explanatory variables.

Alberini & Filippini (2015) use a large panel dataset comprised of over 40,000 US households observed over seven survey waves between 1997 and 2009. In order to measure the total energy efficiency in disaggregated residential energy consumption they use a stochastic frontier model and further decomposes the level of energy efficiency into a transient and a persistent part, a concept, that was recently introduced by Colombi et al. (2014) and Filippini & Greene (2015). Using energy price, income, climate variables, household and home characteristics in the model they find persistent inefficiency to be around 10% and transient inefficiency around 17% at an average. Although they use a much richer model than Weyman-Jones et al. (2015), both these studies do not have information on capital stock and energy services. However in case of the estimation of energy efficiency based on household production theory, both these variables are important as they represent input and output. Without information on output and input variables it is not possible to estimate technical efficiency. Therefore, no other paper was able to estimate the technical input-specific efficiency using a (sub-vector) distance function on a disaggregated level until now. We use a rich dataset of Swiss households that includes information on capital stock and its price as well as information on the amount of energy services consumed within a household such as the number of meals consumed, hot water, entertainment, lighting and washing. This fact enables us to estimate a sub-vector input distance function, similar to Zhou et al. (2012b), but using household survey data.

3.4 Model specification and econometric estimator

In this chapter we analyse the level of efficiency in the use of electricity using a sub-vector distance frontier function. As discussed previously, the sub-vector distance function measures the technical efficiency. We now develop the empirical models for the input-specific measurement of efficiency in the use of electricity in Swiss households. As mentioned in the section 3.2, the sub-vector distance function is a special case of the distance function. The distance function was introduced by Shephard (1953). In principle, it can be seen as the multiple output version of a production frontier. In addition, it has the advantage of being free of some behavioural assumptions like cost minimisation and profit maximisation. There is also no need for information on the price of outputs. We are in a multi-output production process framework where the different energy services serve as the multiple outputs and there is no price information on them. Therefore, we use the distance function framework.

As previously discussed, in this paper we want to use a non-radial approach to measure the efficiency in the use of electricity. Therefore, we estimate an input distance function where we reduce only

[88] See footnote 87 for details.

one of the inputs and keep the others constant. This results in a so-called sub-vector input distance function and refers to the concept of non-radial efficiency measurement. In this concept an improvement in efficiency does not result from a proportional scaling of all inputs, but some inputs are taken as fixed and one estimates the single-factor efficiency. The difference between the classical radial input distance function and the non-radial sub-vector input distance function is that the first is linearly homogeneous in the input vector while the second is assumed to be linearly homogeneous only in energy input (Lin & Du, 2013). All other properties are inherited from the radial input distance function (Chambers et al., 1996).

In order to be able to estimate the sub-vector input distance function, we need to choose a functional form. This is usually the translog functional form as it is very flexible, easy to calculate and allows to impose linear homogeneity easily. Using a translog functional form we can specify a general sub-vector input demand function as follows:

$$\begin{aligned}\ln(d_i) = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln(x_{mi}) + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn}\ln(x_{mi})\ln(x_{ni}) + \sum_{k=1}^{K}\beta_k \ln(y_{ki}) \\ +\frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\beta_{kl}\ln(y_{ki})\ln(y_{li}) + \sum_{k=1}^{K}\sum_{m=1}^{M}\delta_{km}\ln(y_{ki})\ln(x_{mi}) + \nu_i \end{aligned} \tag{33}$$

where d_i represents the sub-vector distance function, x_{mi} represents the set of all input vectors which can produce the output vectors y_{ki}, ln stands for the natural logarithm and ν_i is a symmetric and normally distributed disturbance term. Since $\ln(d_i)$ is not directly measurable, we get the following after some algebra:

$$\begin{aligned}-\ln(x_{Mi}) = \alpha_0 + \sum_{m=1}^{M-1} \alpha_m \ln(x_{mi}) + \frac{1}{2}\sum_{m=1}^{M-1}\sum_{n=1}^{M-1} \alpha_{mn}\ln(x_{mi})\ln(x_{ni}) + \sum_{k=1}^{K}\beta_k \ln(y_{ki}) \\ +\frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\beta_{kl}\ln(y_{ki})\ln(y_{li}) + \sum_{k=1}^{K}\sum_{m=1}^{M-1}\delta_{km}\ln(y_{ki})\ln(x_{mi}) + \nu_i - \ln(d_i) \end{aligned} \tag{34}$$

If we want to empirically estimate equation (34) we use $\ln(d_i) = \upsilon_i$, where υ_i is a one-sided non-negative random disturbance term assumed to follow a half-normal distribution.

In our empirical analysis we are interested to measure the level of efficiency in the use of electricity of a sample of Swiss households. For this purpose, we assume that the households use three inputs to produce several energy services. More specifically, we include three inputs: electricity, labour and capital. Capital stock is represented by the stock of household appliances. As labour input, we should actually measure the total hours worked for household work. However, we do not have this information and approximate the labour input with the household size (number of household members). These three inputs are used as production factors to produce energy services in the households. As energy services we measure the amount of washing, the amount of meals cooked at home, the number of hours spent on entertainment and the amount of hot water services. Lighting is also an important component of energy services. However, we use the number of rooms as an approximation since we do not have information on the number of hours that lights are switched on. Therefore, we can specify our sub-vector electricity distance frontier function by using a translog functional form as[89,90]

$$
\begin{aligned}
-\ln(E_i) = {} & \alpha_0 + \alpha_K \ln(K_i) + \alpha_{HS} \ln(HS_i) + \sum_j \beta_S \ln(S_{ij}) \\
& + \frac{1}{2}\,\alpha_{KK} \ln(K_i)^2 + \frac{1}{2}\alpha_{HSHS} \ln(HS_i)^2 + \frac{1}{2}\sum_j \beta_{SS1} \ln(S_{ij})^2 \\
& + \sum_j \delta_1 \ln(S_{ij}) \ln(K_i) + \sum_j \delta_2 \ln(S_{ij}) \ln(HS_i) \\
& + \alpha_{KHS} \ln(K_i) \ln(HS_i) + \sum_m \sum_j \beta_{SS2} \ln(S_{mi}) \ln(S_{ji}) \\
& + Z_i\gamma + \nu_i - \upsilon_i \qquad (35)
\end{aligned}
$$

where E_i is the electricity input (in kilowatt hours), K_i denotes the stock of appliances (in Watt), HS_i is the household size, S_i is a vector of energy services, j is the number of energy services, γ is a vector of parameters to be estimated for household characteristics Z_i that consider the different productivities of households, ν_i, is a symmetric and normally distributed disturbance term, υ_i is a one-sided non-negative random disturbance term assumed to follow a half-normal distribution and ln stands for the natural logarithm. This function gives us the minimal electricity needed for the production of the energy service vector, given all the other non-electricity inputs. In addition to the translog functional form we also estimate the sub-vector distance function using a Cobb-Douglas functional form, which is less flexible. However, as in the translog functional form one includes multiple interactions, sometimes problems of multicollinearity might occur (Boisverf, 1982). Therefore, we use the Cobb-Douglas functional form as another specification.

We use the stochastic frontier function approach introduced by Aigner et al. (1977) to estimate equations (35). Traditionally, the stochastic frontier function is used in production theory to empirically measure the economic performance of production processes. The main concept of the stochastic frontier approach is that the frontier function estimates the maximum (or minimum) level of an economic indicator reachable by a decision-making unit (e.g. a company or a household). In our case, the frontier indicates the minimum level of electricity input used by a household for any given level of energy services. The difference between the observed input and the optimal input demand on the frontier represents inefficiency (Kumbhakar & Lovell, 2000). In the SFA approach the error term is composed of two independent parts. The first part, ν_i, is a symmetric disturbance term assumed to be normally distributed as the usual error term. The second part, υ_i is interpreted as an indicator of the inefficient use of residential electricity. The efficiency in the use of electricity is defined as a one-sided non-negative random disturbance term and is here assumed to follow a

[89] Very often researcher choose the translog functional form, as it is a very flexible functional form.

[90] As the translog functional form can be seen as a second-order Taylor approximation, it requires the approximation of the underlying function (here the distance function) to be made at a local point, which in our case is taken at the median point of all variables. Therefore, all independent variables are normalized at their median point.

half-normal distribution.[91] The approach used in this study is therefore based on the assumption that the level of the energy efficiency of Swiss households can be approximated by the one-sided non-negative term $\upsilon_{i,t}$. In order to be able to estimate these two error terms, one needs to use maximum likelihood techniques.[92]

Following Jondrow et al. (1982), the level of efficiency in the use of electricity can be expressed as:

$$EF_i = \frac{E_i^F}{E_i} = exp(-\hat{\upsilon}_i) \tag{36}$$

where E_i is the observed electricity consumption and E_i^F is the frontier or minimum demand of household i. An electricity efficiency level of one indicates a household on the frontier, thereby implying an efficiency level of 100%, while households not on the frontier receive efficiency values below one, thereby implying an efficiency level of less than 100%.

3.5 Data

In this chapter we use the same database as in chapter 1 with minor changes (see section 3.5.3). The major source of the database is the association of Swiss electricity companies, the Verband der Schweizerischen Elektrizitätsunternehmen (VSE). VSE conducted two surveys on around 2,400 Swiss households served by seven different utility companies. The first survey was conducted in 2005 and the second survey in 2011, both through telephone interviews. In each of the surveys data were collected from residential customers of five utilities for a total of 1,200 households. Three of those five utilities were common to both the 2005 and the 2011 surveys but the households were not necessarily the same. These seven utilities serve around 25% of the residential electricity consumption within Switzerland. Information collected include the characteristics of houses, the demographics of households, the stock of appliances, rough characteristics of appliances (e.g. if the appliance was older than 10 years), the usage of appliances (energy services) and the annual electricity consumption of the household. Table 3.2 provides the summary statistics of all the variables used in the estimation.

In addition to the survey, we also collected data on appliance stock price information and the household aggregate stock of appliances that we define as the sum of the estimated reference capacities of eleven major appliances. These variables and the energy services are explained in more detail in sections 3.5.1 and 3.5.2. Section 3.5.3 highlights the steps needed to prepare the data for our analyses.

[91] The half-normal distribution is the most common used distribution in SFA. However, other distributions, e.g. truncated normal, exponential or gamma distributions can also be used (Kumbhakar & Lovell, 2000).

[92] These estimation procedures are available in Stata (Belotti et al., 2012) and Limdep.

3.5.1 Appliance stock

We use the same method to measure capital stock and its price as in chapter 1. We construct an appliance index that aggregates the appliances owned by a household into one index that can be compared across the households in our survey. We do this by using a measure of the approximate power used by the major household appliances that we refer to as the "estimated capacity". The estimated capacity of the 11 major appliances[93] is obtained by dividing the appliances into their vintage (older than 5 or 10 years) and size. The estimated capacity of an appliance is the average power used by the appliance while in use.[94] Further, we define the appliance index of household i (AI_i) as the sum of the estimated reference capacities over the 11 major household appliances.

In addition, we calculate the "user cost" of appliances (P'_k) that reflects the price of services obtained from a durable good even though it has been purchased by the household. The user cost is a function of the purchase price, depreciation and opportunity cost. Finally, dividing the sum of the user costs of the eleven appliance categories by the sum of the estimated capacity (AI_i) we can create a price per installed capacity (in Watts) for each household.[95]

3.5.2 Energy Services

We use four of the major energy services as outputs in the empirical model. Measuring the level of energy services is a critical issue when using SFA (Filippini et al., 2014). The VSE survey also contains information on some activities by households with regard to energy usage in the week prior to the survey being undertaken. We combine energy usage into four broad categories: the amount of washing, the amount of meals cooked at home, the number of hours spent on entertainment and the amount of hot water services. We combine the usage of a clothes washer, tumble dryer and dehumidifier as representing the amount of washing. The amount of meals cooked at home is defined as the sum of breakfasts, lunches and dinners made at home. We obtain the number of hours spent on entertainment by adding the hours spent on a personal computer and on watching television. Hot water services are calculated by adding the number of showers and baths taken. Table 3.2 provides summary statistics of these variables. Lighting is also an important component of energy services. However, we use the number of rooms as an approximation since we do not have information on the number of hours that lights are switched on.

3.5.3 Data preparation

In order to estimate the level of efficiency in the use of electricity using household data it is important to exclude outliers from the analysis . For instance, using disaggregated data it is

[93] Refrigerator, freezer, electric stove, electric oven, microwave, dishwasher, clothes washer, tumble dryer, electric boiler, television sets and personal computers.

[94] The estimated reference capacities (in Watt) have been provided by Schweizerische Agentur für Energie Effizienz (SAFE).

[95] For more details see Boogen et al. (2015).

Table 3.2: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Inputs – Energy, Capital and Labour					
Total consumption in kWh	3955.17	3124.27	498	29476	1868
Capital Stock in Watt	5215.47	2060.72	141.30	11605.10	1868
Household size	2.38	1.22	1	8	1868
Outputs – Energy Services					
No. of meal services	16.79	7.17	1	91	1868
No. of washing services	3.28	4.64	0	54	1868
No. of hot water services	8.88	9.88	0	113	1868
No. of entertainment services	7.41	9.19	1	176	1868
No. of rooms	4.14	1.46	1	9	1868
Household characteristics (Z)					
Single family housing dummy	0.34	0.47	0	1	1868
Tenant dummy	0.55	0.5	0	1	1868
Urban dummy	0.59	0.49	0	1	1868
Time-of-use dummy	0.78	0.41	0	1	1868
Utility 1 in 2011 dummy	0.08	0.28	0	1	1868

possible to observe very low consumption for some households, because people may be travelling a lot. In the survey the amount of energy services was asked to be reported from the last week and not from a typical week in the previous year. Therefore, we can imagine cases where people are travelling a lot but are at home at the time of the interview. These people reported the amount of energy services from the previous week correctly but the typical amount of energy services in the previous year might be very different. Therefore, these reported energy services are overestimated in comparison to their actual electricity consumption. For this reason, we exclude observations that, assuming minimum standards, are outliers.

We define the minimum standard using a bottom-up approach in three steps. Firstly, we define minimum energy services that are consumed within a year. This minimum energy services are displayed in table A.12 in the appendix and can be transformed into electricity consumption in kWh under certain assumptions.[96] Secondly, we aggregate the consumption per energy service to get minimum electricity consumption for a single household. Here we distinguish between three cases. The base case considers households where water heating and washing is either not done using electricity or is not measured by the individual electricity meter. Then we include two cases where either washing or showering is included. Thirdly, for each additional household member we can aggregate the minimal electricity consumption for all energy services except for cooling and cooking, where we assume scale effects.[97] Table A.12 in the appendix shows the minimal electricity consumption standard for single households and for households with additional members. We believe that these minimum standards are a conservative estimate, as e.g. we do not include standby consumption.

[96] For example, we assume that an average shower uses 45 litres of water that needs to be heated from 20°C to 50°C and that an average meal needs 20 minutes of cooking.

[97] For example a 100 Litre fridge uses approximately the same amount of electricity regardless of the number of people.

3.6 Results

The sub-vector input distance function, as defined in equation (35), is estimated using the maximum likelihood estimator for frontier functions proposed by Aigner et al. (1977) and the results are in Table 3.3. The estimates using the Cobb-Douglas functional form are in column (1), while column (2) uses the translog form. Generally, the values of the first order coefficients are similar. We include five household characteristics in the sub-vector distance function that may not be captured by energy services but have important effects on the productivity of the households (represented by Z_i in equation (35)). These characteristics include binary variables for households that live in a single family house, households in urban areas, households that are tenants and households that have a time-of-use tariff scheme. We also include an indicator for whether a household is a customer of utility 1 in 2011 since the electricity consumption in that particular utility is quite different to the rest of the utilities in the survey.[98] We also use an indicator for the survey year. The indicator of the relative contribution of $\nu_{i,t}$ and $\upsilon_{i,t}$ to the error term, λ, is significant in both specifications.[99] This implies significant inefficiency in the households.

For the further interpretation of the coefficients of a distance function, we should point out that a negative coefficient is associated with an expansion in the input set, while a positive coefficient implies a contraction of the feasible input set. The first-order elasticities of the sub-vector distance function for all five outputs are significant in both specifications except for the number of meal services. They are also all negative at the sample median as expected. Since we do not have information on the number of hours the lights are switched on we use the number of rooms as an approximation for this energy service. The number of rooms and entertainment services also have the highest coefficients among all outputs in the sub-vector distance function.

With respect to inputs, the first-order sub-vector distance function elasticities are also significant at the sample median in both specifications. Capital and energy are supposed to be substitutes in the production of energy services and we expect a positive sign on the coefficient of the capital stock. However, this is not the case. This is explained by how we measure the capital stock. Keeping energy services constant, an increase in the capacity (in Watt) will usually lead to higher electricity consumption.[100]

A better way to measure the capital stock would incorporate the aspect of quality of the appliances. In case of household appliances the quality could be measured as energy efficiency. The capacity alone does not measure this aspect. For example, consider two washing machines with the same characteristics (e.g. for 7 kg of clothes), both with a capacity of a 1000 Watt. The electricity consumption for one cycle of washing, at the same washing temperature, could be different between the two machines. This difference might be caused by, e.g. different software programming of the washing cycle or different water use. As an alternative, the price of the appliance might also be used as proxy for the quality aspect. However, as we measure the price as reference prices in our

[98] For a more detailed discussion on this issue see Boogen et al. (2015). However, we also estimated a model excluding the customers of utility 1 in 2011. The results are similar to the estimation using the full sample.

[99] Note that $\lambda = \frac{\sigma_\upsilon}{\sigma_\nu}$.

[100] This is due to the physical relationship of $E = Watt \times hours$.

sample, it also does not reflect the energy efficiency or quality aspect of the appliances.

Table 3.3: Sub-vector distance function

	(1)	(2)
First order terms		
(Ln) Capital Stock	-0.186[a]	-0.302[a]
	(0.027)	(0.039)
(Ln) Household size	-0.288[a]	-0.259[a]
	(0.027)	(0.033)
(Ln) No. of washing services	-0.031[a]	-0.047[a]
	(0.007)	(0.010)
(Ln) No. of meal services	-0.038	-0.005
	(0.024)	(0.033)
(Ln) No. of entertainment services	-0.129[a]	-0.114[a]
	(0.015)	(0.017)
(Ln) No. of hot water services	-0.036[a]	-0.028[a]
	(0.005)	(0.009)
(Ln) No of rooms	-0.228[a]	-0.243[a]
	(0.040)	(0.047)
Z-variables		
Utility 1 in 2011 dummy	-0.259[a]	-0.246[a]
	(0.045)	(0.044)
Year 2011 dummy	-0.085[b]	-0.120[a]
	(0.035)	(0.036)
Single family housing dummy	-0.250[a]	-0.255[a]
	(0.034)	(0.035)
Time-of-use dummy	-0.211[a]	-0.216[a]
	(0.027)	(0.027)
Urban dummy	0.105[a]	0.107[a]
	(0.025)	(0.025)
Tenant dummy	0.075[b]	0.074[b]
	(0.031)	(0.030)
Second order terms		
(Ln) y1y2		0.014
		(0.013)
(Ln) y1y3		0.015[c]
		(0.009)
(Ln) y1y4		0.003[c]
		(0.002)
(Ln) y1y5		0.051[b]
		(0.023)
(Ln) ky1		-0.032[c]
		(0.018)
(Ln) hsy1		-0.010
		(0.015)
(Ln) y2y3		-0.050
		(0.031)
(Ln) y2y4		-0.010
		(0.008)
(Ln) y2y5		-0.042
		(0.078)
(Ln) ky2		-0.001
		(0.042)
(Ln) hsy2		-0.038
		(0.060)

Continued on next page

Table 3.3 – continued from previous page

	(1)	(2)
(Ln) y3y4		0.009^{c}
		(0.005)
(Ln) y3y5		0.020
		(0.048)
(Ln) ky3		-0.010
		(0.039)
(Ln) hsy3		0.067^{c}
		(0.035)
(Ln) y4y5		0.007
		(0.012)
(Ln) ky4		-0.008
		(0.009)
(Ln) hsy4		-0.002
		(0.009)
(Ln) ky5		-0.218^{b}
		(0.086)
(Ln) hsy5		0.046
		(0.093)
(Ln) khs		0.097
		(0.064)
(Ln) kk		-0.057
		(0.059)
(Ln) hshs		-0.096
		(0.105)
(Ln) y1y1		-0.036^{a}
		(0.010)
(Ln) y2y2		0.094^{c}
		(0.051)
(Ln) y3y3		-0.085^{a}
		(0.025)
(Ln) y4y4		0.012
		(0.009)
(Ln) y5y5		-0.007
		(0.128)
Observations	1,868	1,868
Prob > χ^2	0.000	0.000
λ	0.829	0.658
P-Value of λ	0.000	0.000
Log likelihood	-1216.910	-1178.757

Standard errors in parentheses
^{a}, ^{b}, ^{c}: Significant at the 1%, 5% and 10% levels, respectively.
y1: No. of washing services
y2: No. of meal services
y3: No. of entertainment services
y4: No. of hot water services
y5: No of rooms

Moreover, the coefficient of the household size, our proxy measure of labour input, is also negative in both specifications. This can be explained in a similar way as the capital stock: A larger household will usually use more electricity. However, as mentioned previously, we should actually measure the hours worked in the household instead of the number of household members. These two measurement issues of the inputs might be part of further research.

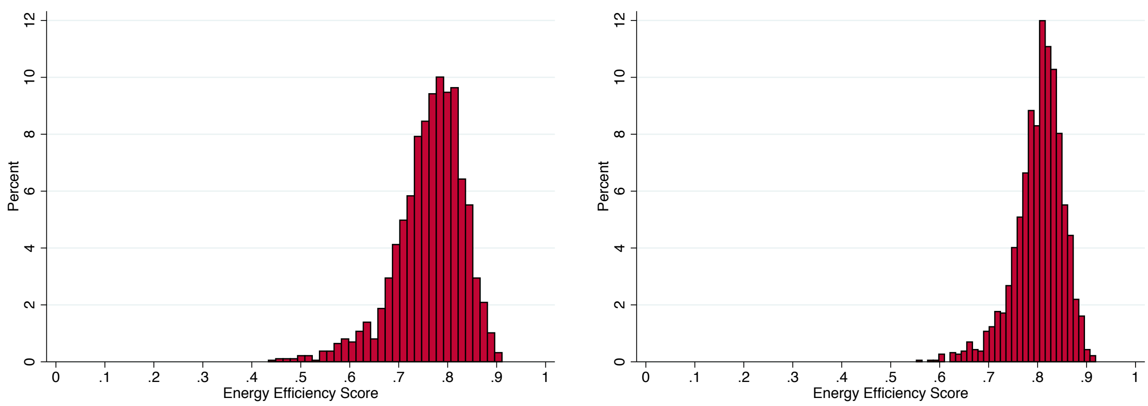
Some of the second order sub-vector distance function coefficients in the translog specification are also significant. We can compare the two specifications, Cobb-Douglas and translog, by comparing the log likelihoods. A log likelihood test shows that the translog specification is preferred.

Another issue in specifying a distance function is that the input of interest is a function of all other inputs and outputs. This could possibly create an endogeneity problem, especially in cases when the input of interest is jointly determined with the output (Guan et al., 2009). Due to this we could also get biased estimates in the sub-vector distance function. However, solving the problem of endogeneity in non-linear models, such as in the stochastic frontier approach (SFA), is not straightforward. At the moment there is no accepted approach for estimating unbiased efficiency estimates for SFA accounting for endogenous variables (Mutter et al., 2013). Furthermore, Coelli (2000) show that the distance functions do not face a greater risk of endogeneity bias compared to production functions, at least under profit maximisation behaviour. Therefore we do not correct for endogeneity.

The results of the econometric estimations in Table 3.3 can be used to estimate the efficiency levels as described in equation 36. Table 3.4 provides the summary statistics of the estimated efficiency levels for the Cobb-Douglas and the translog functional form. The median efficiency level is about 0.75 with a standard deviation of 0.07 for the Cobb-Douglas case and 0.8 with a standard deviation of 0.05 for the translog case. We can also observe this in Figure 3.3 that plots the distribution of the efficiency levels.

Table 3.4: Statistics of efficiency levels

	Mean	**Median**	**SD**	**Min.**	**Max.**	**N**
Cobb-Douglas	0.763	0.774	0.069	0.434	0.911	1868
Translog	0.803	0.809	0.049	0.553	0.918	1868



(a) Cobb-Douglas (b) Translog

Figure 3.3: Estimated energy efficiency levels

3.7 Conclusions

The demand for residential electricity is a derived demand that can be modelled as a production process whereby households combine electricity and capital goods as inputs to provide services. This production process may be inefficient and to measure this inefficiency in the use of electricity in Swiss households we estimate a stochastic frontier model for residential electricity demand. We use data from a Swiss household survey conducted in 2005 and 2011 and find an average inefficiency of around 20%.

From the point of view of policy makers we conclude that there is considerable potential for improving the efficient use of electricity in some households. While Weyman-Jones et al. (2015) use an input demand frontier function to find inefficiency levels between 4 and 43% for Portuguese households depending on the variables included. Our results lie well in between the range estimated by Weyman-Jones et al. (2015). We should note, that an input demand frontier function estimates the overall productive efficiency whereas the sub-vector distance function used in this paper estimates the technical efficiency.

Prognos (2011) uses a bottom-up economic-engineering approaches to estimate the energy efficiency potential in Switzerland and finds that the electricity consumption for households can be reduced compared to the reference scenario by around almost 15% (by 2035) and 20% (2050). Comparing our results to this bottom-up economic-engineering approach, our estimates lie at the upper end.

Lastly, we should note that households are very diverse and there may exist significant unobserved heterogeneity that we cannot account for in this paper. However, this can be solved by using panel data in future work combining the approach used in this paper and the approach by Alberini & Filippini (2015).

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Appendix

Appendix for Essay 1

First stage regressions

Table A.1 below presents the results of estimating equations (17a) and (17b) for the short-run electricity demand. The endogenous variables are the average electricity price (equation (17a)) and the measure of appliance stock (equation (17b)). In column (1), (a) estimates (17a) and (b) estimates (17b) with only household and socio-demographic characteristics corresponding to the electricity demand equation (11b). In column (2), (a) estimates (17a) and (b) estimates (17b) but with energy services and some household and socio-demographic characteristics corresponding to the electricity demand equation (11a).

Table A.2 presents the first-stage results of estimating the long-run electricity demand. In columns (1) and (3) we use the prices of individual appliances listed in Table 1.8. We have only endogenous variable here, the average price of electricity. We estimate equation (18) with only household and socio-demographic characteristics in column (1) and with energy services and some household and socio-demographic characteristics in column (3). In column (2) and (4) we use the price of appliances (per installed Watt). The endogenous variables are the average price of electricity and the price of appliances. Therefore, we estimate equations (19a) (average price of electricity) and (19b) (price of appliances) in (a) and (b), respectively. We consider only household and socio-demographic characteristics in column (2) and energy services and some household and socio-demographic characteristics in column (4).

Table A.3 presents the first-stage results of estimating the long-run capital stock demand. We have only endogenous variable here, the average price of electricity. We estimate equation (20) with only household and socio-demographic characteristics in column (1) and with energy services and some household and socio-demographic characteristics in column (2).

Table A.4 and A.6 are built like Table A.1 and Table A.5 and A.7 are built like Table A.2, but using alternative instruments as described in section 1.4.4. Table A.8 presents the first-stage results of estimating the short and long-run electricity demand using interactions of electricity price and income. Column (1) and (4) are the first stage regressions of average electricity price, column (2) and (5) are the first stage regression of the interaction term and column (3) and (6) are the first stage regression of the appliance stock and its price.

Table A.1: First-stage regression of short-run log electricity demand

	(1)		(2)	
	(a)	(b)	(a)	(b)
(Log) ElCom price	0.99[a]	-0.20[a]	0.99[a]	-0.21[a]
	(0.02)	(0.05)	(0.02)	(0.05)
(Log) Average (neighbouring) price per Watt	-0.17[a]	-0.54[a]	-0.16[a]	-0.55[a]
	(0.02)	(0.09)	(0.02)	(0.09)
(Log) Midpoint income	-0.01	0.18[a]		
	(0.01)	(0.02)		
(Log) Household size	0.00	0.16[a]		
	(0.01)	(0.04)		
Children dummy	0.02	-0.01		
	(0.01)	(0.03)		
Retired dummy	0.02[b]	0.01		
	(0.01)	(0.03)		
Share of females	0.01	0.00		
	(0.01)	(0.04)		
No. of meals per day			0.00	0.01
			(0.00)	(0.01)
Hours of entertainment per day			-0.00	0.00[b]
			(0.00)	(0.00)
No. of hot water services per day			-0.01[a]	0.06[a]
			(0.00)	(0.01)
No. of washing services per week			0.00	0.02[a]
			(0.00)	(0.00)
(Log) No. of rooms			0.02	0.30[a]
			(0.01)	(0.04)
Single family housing dummy	0.16[a]	-0.01	0.16[a]	-0.14[a]
	(0.01)	(0.03)	(0.01)	(0.03)
Urban dummy	-0.00	-0.06[a]	-0.00	-0.03
	(0.01)	(0.02)	(0.01)	(0.02)
Tenant dummy	0.00	-0.22[a]	0.00	-0.19[a]
	(0.01)	(0.03)	(0.01)	(0.03)
Utility 1 dummy	-0.04[a]	0.04[c]	-0.03[a]	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)
Time-of-use dummy	-0.11[a]	-0.03	-0.11[a]	-0.03
	(0.01)	(0.03)	(0.01)	(0.03)
Year 2011 dummy	-0.07[a]	-0.07[a]	-0.08[a]	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)
Intercept	0.06	7.09[a]	0.02	8.15[a]
	(0.08)	(0.28)	(0.07)	(0.18)
Observations	1,844	1,844	1,844	1,844
Adjusted R^2	0.82	0.30	0.82	0.34

Heteroscedasticity-robust standard errors in parentheses.
[a], [b], [c]: Significant at the 1%, 5% and 10% levels, respectively.

Table A.2: First stage regression of long-run log electricity demand

	(1)	(2)		(3)	(4)	
		(a)	(b)		(a)	(b)
(Log) ElCom price	0.97[a]	0.99[a]	0.08[c]	0.97[a]	0.99[a]	0.09[b]
	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)	(0.04)
(Log) Average (neighbouring) price per Watt		-0.17[a]	0.38[a]		-0.16[a]	0.34[a]
		(0.02)	(0.08)		(0.02)	(0.08)
(Log) Midpoint income	-0.00	-0.01	0.01			
	(0.01)	(0.01)	(0.02)			
(Log) Household size	0.04	0.00	0.04			
	(0.04)	(0.01)	(0.03)			
Children dummy	0.02[c]	0.02	0.00			
	(0.01)	(0.01)	(0.03)			
Retired dummy	0.01	0.02[b]	-0.14[a]			
	(0.01)	(0.01)	(0.02)			
Share of females	0.01	0.01	-0.02			
	(0.01)	(0.01)	(0.04)			
No. of meals per day				0.00	0.00	-0.01
				(0.00)	(0.00)	(0.01)
Hours of entertainment per day				-0.00	-0.00	0.01[a]
				(0.00)	(0.00)	(0.00)
No. of hot water services per day				-0.01[a]	-0.01[a]	-0.02[b]
				(0.00)	(0.00)	(0.01)
No. of washing services per week				0.00	0.00	-0.01[b]
				(0.00)	(0.00)	(0.00)
(Log) No. of rooms				0.01	0.02	0.04
				(0.01)	(0.01)	(0.04)
Single family housing dummy	0.17[a]	0.16[a]	0.06[a]	0.16[a]	0.16[a]	0.10[a]
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.03)
Urban dummy	-0.02[a]	-0.00	0.05[b]	-0.02[a]	-0.00	0.04[c]
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Tenant dummy	-0.00	0.00	0.09[a]	-0.00	0.00	0.09[a]
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Utility 1 dummy	-0.04[a]	-0.04[a]	0.01	-0.03[a]	-0.03[a]	0.00
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Time-of-use dummy	-0.13[a]	-0.11[a]	0.01	-0.13[a]	-0.11[a]	0.02
	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.03)
Year 2011 dummy	0.06	-0.07[a]	0.03[c]	0.06	-0.08[a]	-0.00
	(0.07)	(0.01)	(0.02)	(0.07)	(0.01)	(0.02)
Intercept	-4.85[c]	0.06	-1.03[a]	-5.14[b]	0.02	-1.07[a]
	(2.57)	(0.08)	(0.26)	(2.56)	(0.07)	(0.17)
Observations	1,844	1,844	1,844	1,844	1,844	1,844
Adjusted R^2	0.82	0.82	0.07	0.82	0.82	0.06

Heteroscedasticity-robust standard errors in parentheses.
[a], [b], [c]: Significant at the 1%, 5% and 10% levels, respectively.

Table A.3: First stage regression of long-run log capital demand

	(1)	(2)
(Log) Average (neighbouring) price per Watt	0.39[a]	0.36[a]
	(0.08)	(0.08)
(Log) Average price	0.09[a]	0.09[a]
	(0.04)	(0.03)
(Log) Midpoint income	0.02	
	(0.02)	
(Log) Household size	0.04	
	(0.03)	
Children dummy	-0.01	
	(0.03)	
Retired dummy	-0.14[a]	
	(0.02)	
Share of females	-0.03	
	(0.04)	
No. of meals per day		-0.02
		(0.01)
Hours of entertainment per day		0.01[a]
		(0.00)
No. of hot water services per day		-0.01
		(0.01)
No. of washing services per week		-0.01[a]
		(0.00)
(Log) No. of rooms		0.04
		(0.03)
Single family housing dummy	0.05[b]	0.07[a]
	(0.02)	(0.02)
Urban dummy	0.05[a]	0.04[b]
	(0.02)	(0.02)
Tenant dummy	0.08[a]	0.08[a]
	(0.02)	(0.02)
Utility 1 dummy	0.02	0.01
	(0.02)	(0.02)
Time-of-use dummy	0.03	0.03
	(0.03)	(0.03)
Year 2011 dummy	0.04[b]	0.01
	(0.02)	(0.02)
Intercept	-1.12[a]	-1.05[a]
	(0.24)	(0.15)
Observations	1,944	1,944
Adjusted R^2	0.07	0.06

Heteroscedasticity-robust standard errors in parentheses.
[a], [b], [c]: Significant at the 1%, 5% and 10% levels, respectively.

Table A.4: First-stage regression of short-run log electricity demand: Alternative instrument

	(1)		(2)	
	(a)	(b)	(a)	(b)
(Log) Neighbouring Elcom Price	0.78^a	-0.08	0.78^a	-0.10^c
	(0.02)	(0.06)	(0.02)	(0.05)
(Log) Average (neighbouring) price per Watt	0.10^a	-0.55^a	0.10^a	-0.57^a
	(0.03)	(0.09)	(0.03)	(0.09)
(Log) Midpoint income	-0.02^a	0.18^a		
	(0.01)	(0.02)		
(Log) Household size	-0.01	0.17^a		
	(0.01)	(0.03)		
Children dummy	0.03^a	-0.01		
	(0.01)	(0.03)		
Retired dummy	0.02^b	0.01		
	(0.01)	(0.03)		
Share of females	-0.01	0.01		
	(0.02)	(0.04)		
No. of meals per day			0.01^b	0.01
			(0.00)	(0.01)
Hours of entertainment per day			-0.00^a	0.00^b
			(0.00)	(0.00)
No. of hot water services per day			-0.01	0.05^a
			(0.00)	(0.01)
No. of washing services per week			-0.00^b	0.02^a
			(0.00)	(0.00)
(Log) No. of rooms			0.00	0.31^a
			(0.01)	(0.04)
Single family housing dummy	0.07^a	0.02	0.08^a	-0.11^a
	(0.01)	(0.03)	(0.01)	(0.03)
Urban dummy	-0.04^a	-0.05^b	-0.04^a	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)
Tenant dummy	-0.02^c	-0.21^a	-0.02	-0.18^a
	(0.01)	(0.03)	(0.01)	(0.03)
Utility 1 dummy	-0.04^a	0.04^c	-0.03^b	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)
Time-of-use dummy	-0.10^a	0.00	-0.10^a	-0.01
	(0.02)	(0.03)	(0.02)	(0.03)
Year 2011 dummy	0.02^a	-0.09^a	0.02^c	-0.03
	(0.01)	(0.02)	(0.01)	(0.02)
Intercept	0.98^a	6.69^a	0.81^a	7.81^a
	(0.09)	(0.29)	(0.07)	(0.20)
Observations	1,858	1,858	1,858	1,858
Adjusted R^2	0.68	0.29	0.68	0.33

Heteroscedasticity-robust standard errors in parentheses.
^{a}, ^{b}, ^{c}: Significant at the 1%, 5% and 10% levels, respectively.

Table A.5: First stage regression of long-run log electricity demand: Alternative instrument

	(1)	(2)		(3)	(4)	
		(a)	(b)		(a)	(b)
(Log) Neighbouring Elcom Price	0.71^{a}	0.78^{a}	-0.02	0.71^{a}	0.78^{a}	0.00
	(0.02)	(0.02)	(0.05)	(0.02)	(0.02)	(0.05)
(Log) Average (neighbouring) price per Watt		0.10^{a}	0.38^{a}		0.10^{a}	0.35^{a}
		(0.03)	(0.08)		(0.03)	(0.08)
(Log) Midpoint income	-0.02^{b}	-0.02^{a}	0.01			
	(0.01)	(0.01)	(0.02)			
(Log) Household size	0.02	-0.01	0.04			
	(0.05)	(0.01)	(0.03)			
Children dummy	0.04^{a}	0.03^{a}	0.00			
	(0.01)	(0.01)	(0.03)			
Retired dummy	0.02	0.02^{b}	-0.14^{a}			
	(0.01)	(0.01)	(0.02)			
Share of females	-0.01	-0.01	-0.02			
	(0.02)	(0.02)	(0.04)			
No. of meals per day				0.01^{c}	0.01^{b}	-0.01
				(0.00)	(0.00)	(0.01)
Hours of entertainment per day				-0.00^{b}	-0.00^{a}	0.01^{a}
				(0.00)	(0.00)	(0.00)
No. of hot water services per day				-0.01^{c}	-0.01	-0.01
				(0.00)	(0.00)	(0.01)
No. of washing services per week				-0.00^{c}	-0.00^{b}	-0.01^{a}
				(0.00)	(0.00)	(0.00)
(Log) No. of rooms				-0.00	0.00	0.04
				(0.01)	(0.01)	(0.04)
Single family housing dummy	0.06^{a}	0.07^{a}	0.04^{c}	0.06^{a}	0.08^{a}	0.08^{a}
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Urban dummy	-0.03^{a}	-0.04^{a}	0.04^{c}	-0.03^{a}	-0.04^{a}	0.03
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Tenant dummy	-0.01	-0.02^{c}	0.08^{a}	-0.01	-0.02	0.09^{a}
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Utility 1 dummy	-0.06^{a}	-0.04^{a}	0.01	-0.05^{a}	-0.03^{b}	0.00
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Time-of-use dummy	-0.15^{a}	-0.10^{a}	-0.02	-0.15^{a}	-0.10^{a}	-0.01
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Year 2011 dummy	0.53^{a}	0.02^{a}	0.04^{b}	0.53^{a}	0.02^{c}	0.01
	(0.08)	(0.01)	(0.02)	(0.08)	(0.01)	(0.02)
Intercept	-18.96^{a}	0.98^{a}	-0.69^{a}	-19.24^{a}	0.81^{a}	-0.77^{a}
	(3.31)	(0.09)	(0.27)	(3.32)	(0.07)	(0.18)
Observations	1,858	1,858	1,858	1,858	1,858	1,858
Adjusted R^2	0.69	0.68	0.07	0.69	0.68	0.05

Heteroscedasticity-robust standard errors in parentheses.
^{a}, ^{b}, ^{c}: Significant at the 1%, 5% and 10% levels, respectively.

Table A.6: First-stage regression of short-run log electricity demand: Alternative instrument

	(1)		(2)	
	(a)	(b)	(a)	(b)
(Log) Grouped Mean of Average Price	0.93[a]	-0.15[a]	0.93[a]	-0.14[a]
	(0.02)	(0.04)	(0.02)	(0.04)
(Log) Average (neighbouring) price per Watt	-0.02	-0.56[a]	-0.02	-0.56[a]
	(0.02)	(0.09)	(0.02)	(0.09)
(Log) Midpoint income	-0.00	0.17[a]		
	(0.00)	(0.02)		
(Log) Household size	0.01	0.18[a]		
	(0.01)	(0.03)		
Children dummy	0.01	-0.01		
	(0.01)	(0.03)		
Retired dummy	0.02[a]	0.01		
	(0.01)	(0.02)		
Share of females	0.01	0.01		
	(0.01)	(0.04)		
No. of meals per day			0.00	0.01
			(0.00)	(0.01)
Hours of entertainment per day			-0.00	0.00[b]
			(0.00)	(0.00)
No. of hot water services per day			-0.01[a]	0.05[a]
			(0.00)	(0.01)
No. of washing services per week			0.00	0.02[a]
			(0.00)	(0.00)
(Log) No. of rooms			0.02[b]	0.31[a]
			(0.01)	(0.04)
Single family housing dummy	-0.01	0.01	-0.02[c]	-0.10[a]
	(0.01)	(0.02)	(0.01)	(0.02)
Urban dummy	0.01	-0.06[a]	0.01	-0.02
	(0.01)	(0.02)	(0.01)	(0.02)
Tenant dummy	-0.00	-0.21[a]	0.00	-0.18[a]
	(0.01)	(0.03)	(0.01)	(0.03)
Utility 1 dummy	0.02[b]	0.03	0.02[a]	-0.02
	(0.01)	(0.02)	(0.01)	(0.02)
Time-of-use dummy	-0.08[a]	-0.02	-0.07[a]	-0.02
	(0.01)	(0.03)	(0.01)	(0.03)
Year 2011 dummy	-0.00	-0.10[a]	-0.01[c]	-0.04
	(0.01)	(0.02)	(0.01)	(0.02)
Intercept	0.25[a]	6.98[a]	0.23[a]	7.95[a]
	(0.07)	(0.26)	(0.06)	(0.17)
Observations	1,944	1,944	1,944	1,944
Adjusted R^2	0.86	0.30	0.86	0.34

Heteroscedasticity-robust standard errors in parentheses.
[a], [b], [c]: Significant at the 1%, 5% and 10% levels, respectively.

Table A.7: First stage regression of long-run log electricity demand: Alternative instrument

	(1)	(2)		(3)	(4)	
		(a)	(b)		(a)	(b)
(Log) Grouped Mean of Average Price	0.91[a]	0.93[a]	0.03	0.91[a]	0.93[a]	0.04
	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)	(0.04)
(Log) Average (neighbouring) price per Watt		-0.02	0.39[a]		-0.02	0.35[a]
		(0.02)	(0.08)		(0.02)	(0.08)
(Log) Midpoint income	-0.00	-0.00	0.01			
	(0.00)	(0.00)	(0.02)			
(Log) Household size	0.02	0.01	0.03			
	(0.03)	(0.01)	(0.03)			
Children dummy	0.01[c]	0.01	-0.00			
	(0.01)	(0.01)	(0.03)			
Retired dummy	0.02[a]	0.02[a]	-0.14[a]			
	(0.01)	(0.01)	(0.02)			
Share of females	0.01	0.01	-0.03			
	(0.01)	(0.01)	(0.04)			
No. of meals per day				0.00	0.00	-0.02
				(0.00)	(0.00)	(0.01)
Hours of entertainment per day				-0.00	-0.00	0.01[a]
				(0.00)	(0.00)	(0.00)
No. of hot water services per day				-0.01[a]	-0.01[a]	-0.01
				(0.00)	(0.00)	(0.01)
No. of washing services per week				0.00	0.00	-0.01[a]
				(0.00)	(0.00)	(0.00)
(Log) No. of rooms				0.01	0.02[b]	0.04
				(0.01)	(0.01)	(0.03)
Single family housing dummy	-0.01	-0.01	0.05[b]	-0.01	-0.02[c]	0.07[a]
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Urban dummy	0.01	0.01	0.05[b]	0.01	0.01	0.04[c]
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Tenant dummy	-0.00	-0.00	0.08[a]	0.00	0.00	0.08[a]
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Utility 1 dummy	0.01	0.02[b]	0.02	0.02[b]	0.02[a]	0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Time-of-use dummy	-0.09[a]	-0.08[a]	-0.00	-0.09[a]	-0.07[a]	0.01
	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.03)
Year 2011 dummy	0.16[a]	-0.00	0.04[b]	0.17[a]	-0.01[c]	0.01
	(0.05)	(0.01)	(0.02)	(0.05)	(0.01)	(0.02)
Intercept	-6.26[a]	0.25[a]	-0.90[a]	-6.86[a]	0.23[a]	-0.89[a]
	(2.07)	(0.07)	(0.24)	(2.06)	(0.06)	(0.16)
Observations	1,944	1,944	1,944	1,944	1,944	1,944
Adjusted R^2	0.86	0.86	0.07	0.86	0.86	0.06

Heteroscedasticity-robust standard errors in parentheses.
[a], [b], [c]: Significant at the 1%, 5% and 10% levels, respectively.

Table A.8: First stage regression of log electricity demand using price and income interaction

	(Short-run)			(Long-run)		
	(1)	(2)	(3)	(1)	(2)	(3)
(Log) ElCom price	0.78^a	-1.59	-1.31^b	0.78^a	-1.59	0.59
	(0.16)	(1.35)	(0.59)	(0.16)	(1.35)	(0.52)
(Log) Midpoint income x (Log) ElCom price	0.02	1.17^a	0.13^c	0.02	1.17^a	-0.06
	(0.02)	(0.16)	(0.07)	(0.02)	(0.16)	(0.06)
(Log) Average (neighbouring) price per Watt	-0.17^a	-1.47^a	-0.55^a	-0.17^a	-1.47^a	0.39^a
	(0.02)	(0.18)	(0.09)	(0.02)	(0.18)	(0.08)
(Log) Midpoint income	-0.07	-0.46	-0.17	-0.07	-0.46	0.17
	(0.05)	(0.43)	(0.18)	(0.05)	(0.43)	(0.16)
(Log) Household size	0.00	0.03	0.16^a	0.00	0.03	0.05
	(0.01)	(0.09)	(0.04)	(0.01)	(0.09)	(0.03)
Children dummy	0.02	0.16^c	-0.00	0.02	0.16^c	-0.00
	(0.01)	(0.09)	(0.03)	(0.01)	(0.09)	(0.03)
Retired dummy	0.02^b	0.15^b	0.01	0.02^b	0.15^b	-0.14^a
	(0.01)	(0.06)	(0.03)	(0.01)	(0.06)	(0.02)
Share of females	0.01	0.10	0.00	0.01	0.10	-0.02
	(0.01)	(0.10)	(0.04)	(0.01)	(0.10)	(0.04)
Single family housing dummy	0.16^a	1.40^a	-0.01	0.16^a	1.40^a	0.06^a
	(0.01)	(0.10)	(0.03)	(0.01)	(0.10)	(0.02)
Urban dummy	-0.00	0.00	-0.06^a	-0.00	0.00	0.05^b
	(0.01)	(0.08)	(0.02)	(0.01)	(0.08)	(0.02)
Tenant dummy	0.00	0.01	-0.22^a	0.00	0.01	0.09^a
	(0.01)	(0.07)	(0.03)	(0.01)	(0.07)	(0.02)
Utility 1 dummy	-0.04^a	-0.35^a	0.04^c	-0.04^a	-0.35^a	0.01
	(0.01)	(0.08)	(0.02)	(0.01)	(0.08)	(0.02)
Time-of-use dummy	-0.12^a	-1.00^a	-0.03	-0.12^a	-1.00^a	0.01
	(0.01)	(0.09)	(0.03)	(0.01)	(0.09)	(0.03)
Year 2011 dummy	-0.07^a	-0.64^a	-0.07^a	-0.07^a	-0.64^a	0.03^c
	(0.01)	(0.06)	(0.02)	(0.01)	(0.06)	(0.02)
Intercept	0.62	4.11	10.12^a	0.62	4.11	-2.44^c
	(0.44)	(3.72)	(1.59)	(0.44)	(3.72)	(1.42)
Observations	1,844	1,844	1,844	1,844	1,844	1,844
Adjusted R^2	0.82	0.86	0.30	0.82	0.86	0.07

Heteroscedasticity-robust standard errors in parentheses.
^{a}, ^{b}, ^{c}: Significant at the 1%, 5% and 10% levels, respectively.

Tables

Table A.9 shows the summary statistics of the electricity price components, while table A.10 and A.11 tabulate the depreciation rate ($\delta_{lifetime}$) and the interest rate ($r_{t,canton}$) used in equation 15.

Table A.9: Summary statistics of electricity prices.

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Marginal price peak (Rp./kWh)	17.03	2.72	14.28	22.25	1502
Marginal price off-peak (Rp./kWh)	8.18	2.15	4.20	12.26	1502
Fixed fee for time-of-use tariff (CHF/year)	77.55	71.77	0.00	444.00	1502
Marginal prices for single tariff (Rp./kWh)	18.33	2.61	15.00	21.75	442
Fixed fee for single tariff (CHF/year)	101.21	35.53	42.00	306.00	442
Average price (Rp./kWh)	17.28	5.73	2.83	62.80	1944
ElCom price (Rp./kWh)	16.03	4.37	8.02	29.75	1844

Table A.10: Depreciation rates used for different appliances.

Appliance	**Lifetime (years)**	**Depreciation rate**
PC, TV	5	0.2
Dishwasher, microwave	10	0.1
Clothes washer, tumble dryer, refrigerator	12	0.08
Freezer	15	0.07
Boiler, stove	20	0.05

Table A.11: Annual interest rates for different locations and years.

Utility	**2005**	**2011**
1	3.658	2.991
2 and 7	3.545	3.000
3 and 6	3.667	2.821
4	3.540	2.841
5	3.676	2.984

Appendix for Essay 2

Electricity Price

Based on the information from residential electricity tariffs, we calculate a weighted average electricity price for each utility and year as

$$
\begin{aligned}
P_{average} = {} & \frac{customer_{tou}}{customer_{total}} \cdot \frac{E_{peak} \cdot MP_{peak} + E_{off-peak} \cdot MP_{off-peak} + FixedFee_{tou}}{E_{tou}} \\
& + \left(1 - \frac{customer_{tou}}{customer_{total}}\right) \cdot \frac{E_{single} \cdot MP_{single} + FixedFee_{single}}{E_{single}},
\end{aligned} \tag{37}
$$

where E_{peak} is the peak period consumption per customer with a time-of-use tariff, $E_{off-peak}$ is the off-peak period consumption per customer with a time-of-use tariff, E_{single} is the consumption of a customer with a single tariff, MP_{peak} is the marginal price of electricity in peak periods, $MP_{off-peak}$ is the marginal price of electricity in off-peak periods, MP_{single} is the marginal price of electricity for customers with a single tariff system, $customer_{total}$ is the total number of customers of a particular utility, $customer_{tou}$ is the number of customers of a particular utility that have a time-of-use scheme, $customer_{single}$ is the number of customers of a particular utility that have a single tariff system, and $FixedFee$ is the fixed fee with subscripts tou and $single$ denoting the tariff scheme to which a customer belongs.

Cover Letter - German

Sehr geehrter Herr/Frau ...,

Das Centre for Energy Policy and Economics (CEPE) der ETH Zürich befasst sich seit langem mit dem Thema Stromnachfrage in der Schweiz. Das CEPE führt nun wiederum eine Untersuchung durch, nachdem im Jahr 2008 eine wissenschaftliche Studie zum Effekt zeitabhängiger Strompreise (Hoch-/Niedertarif) auf das Nachfrageverhalten erstellt wurde. Eine Zusammenfassung dieser Studie finden Sie im Anhang. Nun sollen diese Ergebnisse im Hinblick auf die Energiestrategie 2050, welche der Energieeffizienz eine grosse Rolle beimessen wird, aktualisiert und erweitert werden. Die Studie "*Eine Evaluation der Auswirkungen von Energieeffizienzmassnahmen auf den Stromverbrauch von Haushalten*" wird mit der Finanzierung des Bundesamts für Energie (BFE) und der Unterstützung des Verbands Schweizerischer Elektrizitätsversorgern (VSE) durchgeführt.

Im Rahmen dieses Projektes führen wir eine Befragung bei Schweizer Elektrizitätsversorgern durch, wobei wir Daten zum Stromabsatz an Haushaltskunden, zur Anzahl Haushaltskunden und zu den Stromtarifen für die Jahre 2006 bis 2012 sammeln. Zusätzlich möchten wir in einem zweiten Schritt auch Daten zu durchgeführten Effizienzmassnahmen bei Haushaltskunden und deren Kosten erheben.

Wir sind überzeugt, dass die Ergebnisse dieser neuen Untersuchung sowohl als hilfreiches Element für die zukünftige Ausgestaltung energiepolitischer Massnahmen, als auch für das Beantworten von unternehmens-strategische Fragestellungen dienen. Wir wären Ihnen daher sehr dankbar, wenn Sie das angehängte Excel-File bis spätestens am XX. YY 2013 ausfüllen könnten. Die Daten werden streng vertraulich behandelt und nur im Rahmen des Projektes und für wissenschaftliche Arbeiten am CEPE verwendet. Zudem werden die Daten nur in aggregierter und anonymisierter Form publiziert.

Wir danken Ihnen im Voraus für die wertvolle Unterstützung. Am Ende des Fragebogens haben Sie die Möglichkeit anzugeben, ob Sie über die Resultate informiert werden möchten. Bei Rückfragen steht Ihnen Frau Nina Boogen (nboogen@ethz.ch, +41 44 632 88 45) gerne zur Verfügung.

Mit freundlichen Grüssen

Nina Boogen

Cover Letter - French

Monsieur/Madame ...,

Le Centre for Energy Policy and Economics (CEPE) de l'EPF Zurich travaille depuis longtemps sur le théme de la demande d'électricité en Suisse. Le CEPE effectue à présent une nouvelle étude faisant suite à l'étude scientifique de 2008 qui traitait des effets de la tarification de l'électricité en fonction de l'heure (haut/bas tarif) sur la demande. Vous trouverez un résumé de cette étude en annexe. Ces résultats doivent maintenant être actualisés et élargis dans l'optique de la Stratégie énergétique 2050, laquelle accorde un rôle majeur à l'efficacité énergétique. Cette étude "*Eine Evaluation der Auswirkungen von Energieeffizienzmassnahmen auf den Stromverbrauch von Haushalten*" (Une évaluation des effets des mesures d'efficacité énergétique sur la consommation en électricité des ménages) est réalisée grâce au financement de l'Office fédéral de l'énergie (OFEN) et au soutien de l'Association des entreprises électriques suisses (AES).

Dans le cadre de ce projet, nous effectuons un sondage auprès des entreprises électriques suisses et collectons ainsi des données sur les ventes d'électricité aux ménages, le nombre de ménages clients et les tarifs de l'électricité dans les années 2006 á 2012. Nous aimerions de plus, au cours d'une deuxième étape, récolter des données relatives aux mesures d'efficacité appliquées auprès des ménages et á leurs coûts.

Nous sommes convaincus que les résultats de cette nouvelle étude constitueront des aides précieuses pour l'organisation future des mesures de politique énergétique ainsi que pour répondre aux questions d'ordre stratégique des entreprises. Nous vous serions donc très reconnaissants de remplir le fichier Excel ci-joint d'ici le XX. YY 2013 au plus tard. Ces données seront traitées de manière strictement confidentielle et ne seront utilisées que dans le cadre du projet et de travaux scientifiques au CEPE. Elles ne seront en outre publiées que sous forme regroupée et anonyme.

Nous vous remercions d'avance de votre précieux soutien. Vous avez la possibilité, en fin de questionnaire, d'indiquer si vous souhaitez être informé des résultats. Madame Nina Boogen (nboogen@ethz.ch, +41 44 632 88 45) se tient volontiers à votre disposition pour tout complément d'information.

Meilleures salutations,

Nina Boogen

Cover Letter - Italian

Gentile Signor/Signora...,

il "Centre for Energy Policy and Economics (CEPE)" del Politecnico Federale di Zurigo e diretto dal Prof. Massimo Filippini, si occupa da tempo di analizzare con metodi empirici i fattori che influenzano la domanda di energia elettrica. A questo proposito il CEPE ha pubblicato nel 2008 uno studio scientifico sull'effetto delle tariffe differenziate nel tempo (giorno-notte) sulla domanda di elettricitá (si veda il riassunto nel documento allegato).

Nell'ambito dei progetti di ricerca promossi dall'Ufficio federale dell'energia per la realizzazione della Strategia Energetica 2050, il CEPE sta realizzando un nuovo studio sulla domanda di energia elettrica e sull'impatto sulla domanda delle misure a favore dell'efficienza energetica. Il titolo dello studio realizzato anche con l'appoggio della Verband der schweizerischen Elektrizitätsunternehmen (VSE) è: "*Eine Evaluation der Auswirkungen von Energieeffizienzmassnahmen auf den Stromverbrauch von Haushalten*"

Per svolgere questo studio sono necessari dei dati riguardanti la domanda di energia elettrica come ad esempio le vendite ed il numero di clienti. A questo proposito stiamo conducendo un'inchiesta presso un campione di aziende di distribuzione di energia elettrica. Inoltre, in una seconda parte dell'inchiesta verranno chieste informazioni su misure introdotte dalle singole aziende elettriche a favore di un miglioramento dell'efficienza energetica

Siamo convinti che i risultati di questa nuova indagine possano sia all'Ufficio federale dell'energia che alle aziende elettriche nella definizione delle nuove strategie di politica energetica. Le saremmo pertanto molto grati se potesse compilare il file Excel allegato entro e non oltre il XX. YYY 2013. I dati verranno trattati in modo strettamente confidenziale e utilizzati esclusivamente nell'ambito del progetto e per lavori scientifici presso il CEPE. Inoltre, i dati verranno pubblicati solamente in forma aggregata e anonima.

La ringraziamo anticipatamente per il prezioso sostegno! Alla fine del questionario Le viene fornita la possibilità di indicare se desidera ricevere informazioni sui risultati dello studio. In caso di chiarimenti può rivolgersi a Nina Boogen (nboogen@ethz.ch, +41 44 632 88 45) che è a Sua completa disposizione.

Cordiali saluti,

Nina Boogen

Survey - German

Bitte füllen Sie diese Tabelle möglichst vollständig aus. Bei Fragen steht Ihnen Frau Nina Boogen (nboogen@ethz.ch, +41 44 632 88 45) gerne zur Verfügung. Haushaltskunden werden hier als Kleinkunden (Niederspannung) ohne Leistungsmessung definiert. Wenn möglich geben sie die Angaben in den Kalenderjahren an. Falls sich Ihre Daten auf das hydrologische Jahr bezieht, bemerken Sie das bitte.

Unternehmen
Bezeichnung

Preise	2006	2007	2008	2009	2010	2011	2012
Hochtarif (Rp./kWh)							
Niedertarif (Rp./kWh)							
Monatlicher Grundtarif Doppeltarif (CHF)							
Einheitstarif (Rp./kWh)							
Monatlicher Grundtarif Einheitstarif (CHF)							

Anteil der Kunden des repräsentativsten Produkts	2006	2007	2008	2009	2010	2011	2012
50-70%							
70-90%							
über 90%							

Grüner Strom	2006	2007	2008	2009	2010	2011	2012
0-5%							
5-10%							
10-15%							
über 15%							

	Ja	Nein
Haben sie in der Periode zwischen 2006 und 2012 die Tarifzeiten für Hoch und Niedertarifstrom geändert?		

Anzahl private Haushaltskunden	2006	2007	2008	2009	2010	2011	2012
Anzahl Haushaltskunden total							
Anzahl Haushaltskunden im Doppeltarifsystem							
Anzahl Haushaltskunden im Einheitstarifsystem							

Stromlieferungen an private Haushaltskunden	2006	2007	2008	2009	2010	2011	2012
Hochtarif (MWh)							
Niedertarif (MWh)							
Einheitstarif (MWh)							

Kontaktperson für Energieeffizienzmassnahmen
Name
E-Mail
Telefon

Rechtsform des Unternehmens	Ja
unselbstständige öffentlich rechtliche Anstalt	
selbstständige öffentlich rechtliche Anstalt	
Aktiengesellschaft: 100% öffentlich	
Aktiengesellschaft: mehrheitlich öffentlich	
Aktiengesellschaft: minderheitlich öffentlich	

Eigenproduktion	0-25%	25-50%	50-75%	75-100%
Anteil Eigenproduktion am Verkauf				

Gas	2006	2007	2008	2009	2010	2011	2012
Gas-Produktpreis (Rp./kWh)							
Grundpreis (CHF/Monat)							

	Ja	Nein
Möchten Sie über die Ergebnisse dieser Studie informiert werden?		

Kommentar:

Figure A.1: Survey questions part I – German

Bitte füllen Sie diese Tabelle möglichst vollständig aus. Bei Fragen steht Ihnen Frau Nina Boogen (nboogen@ethz.ch, +41 44 632 88 45) gerne zur Verfügung. Haushaltskunden werden hier als Kleinkunden (Niederspannung) definiert. Wenn möglich geben sie die Angaben in den Kalenderjahren an. Falls sich Ihre Daten auf das hydrologische Jahr bezieht, bemerken Sie das bitte.

	Unternehmen	
1	Bezeichnung	

		Ja	**Nein**	**Seit wann**
2a	Hat Ihr Unternehmen einen gesetzlichen Leistungsauftrag zur Steigerung der Stromeffizienz bei Haushaltskunden			
2b	Verfügt Ihr Unternehmen über eine Strategie und konkrete Ziele zur Steigerung der Stromeffizienz bei Haushaltskunden			

	Falls 2a oder 2b mit ja beantwortet:	**Ja**	**Nein**	**Seit wann**
2c	Sind Ihre Ziele quantifiziert?			
2d	Hat Ihr Unternehmen aufgrund des gesetzlichen Leistungsauftrag / Strategie ein Fonds für Effizienzmassnahmen bei Haushaltskunden?			

	Tarifstruktur für Haushaltskunden	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
3a	Haben Sie verschiedene Tarife für Haushaltskunden entsprechend ihrem Verbrauch							
3b	Falls ja: Sin d diese Tarife abfallend mit steigendem Verbrauch							
3c	Falls ja: Sin d diese Tarife ansteigend mit steigendem Verbrauch							
3d	Haben Sie einen Tarif für unterbrechbare/sperrbare Geräte für Haushaltskunden							

	Welche der folgenden Massnahmen führen Sie in Ihrem EVU zur Förderung der Stromeffizienz bei Haushaltskunden durch? Bitte zutreffendes ankreuzen	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
4a	Informationsmaterial							
4b	Öffentlichkeitsarbeit							
4c	Verleih Strommessgeräte							
4d	Information zur Entwicklung des Stromverbrauchs der einzelnen Kunden							
4e	Energieberatungszentrum							
4f	Persönliche Energieberatung							
4g	Beratung Ersatz ineffizienter Haushaltsgeräte							
4h	Beratung Ersatz Elektrospeicherheizungen und Elektroboilern							
4i	Finanzielle Förderung Ersatz ineffizienter Haushaltsgeräte							
4j	Finanzielle Förderung Ersatz Elektrospeicherheizungen und Elektroboilern							
4k	Tarifliche Massnahmen zur Lenkung des Stromverbrauchs							
4l	Andere (bitte im Kommentarfeld spezifizieren)							

	Ausgaben	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
5a	Jährliche Ausgaben für alle Energieeffizienzmassnahmen bei Haushaltskunden (CHF)							
5b	Jährliche Ausgaben für die Finanziellen Förderprogramme bei Haushaltskunden (CHF)							

	Ja	**Nein**
Möchten Sie über die Ergebnisse dieser Studie informiert werden?		

Kommentar:

Figure A.2: Survey questions part II – German

Survey - French

Merci de compléter au mieux ce tableau. Madame Nina Boogen (nboogen@ethz.ch, +41 44 632 88 45) se tient volontiers à votre disposition pour toute question. Les ménages sont ici définis comme de petits clients (basse tension) sans mesure de puissance. Indiquez si possible les informations par année civile. Si vos données se rapportent à l'année hydrologique, merci de le mentionner.

Entreprise
Désignation

Prix	2006	2007	2008	2009	2010	2011	2012
Haut tarif (cts/kWh)							
Bas tarif (cts/kWh)							
Tarif de base mensuel tarif double (CHF)							
Tarif simple (cts/kWh)							
Tarif de base mensuel tarif simple (CHF)							

Part des clients utilisant le produit le plus représentatif	2006	2007	2008	2009	2010	2011	2012
50-70%							
70-90%							
Plus de 90%							

Courant vert	2006	2007	2008	2009	2010	2011	2012
0-5%							
5-10%							
10-15%							
Plus de 15%							

	Oui	Non
Avez-vous modifié les périodes tarifaires de l'électricité à haut et bas tarif entre 2006 et 2012?		

Nombre de ménages privés	2006	2007	2008	2009	2010	2011	2012
Nombre total de ménages							
Nombre de ménages au sein du système de tarif double							
Nombre de ménages au sein du système de tarif simple							

Livraison d'électricité aux ménages privés	2006	2007	2008	2009	2010	2011	2012
Haut tarif (MWh)							
Bas tarif (MWh)							
Tarif simple (MWh)							

Personne à contacter pour les mesures d'efficacité énergétique
Nom
E-mail
Téléphone

Forme juridique de l'entreprise	Oui
Etablissement de droit public non autonome	
Etablissement de droit public autonome	
Société anonyme 100% ouverte au public	
Société anonyme: majoritairement ouverte au public	
Société anonyme: majoritairement privée	

Production personnelle	0-25%	25-50%	50-75%	75-100%
Part de la production personnelle dans les ventes				

Gaz	2006	2007	2008	2009	2010	2011	2012
Prix du gaz (cts/kWh)							
Prix de base (CHF/mois)							

	Oui	Non
Souhaitez-vous être informé des résultats de cette étude?		

Commentaire

Figure A.3: Survey questions part I – French

Merci de compléter au mieux ce tableau. Madame Nina Boogen (nboogen@ethz.ch, +41 44 632 88 45) se tient volontiers à votre disposition pour toute question. Les clients particulier (ménages) sont ici définis comme de petits clients (basse tension). Indiquez si possible les informations par année civile. Si vos données se rapportent à l'année hydrologique, merci de le mentionner.

	Entreprise			
1	Désignation			
		Oui	**Non**	**Depuis quand**
2a	Est-ce que votre entreprise a un mandat légal pour accroître l'efficacité énergétique des clients particuliers (ménages)?			
2b	Votre entreprise dispose-t-elle d'une stratégie et d'objectifs précis pour accroître l'efficacité énergétique des particuliers (ménages)?			
	Si vous avez répondu "oui" à 2a ou 2b:	**Oui**	**Non**	**Depuis quand**
2c	Avez-vous quantifié ces objectifs?			
2d	Votre entreprise dispose-t-elle d'un fonds destiné aux mesures d'efficacité énergétique des particuliers (ménages) qui résulte du mandat légal/de la stratégie?			

	Tarifs payés par les particuliers	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
3a	Appliquez-vous des tarifs différents en fonction de la consommation des particuliers (ménages)?							
3b	Si oui, ces tarifs baissent-ils avec la consommation?							
3c	Si oui, ces tarifs augmentent-ils avec la consommation?							
3d	Appliquez-vous un tarif propre aux appareils interruptibles / verrouillables des particuliers (ménages)?							

	Parmi les mesures suivantes, quelles sont celles que votre entreprise effectue afin de promouvoir l'efficacité énergétique des particuliers (ménages)? Veuillez cocher les cases correspondantes	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
4a	Matériel d'information							
4b	Relations publiques							
4c	Location de Power Meters							
4d	Informations relatives au développement de la consommation d'énergie du client							
4e	Centre de conseil destiné à l'efficacité énergétique							
4f	Entretiens individuels pour promouvoir l'efficacité énergétique							
4g	Conseils concernant le remplacement des appareils inefficaces							
4h	Conseils concernant le remplacement des chaudières et des chauffages électriques							
4i	Soutien financier au remplacement des appareils inefficaces							
4j	Soutien financier au remplacement des chaudières et des chauffages électriques							
4k	Mesures tarifaires pour diriger la consommation d'électricité							
4l	Autre (veuillez préciser dans les commentaires)							

	Dépenses	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
5a	Dépenses annuelles pour toutes les mesures d'efficacité énergétique des clients particuliers(CHF)							
5b	Dépenses annuelles pour les programmes de soutien financier destinés aux clients particulier (CHF)							

	Oui	**Non**
Souhaitez-vous être informé des résultats de cette étude?		

Commentaire

Figure A.4: Survey questions part II – French

Survey - Italian

La preghiamo di compilare questa tabella nel modo più completo possibile. Può rivolgere eventuali domande a Nina Boogen (nboogen@ethz.ch, +41 44 632 88 45) che è a Sua completa disposizione. I clienti domestici vengono qui definiti come piccoli clienti (bassa tensione) senza misurazione della potenza. Se possibile, riporti i dati negli anni civili. Se i Suoi dati sono riferiti all'anno idrologico, La preghiamo di annotarlo sul questionario.

Azienda
Nome

Prezzi	2006	2007	2008	2009	2010	2011	2012
Tariffa alta (ct./kWh) (tariffa diurna)							
Tariffa bassa (ct./kWh) (tariffa notturna)							
Tariffa di base mensile (CHF) per clienti con alta e bassa tariffa							
Tariffa unitaria (ct./kWh)							
Tariffa di base mensile (CHF) per clienti con tariffa unitaria							

Quota dei clienti con il tariffa più rappresentativa	2006	2007	2008	2009	2010	2011	2012
50-70%							
70-90%							
oltre il 90%							

Corrente verde	2006	2007	2008	2009	2010	2011	2012
0-5%							
5-10%							
10-15%							
oltre il 15%							

	Si	No
Nel periodo dal 2006 al 2012 sono stati modificati gli orari per l'applicazione della tariffa alta/bassa?		

Numero di clienti domestici privati	2006	2007	2008	2009	2010	2011	2012
Numero totale di clienti domestici							
Numero totale di clienti domestici nel sistema a tariffa doppia							
Numero totale di clienti domestici nel sistema a tariffa unitaria							

Forniture di corrente a clienti domestici privati	2006	2007	2008	2009	2010	2011	2012
Tariffa alta (MWh)							
Tariffa bassa (MWh)							
Tariffa unitaria (MWh)							

Referente all'interno dell'azienda per i provvedimenti di efficienza energetica
Nome
E-mail
Telefono

Forma giuridica dell'azienda	Si
Ente dipendente di diritto pubblico	
Ente indipendente di diritto pubblico	
Società anonima: 100% pubblica	
Società anonima: prevalentemente pubblica	
Società anonima: in minoranza pubblica	

Produzione propria	0-25%	25-50%	50-75%	75-100%
Quota di produzione propria nelle vendite				

Gas	2006	2007	2008	2009	2010	2011	2012
Prezzo dei prodotti gas (ct./kWh)							
Prezzo di base (CHF/mese)							

	Si	No
Interessa essere informati sui risultati di questo studio?		

Commento:

Figure A.5: Survey questions part I – Italian

La preghiamo gentilmente di compilare questa tabella nel modo più completo possibile. Può rivolgere eventuali domande a Nina Boogen (nboogen@ethz.ch, +41 44 632 88 45) . I clienti domestici vengono qui definiti come piccoli clienti (bassa tensione). Se possibile, riporti i dati negli anni civili. Se i dati dell'azienda sono riferiti all'anno idrologico, La preghiamo di annotarlo sul questionario.

	Azienda							
1	Nome							
		Si	**No**	**Da che anno**				
2a	La vostra azienda ha un contratto legale per aumentare l'efficienza energetica per i clienti domestici							
2b	La vostra azienda ha definito una strategia e fissato degli obiettivi annuali per aumentare l'efficienza energetica dei clienti domestici							
	Se la risposta alla domanda 2a o 2b è si:	**Si**	**No**	**Da che anno**				
2c	I vostri obiettivi sono quantificati?							
2d	La vostra azienda ha creato un fondo speciale per finanziare la realizzazione di misure di efficienza energetica presso i clienti domestici?							
	Struttura delle tariffe per i clienti domestici	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
3a	La tariffa varia al variare del consumo?							
3b	Se si, la tariffa diminuisce all'aumentare del consumo							
3c	Se si, la tariffa aumenta all'aumentare del consumo							
3d	Avete una tariffa speciale per i clienti con possibilità di blocco della fornitura per apparecchi elettrici?							
	Quale misure sono state adottate dalla vostra azienda per promuovere l'efficienza energetica dei clienti domestici? Apporre una crocetta alla risposta più appropriata	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
4a	Promozione di informazione riguardante l'efficienza energetica							
4b	Eventi pubblici							
4c	Noleggio di misuratori di consumo di elettricità							
4d	Informazioni riguardanti l'andamento del consumo di ogni cliente							
4e	Presenza di un centro di consulenza per l'efficienza energetica							
4f	Offerta di consulenza energetica a domicilio personalmente							
4g	Consulenza per l'acquisto o la sostituzione di elettrodomestici							
4h	Consulenza per l'acquisto o la sostituzione di impianti di riscaldamento elettrici e boiler elettrici							
4i	Sostegno finanziario per la sostituzione di elettrodomestici inefficienti							
4j	Sostegno finanziario per la sostituzione di impianti di riscaldamento elettrici e boiler elettrici							
4k	Avete misure tariffarie particolari per promuovere l'efficienza energetica?							
4l	Altre misure a favore dell'efficienza energetica (specificare nel box commenti)							
	Spese	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
5a	La spesa annua per tutte le misure a favore dell' efficienza energetica per i clienti domestici (CHF)							
5b	Spese annuali per tutti i programmi di sostegno finanziario all'introduzione di misure di efficienza energetica per i clienti domestici (CHF)							
		Si	**No**					
	Interessa essere informati sui risultati di questo studio?							
	Commento							

Figure A.6: Survey questions part II – Italian

Appendix for Essay 3

Table A.12: Minimum energy services

Service	**Appliance**	**Frequency**	**kWh per service**	**kWh per year**
Cooling food	Fridge	–	–	250
Eating at home	Stove	3 meals per week	0.33 per meal	50
Lighting one room	Bulbs	2 hours per day	0.1 per hour	75
Entertainment	TV and PC	2 hours	0.1 per hour	75
Clothes washing	Washing machine	1 per week	1 per cycle	50
Showering	Electric boiler	0.7 per day 250 days per year	1.6 per shower	400

Table A.13: Minimum electricity consumption

	Cooling	**Eating**	**Lighting**	**Entertainment**	**Washing**	**Shower**	**Minimal kWh/year**
Single household	Yes	Yes	Yes	Yes	No	No	450
Single household	Yes	Yes	Yes	Yes	Yes	No	500
Single household	Yes	Yes	Yes	Yes	No	Yes	850
Additional member	Yes	Yes	Yes	Yes	No	No	+100 per person
Additional member	Yes	Yes	Yes	Yes	Yes	No	+150 per person
Additional member	Yes	Yes	Yes	Yes	No	Yes	+500 per person