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Three Essays on Swiss Household Energy Demand

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FACULTÉ DES SCIENCES ÉCONOMIQUES

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sur le rapport des membres du jury

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Autorise l'impression de la présente thèse.

Neuchâtel, le 14 septembre 2021

Le doyen
Valéry Bezençon

Abstract

This dissertation consists of three chapters examining different aspects of Swiss household energy demand. They consecutively address overall household energy requirements, the major energy carrier that households use within their homes – electricity, and finally, the main reason for energy consumption outside the dwelling – car travel. The empirical analyses of the determinants of energy demand in each chapter, in particular the focus on energy prices and/or household income, as well as their study for different groups of consumers, strive to gain a better insight into the energy-related behaviors and decisions of households, and thereby to provide evidence-based inputs for policies targeting reductions in household energy demand.

The first chapter of this thesis analyzes the interactions between direct and embodied energy requirements of Swiss households in order to assess the net impacts of standard energy policies focusing exclusively on direct energy use. By using a system of equations and instrumental variable methods, the empirical analyses provide evidence of complementarity between direct and embodied energy demand. In addition, we find that income has a positive non-linear effect on each energy domain, which is particularly important for embodied energy. These results highlight a concern that economic growth could bring about an increasing global energy demand through the consumption of non-energy commodities. However, policymakers could more actively target direct energy consumption caused by the possibility of positive spillovers to embodied energy. Given the substantial proportion of non-energy goods in total energy demand, this could be coupled with interventions specific to embodied energy use.

The second chapter of this dissertation addresses the question of heterogeneity in the price and income elasticities of Swiss households electricity demand. In particular, the focus is on segments of consumers with different intensity of electricity consumption. Price and income elasticities are analyzed by using a quantile regression approach adapted for panel data. While findings show a price-inelastic electricity demand across all groups, an interesting pattern of variation emerges between frugal and intensive users. Households in the first conditional quartile and at the median react significantly to price variations, whereas those at the lowest quantile and upper quantiles exhibit insignificant price elasticities. In contrast, we find insignificant income effects across all the previous household groups.

The third, final chapter examines heterogeneity in the field of household car travel demand. Price elasticities are estimated for various groups of drivers based on their socio-demographic characteristics, on the features of their vehicles, as well as on their driving intensity. Results show higher short-term gasoline price elasticity of driving demand compared with previous estimations for Switzerland, as well as heterogeneity in price sensitivity across segments of households. Fixed effect models including interaction terms indicate that multiple-member households are significantly more price-elastic compared to households comprising a single member. Quantile regression with correlated random effects shows that only the most intensive drivers exhibit a statistically significant price elasticity. The results from this and the previous chapter emphasize the importance of heterogeneous responses for the efficiency and equity of energy-related policies. These findings reveal that, in addition to energy taxes, non-price measures could be tailored to specific household segments in order to provide supplementary incentives to reduce energy demand and/or avoid penalizing some specific consumer groups.

Résumé

Cette thèse est composée de trois chapitres qui examinent différents aspects de la demande d'énergie des ménages en Suisse. Ils abordent successivement les besoins énergétiques globaux des ménages, la source principale d'énergie utilisée à l'intérieur du logement - l'électricité, et enfin, la principale raison de la consommation d'énergie à l'extérieur du logement - les déplacements en voiture. Les analyses empiriques des déterminants de la demande d'énergie dans chaque chapitre, en particulier l'accent mis sur les prix de l'énergie et/ou le revenu des ménages, ainsi que leur étude pour différents groupes de consommateurs, ont pour objectif de mieux comprendre les comportements et les décisions des ménages, et ainsi de fournir des intrants concrets pour les politiques visant à réduire la demande d'énergie des ménages.

Le premier chapitre de cette dissertation se focalise sur les interactions entre les besoins d'énergie directe et d'énergie grise afin d'évaluer les impacts nets des politiques énergétiques standards se concentrant exclusivement sur l'utilisation d'énergie directe. En utilisant un système d'équations et des méthodes de variable instrumentale, les analyses empiriques montrent que les demandes d'énergie directe et d'énergie grise sont complémentaires. En outre, nous constatons que le revenu a un effet positif non-linéaire sur chaque domaine énergétique, effet qui est particulièrement prononcé pour l'énergie grise. Ces résultats mettent en évidence le fait que la croissance économique pourrait entraîner une augmentation de la demande d'énergie mondiale à travers une augmentation de la consommation de biens et services non-énergétiques. Ainsi, les décideurs politiques pourraient cibler plus activement la consommation directe d'énergie en raison de la possibilité de retombées positives sur l'énergie grise. Au vu de la proportion substantielle de l'énergie grise dans la demande totale d'énergie, cela pourrait être couplé à des interventions spécifiques à ce domaine énergétique.

Le deuxième chapitre de cette thèse aborde la question de l'hétérogénéité des élasticités prix et revenu de la demande d'électricité des ménages suisses. En particulier, l'accent est mis sur les segments de consommateurs ayant une intensité de consommation d'électricité différente. Les élasticités de prix et de revenu sont analysées en utilisant une approche de régression quantile adaptée aux données de panel. Même si nos résultats montrent une demande d'électricité inélastique par rapport au prix dans tous les groupes de consommation, une différence intéressante peut être observée entre les utilisateurs frugaux et les utilisateurs intensifs d'électricité. Les ménages du premier quartile conditionnel et de la médiane réagissent de manière significative aux variations de prix, tandis que ceux du quantile inférieur et des quantiles supérieurs présentent des élasticités-prix non-significatives. En outre, l'analyse de nos données montre des effets de revenu non-significatifs dans tous les groupes de ménages précédents.

Le troisième, et dernier, chapitre examine la présence d'hétérogénéité dans le domaine de la demande de déplacements en voiture des ménages. Des élasticités-prix sont estimées pour divers segments de conducteurs en fonction de leurs caractéristiques sociodémographiques, des caractéristiques de leurs véhicules, ainsi que de leur intensité de conduite. Nos résultats montrent une élasticité-prix de la demande de déplacements en voiture plus élevée que les estimations précédentes pour la Suisse pour le court terme, ainsi que l'existence d'hétérogénéité dans la sensibilité au prix pour différents groupes de ménages. Des modèles à effet fixe avec des termes d'interaction indiquent que les ménages composés de plusieurs membres sont significativement plus élastiques au prix que les ménages simples. Une régression quantile avec des effets aléatoires corrélés montre que seuls les conducteurs les plus intensifs présentent une élasticité-prix statistiquement significative. Les résultats de ce chapitre, ainsi que ceux du chapitre précédent soulignent l'importance de la prise en compte de l'existence d'hétérogénéité pour l'efficacité et l'équité des politiques énergétiques. Ils révèlent notamment qu'en plus des taxes sur l'énergie, des interventions non-tarifaires conçues sur mesure pourraient cibler des segments spécifiques de ménages afin de fournir des incitations supplémentaires à réduire la demande d'énergie et/ou d'éviter de pénaliser certains groupes de consommateurs spécifiques.

Keywords

Households, Switzerland, direct energy requirements, embodied energy requirements, Kuznets curve, electricity demand, electricity price, vehicle kilometers traveled (VKT), car-travel demand, gasoline price, price elasticity, income elasticity, household behavior, heterogeneity, seemingly unrelated regressions (SUR), instrumental variable regression, quantile regression, interaction terms, cross-section data, panel data.

Mots-clés

Ménages, Suisse, consommation d’énergie directe, consommation d’énergie grise, courbe de Kuznets, demande d'électricité, prix d'électricité, kilomètres parcourus en voiture (VKT), demande de déplacements en voiture, prix de l'essence, élasticité-prix, élasticité-revenus, comportement des ménages, hétérogénéité, régressions apparemment indépendantes (SUR), régression par variable instrumentale, régression quantile, termes d'interaction, données transversales, données de panel.

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Q40; Q41; D12, R41, C21.

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Introduction

a. Policy context and motivation

In Switzerland, households account for a one-third share of overall energy demand, thus representing a greater proportion than that of the service sector, or of the construction and the manufacturing sectors combined (OFS, 2020a). In addition, Swiss households account for approximately 30% of overall electricity demand and 60% of total motor fuel demand, with these two energy carriers each representing approximately 20% of the country's overall energy demand (OFS, 2020a).

It is therefore not surprising that the *Energy Strategy 2050* developed by the Swiss Federal Government places a marked emphasis on the reduction of household energy demand[1] in its first package of measures, via its energy efficiency program (OFEN, 2019a; Swiss Federal Council, 2013). This program consists of several action points. First, various subsidies are available to households for building renovations and efficient constructions, such as the insulation of their homes or the replacement of their old heating systems with new or more efficient equipment. In order to encourage investment in building retrofits, the policy plan allows for deducting the invested amounts from income taxation. The efficiency measures in buildings are financed through a CO_2 tax (96 CHF per ton of CO_2) on heating fossil fuels, i.e., heating oil and natural gas. Second, the efficiency program aims at reducing the allowance for average CO_2 emissions for new passenger cars. Importers of new vehicles are obliged to comply with an emission limit, currently 95 grams of CO_2 per kilometer for each new car imported into Switzerland. Households are indirectly affected by this measure, through the price and availability of the new cars they acquire. Also, the purchase of energy-efficient, hybrid or electric vehicles is encouraged in many cantons and municipalities by the offer of substantial tax rebates (see OFEN, 2019b). Third, the

[1] The energy efficiency program is not strictly limited to households, yet most household-targeting measures are found in this domain. More generally, the *Energy Strategy 2050* defines two other domains of action. The first (and main) one concerns the gradual withdrawal from nuclear power. The five existing power plants in Switzerland will be decommissioned at the end of their programmed lifespan, while the construction of new nuclear generators has been banned. The second major domain of action of the *Energy Strategy 2050* addresses the encouragement of energy production from renewable sources. Towards this end, the following measures concerning the industry have been defined: (1) a feed-in remuneration scheme for operators of facilities producing solar, wind, biomass and geothermal energy, (2) non-recurring contributions covering 30% of the investment costs of photovoltaic facilities and hydropower plants, (3) a market premium for big hydropower plants in the case of a drop in market prices below production costs. Also, renewable energy production is financed by the levy of a fixed supplement to all electricity tariffs, currently 2.3 Swiss Cents per kWh of electricity consumption.

efficiency program of the *Energy Strategy 2050* includes public tenders for projects designed to save the highest amount of kWh per Swiss franc invested. Although the majority of the accepted projects target firms, some of them also address household energy usage, such as improving the energy efficiency of elevators and lighting systems in residential buildings, the replacement of halogen floor lamps in households, or electric water heaters with heat pump water heaters.

The review of existing policy measures regarding household energy demand shows that the *Energy Strategy 2050* focuses exclusively on "direct energy" domains. The term "direct energy" refers to the energy used for heating, electricity and private transportation; that is, the *"…energy carriers purchased by the household itself, in order to cater for energy services…"* (Weber & Perrels, 2000, p.551). Yet, the energy content of many goods and services provided by different economic sectors also serves consumer's needs. The embodied energy contained in the value-chain of these commodities can therefore be considered as the *indirect* energy demand of households. Simply put, embodied, indirect or gray energy is the energy contained in all other non-energy goods and services (Druckman & Jackson, 2008; Munksgaard et al., 2000).[2] In order to obtain a complete picture of the demand for energy stemming from the household sector, both direct and indirect energy requirements should be considered by policy analyses. These should be undertaken not only because of the large share of embodied energy in total energy requirements in developed countries,[3] but also because households could treat embodied and direct energy as substitutes. This could lead to an undesirable indirect rebound effect which could counter the purpose of energy reduction strategies. In other words, policies targeting exclusively reduction of direct energy demand could lead to "energy leakages" at the national and/or global levels. Outsourcing the energy burden to other sectors of the Swiss or world economy could put into perspective the efficiency of policy interventions targeting direct energy demand.

[2] Although the *Energy Strategy 2050* does not discuss the topic of embodied energy, during parliamentary sessions in 2011 the Swiss Federal Council was required to answer whether there was an intention to reduce the consumption of embodied energy in Switzerland: *"The Federal Council considers that a general obligation to declare grey energy on all consumer goods is currently neither feasible nor adequate to achieve the desired objectives. However, the Federal Council does not rule out the possibility that, in certain areas, grey energy declarations could be a useful instrument for increasing transparency vis-à-vis consumers. For this reason, the Federal Council would particularly support efforts by the industry to introduce such a declaration on a voluntary basis."* (SwissParliament, 2011). Despite the fact that the efficiency program *energieschweiz.ch* and the well-know *Pusch* foundation (Pusch, 2021) discuss various energy labels, these concern direct energy use.

[3] The energy embodied in goods and services exceeds the energy directly used from electricity and other fuels by about 50% (among others, Bin & Dowlatabadi, 2005; Lenzen et al., 2006; Dürrenberger et al., 2001; Girod & De Haan, 2010).

The brief presentation of the main instruments of the *Energy Strategy 2050* also shows that, in order to achieve the GHG and energy-reduction goals in the household sector, policy instruments other than energy taxation are preferred and implemented in Switzerland. A first general argument against energy taxation can be found in scientific analyses in energy domains such as household electricity or car-travel demand. Several authors (e.g., Bedir et al., 2013; Brounen et al., 2012; Grønhøj & Thøgersen, 2011; Sanquist et al., 2012; Goodwin et al., 2004; Graham & Glaister, 2004; Labandeira et al., 2017) empirically observe that households' energy demand in those domains is price-inelastic, meaning that the average impact of energy taxes is likely to be only limited. A second argument, frequently put forward, especially in political debate, is that price interventions could negatively affect the well-being of some groups of consumers. (see National Assembly, 2019; UK Parliament, 2020; and Swiss Parliament, 2020).[4] Achieving GHG and energy-related goals with the least amount of social welfare distortions is an essential element in many national energy policies, including the Swiss government's *Energy Strategy 2050* (OFEN, 2019a). The topic of population heterogeneity however allows us to consider the two previous arguments differently. The impact of a price increase might be limited on average, but it could be particularly effective in reducing the energy demand of *some* groups of consumers, while imposing a cost burden on *some* other consumer segments which are not able to reduce their energy demand. Therefore, a knowledge of the manner in which price responsiveness varies between consumption sub-groups could be used to design specific interventions that achieve policy goals with a better investment-impact ratio, in shorter time periods and with fewer welfare distortions, compared to "one-size-fits-all" measures based on the profile of a representative consumer. The study of population heterogeneity can thus be seen as a necessary first step in assessing the efficiency and the equity dimensions of (price-related) policy interventions (Gillingham, 2014; Wadud et al., 2009).[5]

[4] For instance, the violent strikes of the so-called "yellow vests" in France at the end of 2018, which originated after the announcement of an increase in diesel taxes, dramatically illustrate the public focus on this field of energy demand. In fact, the strikers' discontent came mainly from rural regions, which often face lower economic development but have to bear a disproportionate fuel tax burden in comparison with large urban centers (for anecdotal evidence, see *The Economist*, 2018)

[5] Addressing heterogeneity responses could be useful not only for policy purposes. For instance, heterogeneity in electricity demand could also provide important insights with respect to the future liberalization of the country's electricity market for private households and small firms. A recent study shows that 49% of Swiss electricity consumers are not satisfied with their electricity provider, while 58% intend change their current provider (BEN Energy, 2020). Thus, it could be expected that the competition between electricity firms to capture or to keep customers would increase the interest in identifying heterogeneous segments of residential consumers.

The topics discussed in the previous paragraphs, as well as the fact that there is no or only limited research in those fields, as will be shown in the next sub-section, provide the starting point, i.e., the motivation for this dissertation. The first part of this thesis therefore concentrates on the interactions between energy domains, which is essential for avoiding undesired policy effects related to "energy leakages". In the second part, the topic of consumer heterogeneity is examined in detail in order to provide specific inputs for the design of more efficient and equitable policy interventions. Thus, the goal of this dissertation is to provide additional inputs for the design of policy measures in the field of household energy demand, based on the study of household energy-related behavior and decisions. More generally, a common thread connecting the three constituent chapters of this thesis is the interest in the determinants of household energy demand. Among those, energy prices and/or household income are of particular policy interest and are at the center of the analyses presented in the different sections of this work. From an academic perspective, this fundamental research attempts to contribute to a large body of existing literature on household energy demand by addressing in detail research questions that have hitherto received little or no attention. The remainder of this general introduction presents some theoretical considerations with respect to energy demand, defines this thesis' precise research questions, highlights their novelty with respect to earlier studies, and finally discusses the connections between chapters.

b. Theoretical framework, literature and research questions

The substitution or complementarity (i.e., trade-offs) between consumption goods is addressed in consumer theory through the study of substitution elasticities. In the presence of two consumption goods that serve as inputs in a given utility function, this concept describes the variation (as a percentage) in their quantities as a response to variation (again, as percentage) in their prices. In the field of households' total energy requirements, direct and embodied energy can be seen as the bundle of goods between which consumers can choose. Thus, if the satisfaction that a given consumer obtains from using direct and embodied energy is captured by the basic utility function $U(D, E)$, with D denoting direct energy requirements and E embodied energy requirements, then the substitution elasticity between these two goods can be written as $\varepsilon = (d\mathrm{D}/\mathrm{D})/(d\mathrm{E}/\mathrm{E}) = d\ln(D/E)/d\ln(\mathrm{MRS}_{\mathrm{D,E}})$, where $(\mathrm{MRS}_{\mathrm{D,E}})$ is the marginal rate substitution between these two goods, and is dependent on their respective prices. Pollak (1971) underscores the convenience of using the conditional, instead of the unconditional demand function in order to estimate the substitution elasticity between two consumption goods. The former allows the estimation of the cross-price elasticities between consumption domains, which is the first direct way to assess the interactions between them.[6] It also allows us to test whether the demand for one good or service depends on the demand for another, all things being equal, and without taking into account the price of the latter. In other words, the demand for direct energy can be modelled as a function of a set of socio-economic and demographic characteristics specific to direct energy, as well as a function of the demand for embodied energy. In this configuration, a test of separability consists of investigating the significance of the coefficient of embodied energy demand.[7]

In practice, consumers could treat direct and embodied energy, either as complements or substitutes, or indeed independently of each other. For instance, households might react to energy policies such as changes in motor fuel taxation by shifting their direct energy requirements to more embodied energy consumption by increasing the volume of their online purchases (see Jopson, 2011), by flying (see Wadud et al., 2010a) or taking public transportation more frequently. In these examples, direct and embodied energy are treated as substitutes. On the other hand, the acquisition of a new car, heating system or electronic appliance will increase the requirements for both direct and embodied energy by households, since these devices can be operated when powered with direct energy; that is, a complementary relationship could exist between certain categories of direct and embodied energy requirements. While different scenarios concerning the interactions between individual energy categories can be conceived, it is more difficult to assume the existence of a specific interaction when *aggregate* direct and *aggregate* embodied energy requirements are analyzed. This open empirical question is therefore central to Chapter 1.

[6] In this context, embodied (direct) energy could be endogenous due to the existence of unobserved covariates influencing simultaneously embodied and direct energy requirements. To address a similar issue, Leth-Petersen (2002) uses an instrumental variable approach.

[7] The concept of elasticities is not the only way to address the interactions between energy categories. This could be also done by examining the effect of common factors on individual domains of energy requirements. For instance, a congruence in those effects would be a sign of complementarity, while coefficients with opposite signs would indicate substitutability.

Starting with Herendeen (1978), Herendeen et al. (1981) and Herendeen & Tanaka (1976), many authors acknowledge the policy importance of total household energy requirements. Some investigate the effect of different socio-economic and socio-demographic factors that shape the overall energy consumption of households, while others address the determinants of direct and/or embodied energy individually (Pachauri & Spreng, 2002; Abrahamse & Steg, 2009; Reinders et al., 2003; Wiedenhofer et al., 2013), or focus on different estimation-related technical issues, such as the use of physical quantities instead of monetary units for the estimation of energy requirements or GHG emissions (e.g., Girod & De Haan, 2010; Vringer & Blok, 1995). Yet none of those earlier works examines the *dynamics* between direct and embodied energy demand. Leth-Petersen (2002), who analyses the dependencies between the residential demand for gas and electricity in Denmark, stresses the need in future research to test the separability between energy and non-energy consumption categories, meaning the possibility that the demand for one energy domain depends on the demand for energy in another. From a policy perspective, this separability hypothesis is extremely important, for households could treat embodied and direct energy as substitutes. The main contribution of Chapter 1 to the existing literature is thus to examine the interdependences between the two categories of total household energy requirements in order to assess the potential risk of energy transfers between them. Hence, Chapter 1 investigates the following principal research question:

> *Is total Swiss households energy demand characterized by trade-offs between direct and embodied energy requirements?*

A second research question addressed in Chapter 1 revolves around the impact of income on direct and embodied energy demand; that is, around the existence of an energy Kuznets curve (EKC). Originally, the Kuznets curve hypothesis stipulated that income inequalities first increase as a result of economic growth, and decrease when a certain level of affluence has been reached (see Kuznets, 1973). There is nevertheless mixed empirical evidence of the existence of a Kuznets curve in the domains of energy use and GHG emissions (see Stern, 2004; Stern et al., 2017; Luzzati & Orsini, 2009; Özokcu & Özdemir, 2017; Dinda, 2004). Even so, the findings of some recent studies support the existence of a concave relationship between income levels and energy demand (Pablo-Romero & Sánchez-Braza, 2017; Pablo-

Romero et al., 2017).[8] Surprisingly, the question of the impact of economic growth on energy demand has been analyzed only once in the literature on total household energy requirements (*cf.* Lenzen et al., 2006). In fact, the vast majority of studies in the field of total household energy consumption assume that energy requirements grow linearly with household income. This topic is therefore particularly relevant to modern economies pursuing economic growth and better life standards for their citizens. Consequently, Chapter 1 addresses the following additional research question:

> *At different levels of income, what is the effect of income variations on direct and indirect energy consumption?*

To answer the first of the two research questions defined above, Chapter 1 proceeds in three stages. It begins with the analysis of the effect of common determinants on the energy demand in each domain. Because household demand for energy and non-energy goods and services occurs simultaneously, their consumption is examined in a system of equations – the seemingly unrelated regression equations (SUR) method developped by Zellner (1962). To our knowledge, former works in this field do not take simultaneity into account and, like Leth-Petersen (2002), rely mostly on OLS regressions for single consumption categories, a situation that could lead to a significant estimation bias. In Chapter 1, SUR allows us to address this issue. Moreover, SUR delivers the cross-equation correlation of the residuals of direct and embodied energy demand. Prior analyses do not examine this important indicator of the relationship between the unobserved factors shaping consumption in each domain. Finally, we employ an approach similar to that of Leth-Petersen (2002) to address the dynamics between direct and embodied energy requirements in a more straightforward way. We use an instrumental variable approach in a system of equations setup – the 3SLS method suggested by Zellner & Theil (1962), which is another innovation with respect to the analysis of separability of Leth-Petersen (2002). Hence, the three-step approach for the study of the dynamics between direct and embodied energy is the major methodological contribution of Chapter 1 to the existing literature. Concerning our empirical approach to the second research question of Chapter 1, we simply include higher order polynomials of income in different model

[8] This inverted U-shape relationship can be theoretically explained by the developments operating in economic agents' consumption patterns over time, and by their growing awareness of social or environmental issues (Dinda, 2004).

specifications. In our preferred specification, we expect to observe negative income elasticities for some levels of income in order to find evidence for the decreasing part of an EKC (see also Lenzen et al., 2006). We apply those methods to a cross section of households obtained by combining expenditures data from the 2011 Swiss Household Budget Survey (SHBS) with data on the energy content of goods and services from input-output analysis and life-cycle analysis.

While the topic of heterogeneity is indirectly introduced at the end of Chapter 1 through the study of the existence of an EKC, it was not central to this chapter. In contrast, Chapters 2 and 3 examine this topic in detail. The notions of consumer heterogeneity and consumer segmentation are closely related. Segmentation is a concept proper to the domain of marketing and is concerned with the practical identification of groups of consumers, whose different modes of behavior matter for entrepreneurial or policy decision-making (see Klöckner, 2015). Previously, it has been also applied to the field of consumption of energy and environmental resources (e.g., Albert & Maasoumy, 2016; Anable, 2005; Klöckner, 2015; Sütterlin et al., 2011). There are, however, few studies addressing whether different groups of electricity consumers react differently to changes in electricity tariffs (e.g., Frondel et al. 2017, Chindarkar & Goyal, 2019). Earlier findings estimating the average price elasticities of electricity demand have been described as "inconsistent" or exhibiting an essential degree of variation (Espey & Espey, 2004; Fan & Hyndman, 2011; Labandeira et al., 2017; Sanquist et al., 2012) – a fact that could be attributed, not only to differences in data aggregation levels, empirical methods and time horizons, but also to heterogeneity of responses between and within populations (see Miller & Alberini (2016) and Jessoe & Rapson (2014)). In Chapter 2, we argue that there is a ready way to address consumer heterogeneity in the field of residential electricity demand. Because households differ mainly in the type of electronic durables they own and in the way they use them, consumer segments can be directly defined based on the combination of those two dimension, i.e., the intensity of electricity demand. Chapter 2 investigates therefore the following research question:

> *Do segments of households with different intensities of electricity consumption exhibit statistically different price and income elasticities of electricity demand?*

Reiss & White (2003) is the only previous work to adopt a similar starting point and examine the price elasticity of the electricity consumption of different electronic appliances. Its authors find striking differences between the price elasticities of households with large electric appliances and households owning only a set of universally owned electronic durables. In order to provide a more comprehensive picture of price elasticities, they additionally analyse household price elasticities for different tiers of electricity usage. The drawback of this approach is that it truncates the dependent variable in a way that can lead to serious estimation bias, as initially discussed by Heckman (1976). The method of quantile regression (QR) suggested by Koenker & Bassett (1978) allows us to address this issue and to interpret conditional quantiles as different levels of intensity of electricity demand. The contribution of Chapter 2 thus consists in establishing a better understanding the existence of price and income heterogeneity in the field of residential electricity demand. For this purpose, we use a quantile regression approach (QR) which we adapt to panel data estimation by the correlated-random effect (CRE) procedure suggested by Wooldridge (2010). To the best of our knowledge, this method has not been used previously in the field of household electricity demand. QR CRE is applied to a four-year panel dataset obtained from the Swiss Household Energy Demand Survey (SHEDS), which is matched with average electricity price data from Switzerland's electricity market regulator, and with weather data from the Swiss meteorological office.

In contrast to the limited number of works that examine heterogeneous price responses of electricity demand, there is an extensive body of literature on the topic of price heterogeneity of car-travel/fuel demand. However, most studies in this field analyze the US context and often find opposing results. While different empirical methods, temporal horizons and data types could explain such differences, Wadud et al. (2010a) illustrate how plausible real-world scenarios could explain contrasting findings. This provides a motivation for addressing the heterogeneity of price responsiveness in countries other than the US. Moreover, the majority of works in this domain use aggregate price data and rely on cross-section datasets. The application of macro-level price data is likely to be problematic, not only for estimating average price elasticities (De Borger et al., 2016; Levin et al., 2017; Oum et al., 1992), but also for identifying differences in the price reactivities of various segments of drivers, since most of the existing variability in prices is "averaged out" in such datasets. The interpretation of the temporal dimension of cross-section data can also be problematic. On one hand, cross-section comparisons have been considered in many studies as medium- to long-run responses (e.g. Bento et al., 2009; Baltagi & Griffin, 1984; Graham & Glaister, 2002; Wadud et al., 2010). On the other, authors such as De Borger et al. (2016a), Espey (1998), Kayser (2000), Spiller et al. (2017) interpret analyses relying on cross section datasets as translating a short-term framework, because technology is assumed to be fixed. Moreover, price elasticities estimated by using cross section data may be biased, because different drivers might choose to refuel at gas stations with lower gasoline prices. The estimates of gasoline price elasticities should not be affected by self-selection in longitudinal analyses with short panels, because in the short run the choice of where to fill the tank can be assumed to be mainly determined through habit and by convenience preferences (see BCG, 2014; GasBuddy, 2021; Kitamura & Sperling, 1987). Unlike cross-section data, panel data can also provide a more straightforward interpretation of temporal horizons, as well as control for potential biases related to time-invariant factors affecting household driving demand. For these reasons, Chapter 3 is a response to the call launched by Gillingham et al. (2015) and Wadud et al. (2010) for additional research in the field of VKT demand. By focusing on the main domain of energy demand outside the dwelling – car-travel demand, Chapter 3 uses micro-level panel data to examine a similar research question as Chapter 2, namely:

> *Do segments of drivers defined on the basis of socio-economic, socio-demographic and vehicle characteristics, as well as on their driving intensity, exhibit statistically different gasoline price elasticities of car-travel demand?*

Another improvement with respect to the existing literature is the investigation of price heterogeneity via the quantile regression approach with correlated random effects (QR CRE) discussed above. Previously, Gillingham et al. (2015) used a QR method for longitudinal data suggested by Canay (2011). A recent study by Besstremyannaya & Golovan (2019) shows that, in the case of a small number of time periods and an important number observations, as in Gillingham et al. (2015), this could lead to a severe estimation bias. Compared to Chapter 2, Chapter 3 provides a somewhat different interpretation of conditional quantiles. We argue that the definition of "intensity of VKT demand" mainly encompasses behaviors related to car travel, such as travel-related preferences or routines. In addition, the concluding chapter of this dissertation examines, not only segments of consumers based on unobserved factors (i.e., the aforementioned driving behaviors), but also groups of drivers defined on the basis of observed socio-demographic and vehicle characteristics. The empirical analyses in Chapter 3 are based on three consecutive waves of the SHEDS and use individual gasoline price data reported by survey participants.

At this stage, several comments with respect to the modelling of *direct* energy in Chapters 1, 2 and 3 are in order. The empirical analyses presented in those chapters are based on an important theoretical framework, the starting point of which is the fact that, when households use direct energy, they obtain utility from the consumption of two complementary goods: the energy-consuming device (a car, refrigerator or radiator) and the energy carrier (gasoline, electricity or heating oil) used to power that device. This point was mentioned earlier, but it has important theoretical implications that are briefly discussed here. In the short run, the stock of energy-consuming capital can be considered fixed; that is, households do not have the possibility to rapidly replace their energy-consuming durables. Thus, the short-run utility function of a given household can be defined in the following manner:[9]

$$U = f_1(N(Q, \bar{S}), G, D, W), \qquad (1)$$

where N is the energy service, Q is the quantity of the energy carrier consumed (kWh of electricity demand or liters of gasoline), $\bar{S}$ is the fixed stock of energy-consuming capital (type of heating system, quantity of electronic durables or number of cars), G represents the aggregate consumption of all other goods and services, D captures household-specific socio-demographic characteristics and W, other features such as weather (e.g., heating degree days) or building characteristics (vintage, insulation), road quality or traffic congestion rates.

The household decision process can be modelled as an optimization problem. Consumers minimize the variable costs from the usage of a given quantity of an energy service N. Thus, the optimization problem can be written as:

[9] The utility framework presented here follows directly the theoretical discussions of Filippini & Heimsch (2016) and Deaton & Muellbauer (1980).

$$\min_{Q,S}\left(P_Q.Q + P_s.\bar{S}\right) \text{ s.t. } N = \widehat{N}(Q,\bar{S}), \tag{2}$$

where P_Q and P_s are the prices of Q and $\bar{S}$, respectively. In the short run, when the energy-consuming capital is fixed, the result of this optimization problem is the variable cost function in equation (3), whereas, in the long run, when capital stock varies, we obtain the total cost function in equation (4):

$$VC = f_2(P_Q, \bar{S}, \widehat{N}) \tag{3}$$

$$TC = f_3\,(P_Q, P_s\,, \widehat{N}) \tag{4}$$

From (3) we derive the short-run energy demand by differentiating with respect to energy price P_Q:

$$D_{SR} = f_4(P_Q, \bar{S}, I, Q, D, W), \tag{5}$$

where I denotes household income. The long-term can be also easily obtained from (4):

$$D_{LR} = f_5(P_Q, P_S, I, Q, D, W) \tag{6}$$

In this thesis, we focus on the estimation of the former general short-run model.[10] Thus, the empirical estimation of direct energy demand can be classified in the "conditional energy demand models", which rely on the concept that *"…the decision for consuming energy is not determined by adjustments in technologies but by adjustments in consumption of energy given the available technology"* (Rehdanz, 2007, p.169). In other words, the stock of energy-consuming capital is considered to be given or fixed.

The implications of (6) are more complex, from a conceptual and econometric point of view, because discrete and continuous choices occur at the same time. This discrete-continuous approach therefore consists of two stages, which are estimated simultaneously via methods such as 3SLS or the so-called bias correction term estimations (see Mannering & Hensher, 1987; Dubin & McFadden, 1984). In essence, the demand for energy-using appliances (discrete choice), such as different types of heating systems, electronic devices or motor vehicles is first considered in relationship to various factors such as their efficiency label, their price (or other features), and a range of buyer socio-demographic,

[10] We use short panel datasets in Chapters 2 and 3, but a cross-section dataset in Chapter 1. While we consider that our analyses in Chapter 1 cover the short run, as mentioned before, there is not a clear-cut consensus in the literature on the topic of interpreting results from cross-section data.

psychological and lifestyle characteristics. Second, the demand for energy per se is modelled (continuous choice), conditional on individual socio-economic, socio-demographic, psychological, lifestyle and the previously discussed energy equipment characteristics. The discrete-continuous approach is justified by the fact that *"…energy is not used directly, rather, it is used to power appliances that produce services such as heating, cooling, cooking, lighting, etc."* (Vaage, 2000, p.650). The advantage of this method is that it provides a way to address the endogeneity of durable-related characteristics in models of energy demand, which include energy-consuming durables in their specifications. Endogeneity itself stems from self-selectivity. As explained by Mannering & Hensher (1987, p.228) *"The issue of selectivity bias arises when we are concerned with questions of the form "if travelers* [or electricity consumers] *were to use. . .", in contrast with questions of the form "if travelers* [or electricity consumers] *do use.. ."* It is however primarily a question of data availability to investigate electricity consumption or energy demand in such a framework. For instance, the choice of a particular appliance may depend on its current price or on the price that a buyer expects in the future, or on their specific environmental attitude or technology-related interest, which may not be directly observable. Moreover, one of the most important factors that guides consumer choice – the price of the device, is itself likely to be endogenous, since it depends on the features of the durable (see Berry et al., 1995; Berry, 1994). For instance, the price of a private car is determined by its efficiency, the number of doors and whether the vehicle has an integrated air-conditioning system. Hence, this is an additional challenge for the application of the discrete-continuous framework. In order to circumvent these problems, many authors include endogenous variables (such as fuel efficiency or the presence of various energy-consuming systems or durables in the household) as controls in their models of energy demand and acknowledging the existing issue, concentrate on other, "non-endogenous" variables of interest, such as energy prices (e.g., Wadud et al., 2010b). They thereby assume that endogeneity does not affect, or has a negligible effect on, the estimated coefficients of these "non-endogenous" variables. This takes us back to the conditional demand model framework discussed above. The discrete-continuous and conditional demand methodologies are both widely and successfully used in the scientific literature on household energy consumption (e.g., Fang, 2008; Spissu et al., 2009; Wadud et al., 2010; Yatchew & No, 2001, Gillingham & Munk-Nielsen, 2019; Kaza, 2010).

c. This thesis as a whole

As mentioned in the beginning of this general introduction, there is a common thread unifying the chapters of this thesis, namely the study of the determinants of household energy demand, whose goal is to answer the previously outlined research questions. Several additional remarks about the transitions between those chapters are necessary here in order to emphasize the wholeness of this work.

As can be noted from the preceding paragraphs, in contrast to Chapter 1, Chapters 2 and 3 concentrate on two specific domains of household direct energy demand: electricity and car-travel demand. The shift to single components of energy consumption, as well as the change of topic, might seem at odds with the analyses presented in Chapter 1. Yet, this transition can be justified in several ways. To begin with, Chapter 1 does not try to convince the reader that a holistic approach is preferable to single-domain analysis. As highlighted above, the first part of this dissertation focuses on the dynamics that exist between energy categories, but it does not argue in favor of an aggregate approach to household energy consumption. Instead, by addressing direct and embodied energy separately *and* simultaneously, it acknowledges the importance of considering each energy domain as a separate entity with its own specificities, and the importance of the interdependence between categories of household energy consumption. Chapter 1 does not argue that categories of direct energy should be addressed together. This is done in our analysis, because direct energy *as a whole* represents the counterpart of embodied energy. In fact, a solid understanding of the interactions between energy domains can be gained only with sufficient knowledge of the individual characteristics shaping each of them, which is why Chapters 2 and 3 address single categories of direct energy requirements. Another reason to explore specific domains of direct energy demand in those two chapters is the fact that energy products are more homogeneous in contrast with the non-energy goods and services forming embodied energy use, thus making them easier targets for policy interventions. Also, the energy intensities (per Swiss franc or per physical unit) of direct energy categories are substantially higher, as shown in Chapter 1, thereby indicating that policy measures leading to similar monetary savings in both categories are likely to achieve more significant energy decreases in the direct domain. In addition, the topic of analysis of the second part of Chapter 1 is closely related to the research questions at the heart of Chapters 2 and 3, and can be seen as a transition to the remainder of this work. In essence, the discussion of the existence of an energy Kuznets curve concerns the heterogeneity of income effects across segments of households with different affluence levels. The study of heterogeneity in household behaviors is at the center of Chapters 2 and 3 as well. But the shift between the Chapter 1 and Chapters 2 and 3 is also motivated by the limitations of the former: Chapter 1 uses data from an expenditure survey, not a specific energy-consumption questionnaire or dataset. This restricts the possibilities for detailed analysis, in particular with respect to energy prices. Ultimately, policymakers are interested in price elasticities as proxies for the effect of taxation. Chapters 2 and 3 inspect the price elasticities of segments of energy consumers. Further, the dataset used in Chapter 1 is a cross-section of households, thus relying on comparisons between observations. The drawback of this approach is that these comparisons probably reflect geographic differences, i.e., between locations, rather than structural differences for the same unit of observation over time. This could be problematic for the interpretation of the time horizon captured by analyses as well as for alleviating estimation bias relating to endogenous time-constant factors. The panel datasets used in the second and third parts of this thesis enable us to address those issues.

An additional note regarding Chapter 3 is needed in order to situate this chapter in the general topic of household energy demand. Chapter 3 investigates the main field of household energy demand outside the dwelling – car-travel demand or, as it is often referred to in the relevant literature – the demand for mileage or vehicle miles/kilometers travelled (VMT/VKT). This chapter does not directly address the demand for energy itself (liters of car fuel consumed), but rather the main purpose this energy serves: private transportation. The difference between car fuel demand and car-travel demand is determined by the vehicle's fuel consumption per kilometer of distance travelled; that is, by its engine intensity (liters per kilometer), or equivalently, by the inverse of this measure – engine efficiency (kilometers per liter). There is a vast body of literature examining both VMT/VKT and car fuel consumption (see Goodwin et al., 2004; Graham & Glaister, 2004; Labandeira et al., 2017), with the choice of the particular dependent variable being theoretically equivalent as long as engine efficiency is taken into account. In practice, however, gasoline or diesel consumption is not directly visible to consumers. Households, rather observe how much they spend on gasoline on a monthly basis, although these expenditures can often be difficult to track, and are dependent on fuel prices. Odometer readings are, on the other hand, directly readable and capture the precise demand for mileage. In the dataset used in Chapter 3, annual driving distances from odometers are available, therefore the analyses presented later in this work use VKT as dependent variable. Because there is a straightforward link between the demand for car travel and car fuel, this third chapter is an integral part of the study of household energy demand.

The remainder of this dissertation is organized as follows. Chapters 1, 2 and 3 are presented consecutively without intermediary discussions. Each chapter has a similar structure: it provides an introduction to a specific research question and underscores the motivation for it. Its precise place in the relevant literature and its value added to existing studies are then discussed in a literature review section. The data and the choice of an econometric approach used for the empirical analyses are presented in separate sections. Our estimations are displayed and discussed in a results section. Each chapter concludes by recapitulating the main findings, their policy implications, the limitations of the analyses, and any possibilities they offer for future research. The general conclusion of this dissertation summarizes the contribution of this empirical work to the field of household energy demand and discusses in greater detail how these analyses could be extended by future research.

Chapter 1: Interactions in Swiss Household Energy Demand: A Holistic Approach

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1. Introduction

In many developed economies household behavior accounts for a substantial share of total energy consumption and greenhouse gas emissions. In Switzerland, for instance, it has been estimated that the domestic sector is responsible for roughly one-third of direct energy use and thus has an environmental impact comparable to that of the transport sector, or of the industry and service sectors combined (OFEN, 2012). In the face of these findings, reducing energy use in the household sector has become one of the primary policy targets in the country's *Energy Strategy 2050.*

Yet, most policies focus on *direct* energy, namely, the energy used for heating, electricity and private transport.[1] Neglecting the energy embodied in other consumption goods and services might lead to an underestimation of households' contribution in the economy's energy demand and their energy conservation potentials. This is especially relevant in countries like Switzerland, where the electricity sector relies on hydropower, hence the embodied energy's contribution in global GHG emissions is relatively important.

More importantly, focusing on reducing demand for direct energy might induce consumers to shift their consumption to high-emission imported commodities, thereby causing a substitution of direct energy consumption by embodied energy. While a growing body of literature has addressed the effects of socio-economic determinants on direct and embodied energy requirements separately (e.g., Abrahamse & Steg, 2009; Reinders et al., 2003; Wiedenhofer et al., 2013), there has been no attempt for a holistic analysis combining the two analyses in a simultaneous household demand system. In this paper, we propose a simultaneous equations approach to study the consumer's trade-offs and inter-relations between direct and embodied energy. In particular, we test whether there is a substitution effect between the two domains that could counter the policy measures aiming at reducing global energy consumption. This contribution draws upon the question of "separability" of energy demand and consumption of non-energy goods, suggested by Leth-Petersen (2002).[2] In addition to policy implications, the

[1] Many goods and services provided by different economic sectors eventually serve the end consumer's needs. The embodied energy contained in the value-chain of these commodities can be therefore considered as households' *indirect* energy demand.
[2] Using data from Danish households, Leth-Peterson (2002) finds evidence for separability of demand for natural gas from electricity demand. There is however little research on testing the separability between embodied and direct energy.

interdependence between demands of embodied and direct energy (non-separability) has an important methodological consequence. Namely, with interdependence, single-equation models could lead to biased estimates due to simultaneity, thus resulting in a misrepresentation of the effect of joint determinants. The simultaneous equations approach adopted in this paper allows testing the separability hypothesis.

The paper's second objective is the assessment of the Environmental Kuznets Curve (EKC) hypothesis at the household level. While examining the effects of various socio-economic variables as well as household attitudes and preferences on their energy demand, we aim at identifying the non-linear effects of income. This is not only a first of its kind for Switzerland, but it provides novelties compared to previous studies (*cf.* Ala-Mantila et al., 2014; Büchs & Schnepf, 2013). Namely, our model has a flexible functional form with higher-order polynomials of income, thus capturing the possibility of inverse U-shaped relationship predicted by the EKC hypothesis. Moreover, we provide a simultaneous analysis of income effects on embodied and direct energy, which accounts for potential correlations among unobservable factors across the two domains.

In order to address the above questions, we use a composed data set combining the Swiss Household Budget Survey (SHBS) with information extracted from Life-Cycle Analysis and Input-Output Tables. We apply a seemingly unrelated regressions (SUR) and an instrumental variable (IV) approach to analyze the interdependence of embodied and direct energy and the related impacts of income. The results provide evidence for interdependence, thus rejecting the separability hypothesis. However, there is no evidence of substitution. Rather, the findings point to various complementarity patterns between embodied and direct energy. Our analyses reject the EKC hypothesis. In fact, income has a persistently positive effect on both direct and embodied energy, with a particularly significant effect on the latter domain. We therefore provide empirical evidence on the effect of economic growth on household energy demand: a slight but steady increase in direct energy demand but more importantly, a potential boost in the consumption of non-energy goods including high-emission imported commodities.

The rest of the paper is organized as follows. *Section 2* reviews the current state of research on household energy demand. *Section 3* discusses the methods and data sets used in our analyses. Results from regression models are presented in *Section 4*. *Section 5* concludes with implications and limitations.

2. Previous research

Research into direct and embodied energy requirements of households was probably initiated by Bullard & Herendeen (1975), Herendeen (1978) and Herendeen et al. (1981). Combining expenditure data from budget surveys with input-output tables from the US and Norway, Herendeen and colleagues showed that the energy embodied in goods and services exceeds the energy directly used from electricity and other fuels by about 50%. Since then, similar findings have been reported for a large number of developing (e.g., Liu et al. 2009, Cohen et al. 2005) and developed countries (among others, Bin & Dowlatabadi, 2005; Lenzen et al., 2006; Wiedenhofer et al., 2013), including Switzerland (Dürrenberger et al., 2001; Girod & De Haan, 2010). This literature has also examined the drivers of total energy demand, identifying household income, size, stage of the life-cycle and location as main influences. One of the main findings of earlier research is that while energy requirements of household increase with income, they do so at decreasing rate. That is, as households become richer, their environmental impact grows, but the energy required per unit of consumption decreases.

In reference to the EKC hypothesis (Grossman & Krueger, 1991), a number of studies have additionally evaluated changes in income elasticities of total energy demand with increasing income. For instance, Lenzen et al. (2006) pool data from 10 countries collected between 1961 and 1998 and find that the relationship between income and total energy demand seems to follow an inverse U-shaped relationship although the identified turning point substantially exceeds observed income values. This finding is in line with a majority of results from the empirical literature on the EKC focusing on the emission of specific pollutants such as CO_2 or fine particles (Ala-Mantila et al., 2014; Büchs & Schnepf, 2013; Kijima et al., 2010; Stern et al., 2017).

Table 1 provides an overview of the main estimates of income- and expenditure elasticities of energy (or emission) requirements, reported in previous research. Some caution is warranted in using these elasticities to infer about the EKC. While variation in elasticities of energy can be used to infer about the impact of wealth, this variation does not cause a similar income variation in energy or emissions. For instance, a constant income elasticity lower than one could produce the increasing side of the inverse U-shaped EKC, but does not give any turning point. Moreover, an inverse U-shape in income elasticities does not imply a similar shape in energy (emission) requirements. In order to model a complete EKC, one needs to include the effect of higher-order polynomials of income. As noted by Lenzen et al. (2006), the EKC requires a negative income elasticity at least at some income levels. This could arise for instance, from a strongly increasing saving rate with income, such that richer households spend a smaller share of their income (*cf.* Vringer & Blok, 1995).

Table 1: Income and expenditure elasticities of total energy / GHG requirements

Country	Year	Reference	Net income elasticity	Expenditure elasticity
USA	(1960-1961) (1972-1973)	(Herendeen & Tanaka, 1976) (Herendeen et al., 1981)		0.87 0.81
Norway	(1973)	(Herendeen, 1978)		0.72
New Zealand	(1980)	(Peet et al., 1985)		0.40
The Netherlands	(1990)	(Vringer & Blok, 1995)	0.63	0.83
Australia	(1993-1994) (1998-1999)	(Lenzen, 1998) (Lenzen et al., 2006)	0.59	0.74 0.78
India	(1993-1994) (1997-1998)	(Pachauri, 2004) (Lenzen et al., 2006)		0.67 0.86
Denmark	(1995) (1999)	(Wier et al., 2001) (Lenzen et al., 2006)	0.48	0.90 0.86
Brazil	(1995-1996) (1999)	(Cohen et al., 2005) (Lenzen et al., 2006)		[1.1 ; 0.9] 1.00
Japan	(1999)	(Lenzen et al., 2006)		0.64
Switzerland	(2002-2005)	(Girod & De Haan, 2010) • Total emissions		0.53
UK	(2006-2009)	(Büchs & Schnepf, 2013) • Residential energy emissions • Transport emissions • Embodied emissions	0.19 0.49 0.60	
Finland	(2006)	(Ala-Mantila et al., 2014) • Direct emissions • Embodied emissions		0.67 0.84

Source: Own extension of similar tables from Pachauri (2004) and Wier et al. (2001).

Despite a general agreement on the importance of some socio-economic variables for determining household energy use, there are a number of unresolved issues. First, while the effect of income and wealth on energy requirements has been extensively studied, many studies remain at the descriptive level or rely on univariate methods potentially biasing the estimates (Wiedenhofer et al., 2013) or with restricted functional forms inadequate for describing non-linear effects. Yet, understanding the potentially non-linear relationship between income and energy demand is essential for predicting changes in energy use, resulting from economic growth or policy measures such as taxation. To deal with these issues, we will estimate multivariate models simultaneously controlling for a range of socio-economic controls.

A second question revolves around the effects of household attitudes, values and preferences on energy requirements. While an increasing number of studies have investigated the effects of these factors on household direct energy demand (Brandon & Lewis, 1999; Martinsson et al., 2011; Volland, 2017), few have addressed their relevance for explaining either total or embodied energy requirements. Notable exceptions are the contributions by Abrahamse & Steg (2009), Gatersleben et al. (2002) and Vringer et al. (2007), who all find that such psychological attributes improve model predictions for energy use in both domains. In the present article, we extend this nascent literature by focusing on the effects of preferences over risk and social outcomes, which have been found to influence direct energy demand (Fischbacher et al., 2015; Torgler et al., 2009; Weber et al., 2017).

Finally, this paper's main contribution is providing insight on the trade-offs and interactions between direct and embodied energy requirements. Understanding the interaction between direct and embodied energy is important for the assessments of the net impacts of national energy policies and for avoiding global energy "leakages" (Bruvoll et al., 2003). However, the issue has scarcely been addressed in the literature.[3] Households may react to energy policies such as fuel taxation by shifting their consumption to non-energy goods.[4] Hence, measures intended to induce energy saving may result in transferring the energy burden to other sectors of the national economy, or through imported goods, to other countries. The latter could be particularly problematic as differences in energy efficiency and fuel types across countries may imply that a relatively low-emission domestic production is replaced by high-emission

[3] To the best of our knowledge, there are no studies that explicitly investigate these tarde-offs. The closest studies are those that study the impact of various socio-economic determinants on GHG emissions resulting from consumptions in different domains (Ala-Mantila et al., 2014; Büchs & Schnepf, 2013).

[4] For instance, a raise in gasoline prices can shift energy use from private transport to delivery services. For anecdotal evidence on the relationship between fuel prices and online purchasing behavior see Jopson (2011).

foreign production, eventually leading to an increase in global energy consumption (Cole, 2004; Grether et al., 2012).

It is likewise possible that households treat the two energy domains as complements, thus creating a positive relationship between embodied and direct energy demand. There are in fact, a number of reasons to believe that substitutability and complementarity co-exist. For instance, household direct energy demand is a function of the household's stock in energy-consuming durables, hence embodied energy. Whether complementarity or substitutability prevails depends on the relative effects of substitution and income. If income effects dominate, we could expect complementarity rather than substitutability. Thus, the net environmental impact is an open empirical question.[5]

3. Data and descriptive statistics

3.1 Datasets and basic assumptions

The primary data set used in this article is the Swiss household budget survey (SHBS), a cross-sectional survey of expenditures by private households in Switzerland. In particular, we use information for 3,066 households from the 2011 wave of the SHBS.[6] Aside from standard socio-economic characteristics, the SHBS collects detailed data on household expenditures at the four-digit COICOP level by using monthly diaries kept by each household. For 25% of commodities, information on physical quantities is additionally provided in the SHBS. Expenditures on 281 commodities, encompassing 80% of expenditure categories surveyed in the SHBS provide the basis for computing household energy requirements. These categories account for 63% of discretionary expenditures, hence excluding compulsory outlays, such as health, unemployment and disability insurances, or payments to pension schemes. Since households hold little discretionary scope over the energy contents of these expenditures and assigning energy intensities to these categories involves a substantial degree of uncertainty (*cf.* Herendeen, 1978), we consider it prudent to exclude them from the analysis. For similar reasons, we

[5] It should be noted that complementarity and substitutability are usually identified through price effects. In this paper, we use the joint variation of the two demand responses as a basis for inferring about the possible trade-offs and interactions between demands for direct and embodied energy.

[6] The SHBS is a continuous cross-sectional survey conducted on an annual basis. The 2011 wave was the latest available wave at the time of writing. The complementary data on embodied energy computed for 2011 is not available for more recent years. From the initial SHBS dataset containing 3,087 households, we dropped 18 observations with zero or negative disposable income and 4 additional households with zero energy expenditures.

omit the categories fees, insurances, financial services, donations, lottery games, rents, mortgages, gifts and monetary transfers.

Following previous research (Lenzen et al., 2006; Pachauri & Spreng, 2002), we link individual expenditure data with energy content of consumption items obtained from Life-Cycle Analysis (LCA) and Environmentally-Extended Input-Output-Analysis (EEIOA) for Switzerland. LCA data on energy intensities are derived from *Ecoinvent* life-cycle inventory, version 2.2 (ESU, 2015).[7] Computations are based on a selection of these data, in which the commodity was provided to Swiss buyers or consumers (last processing stage of the lifecycle recorded in Switzerland). It contains information on average energy intensity measured in Mega Joules (MJ) per physical unit of consumption of the expenditure items collected in the SHBS. Unfortunately, LCA measurements were not available for 85 out of the 281 commodities retained from the SHBS. For these items energy intensities were therefore computed based on EEIOA as provided by the Swiss Federal Office of Energy (ESU, 2015; OFEN, 2011). A drawback of these tables is that energy intensities are given for limited number of categories corresponding to higher COICOP levels. Consequently, commodities for which we lack detailed LCA data, are assigned the EEIOA intensities of the corresponding 2-digit or, where available, 3-digit COICOP level.[8]

Unfortunately, the literature does not provide any sensitivity analysis of the potential impact of LCA versus EEIOA methods on household-level analyses. In our case, LCA data when available, give a better correspondence to consumption categories, especially for direct energy. In fact, the EEIOA data aggregating fuels with several other sectors do not provide accurate values for direct energy categories.[9] There is however, an alternative way of computing embodied energy based uniquely on EEIOA. Our complementary analyses using this alternative method indicate that the adopted method for computing

[7] These data have been previously used in assessing the environmental impacts of Swiss consumption and production in a report published by the Swiss Federal Office of Energy (Jungbluth et al., 2011).
[8] *Appendix 1* presents additional datasets used to assign energy intensities to a number of composite categories.
[9] The main problem is that a few sectors in EEIOA data, are pooled across direct and embodied energy categories. In particular, the housing sector includes building maintenance as well as electricity and heating whereas the transport sector includes motor fuels but also, the production of cars and bicycles, as well as public transportation. Averaging these values in a single sector creates considerable biases by suppressing potentially huge differences in a single sectoral value.

embodied energy has little effect on our main results.[10] In line with previous literature, we prefer the method based on combination of LCA and EEIOA, mainly because of the flexibility in better tuning the consumption category with the LCA data. Similar combinations have been used in previous studies on household energy demand in Switzerland (Girod & De Haan, 2010) and other countries (Chitnis & Sorrell, 2015; Druckman & Jackson, 2008; Jungbluthet al., 2011; Wiedmann et al., 2007).

3.2 Measuring direct and embodied energy requirements

Following the literature on the analysis of the energy requirements (e.g., Chitnis & Sorrell, 2015; Reinders et al., 2003) and environmental footprints of households (e.g., Munksgaard et al., 2000; Steen-Olsen et al., 2016), we compute household energy demand, E^{η}, $\eta \in \{Direct, Embodied\}$, as a product of category expenditures over $\boldsymbol{k}^{\eta}$ categories, and their respective energy intensities:

$$E^{\eta} = \boldsymbol{x}^{\eta}\boldsymbol{\Omega}^{\eta}\boldsymbol{m}^{\eta}, \tag{1}$$

where $\boldsymbol{x}^{\eta}$ is a $1 \times \boldsymbol{k}^{\eta}$ vector of expenditures in CHF, consisting of 6 sub-categories of direct ($\boldsymbol{k}^{Direct} = 6$) and 275 categories of embodied ($\boldsymbol{k}^{Embodied} = 275$) energy requirements, η. $\boldsymbol{m}^{\eta}$ is a corresponding $\boldsymbol{k}^{\eta} \times 1$ vector of energy intensities per physical unit of each commodity, as derived from the LCA data. The diagonal $\boldsymbol{k}^{\eta} \times \boldsymbol{k}^{\eta}$ matrix $\boldsymbol{\Omega}^{\eta}$ then provides the framework for translating expenditures into physical units of consumption. Elements on the diagonal of $\boldsymbol{\Omega}^{\eta}$ therefore give the inverse of individual prices for each expenditure category. To construct $\boldsymbol{\Omega}^{\eta}$, we use average commodity prices for each SHBS item drawing on data collected by the Federal Office of Statistics (Rappo, 2015). In the case where physical units can be directly obtained from the SHBS, vector $\boldsymbol{x}^{\eta}$ gives physical units instead of expenditures and the corresponding element of the main diagonal of $\boldsymbol{\Omega}^{\eta}$ takes a value of one.[11]

Direct energy demand is derived from expenditures on electricity and heating, as well as on fuels for private transport (gasoline and diesel). To account for the fact that at least in larger residential units some energy expenditures are shared by households,[12] we disaggregate reported shared expenditures by households based on a simple imputation scheme described in *Appendix A*. Altogether, we thus compute

[10] Results available in Appendix C. We are indebted to an anonymous reviewer for proposing this complementary analysis.
[11] Our approach thus is a hybrid between the household consumption model based on expenditures (Vringer & Blok, 1995) and the one based on physical units (Girod & De Haan, 2010; Hertwich, 2005).
[12] For example, the energy could be used for lighting and heating of the shared spaces, such as basements and corridors.

direct energy requirements of Swiss households based on six expenditure categories. Notably, energy use on these direct energy commodities are measured based on LCA intensities and therefore include the embodied energy used during their extraction, production and transport. Embodied energy requirement is subsequently computed using expenditures and energy intensities of the remaining 275 non-energy commodities from the SHBS. Hence, the distinction between direct and embodied energy closely traces the common definition of direct energy as the *"...energy carriers purchased by the household itself, in order to cater for energy services..."* (Weber & Perrels, 2000, p.551), and embodied energy as the energy contained in all other non-energy goods and services (Druckman & Jackson, 2008; Munksgaard et al., 2000).

3.3 Independent variables

Our primary variable of interest is the household's disposable income. This variable comprises all non-sporadic revenues from employment, freelance activities and rents of all household members after the deduction of taxes and mandatory insurance costs. In order to avoid difficulties for the interpretation of income coefficients with the presence of quadratic and higher polynomial terms, we normalize disposable income with respect to the sample median. Socio-demographic indicators contain, among others, the age, sex and nationality of the household reference person, the composition of the household or the ownership of the dwelling. We control whether households report shared costs, and if they have been used as a basis for disaggregating shared expenditures. The stock of motor vehicles and several electronic appliances are also included. Finally, to account for unobservable regional and temporal differences, we add a set of geographic controls and the month in which the household completed the survey. Summary statistics for all included variables are given in *Appendix B*.

Finally, we include three characteristics that figure prominently in the growing body of literature on the psychological determinants of household energy demand complete the previous set of determinants. First, environmental attitudes, that is the psychological tendency to view the natural environment as a positive feature worth protecting (Kaiser et al., 1999; Milfont & Duckitt, 2010) has been related to both energy use (e.g., Lange et al., 2014; Volland, 2017) and energy savings (Abrahamse & Steg, 2009). Second, attitudes towards risk taking have been linked with both investment in energy-efficient durables (e.g., Farsi, 2010; Qiu et al., 2014) and energy consumption (Fischbacher et al., 2015; Volland, 2017). Third, since one's energy consumption affects environmental quality and via this channel the welfare of others, social preferences have been linked with pro-environmental behaviours and attitudes (Torgler et al., 2009) including investment into energy-efficient durables (Fischbacher et al., 2015) and in-home energy use (Fischbacher et al., 2015; Volland, 2017). Since the SHBS is a standard consumption survey, direct measures for these characteristics are absent from the data. As a consequence, we draw on the extensive literature about the effect of these characteristics on every-day consumption decisions in order to derive corresponding proxies based on observed expenditure behaviour. In particular, we rely on household insurance coverage and donations for different purposes to establish these proxies. We, thus, measure pro-environmental attitudes using a dummy indicating whether the household donated to environmental organizations during the month of observation.[13] The assumption that giving to such organizations is a sign for the household's agreement with their aims, has been demonstrated by previous research (de Groot & Steg, 2008; Yen et al., 1997). Roughly 10% of all households in the SHBS donate to pro-environmental organizations, and thus qualify as holding pro-environmental preferences. In the same vein, we proxy a household's social preferences by whether it reported expenditures on donations to other non-governmental organizations. Pro-social values have been associated with charitable giving in both economics and sociology (Bekkers & Wiepking, 2011; Kamas & Preston, 2010). Based on this measure about 20% of households in the SHBS exhibit other-regarding preferences. Finally, we obtain a measure for the household's risk aversion by using information on the household's expenditures for legal protection insurance. More precisely, we assume that a household is risk-averse if it has any such expenditures and risk tolerant otherwise. Inferring risk preferences from insurance data is a natural choice as risk aversion is among the main reasons for the existence of insurance markets (Cohen & Einav, 2007). About 34% of respondent's qualify as risk-averse based on our criteria.[14]

[13] The creation of these controls is possible because the underlying expenditures have been excluded from the computation of embodied energy due issues of uncertainty concerning their energy content.

[14] Measuring preferences using observed (and dichotomized) expenditures is a noisy and inefficient operationalization for the underlying psychological concept. However, there is convincing evidence for strong relationships between our proxies and the underlying preference structure. In this sense, our proxies have the advantage of capturing revealed, in contrast to stated behaviours pre-dominant in the preceding literature (Vringer et al., 2007).

3.4 Descriptive statistics

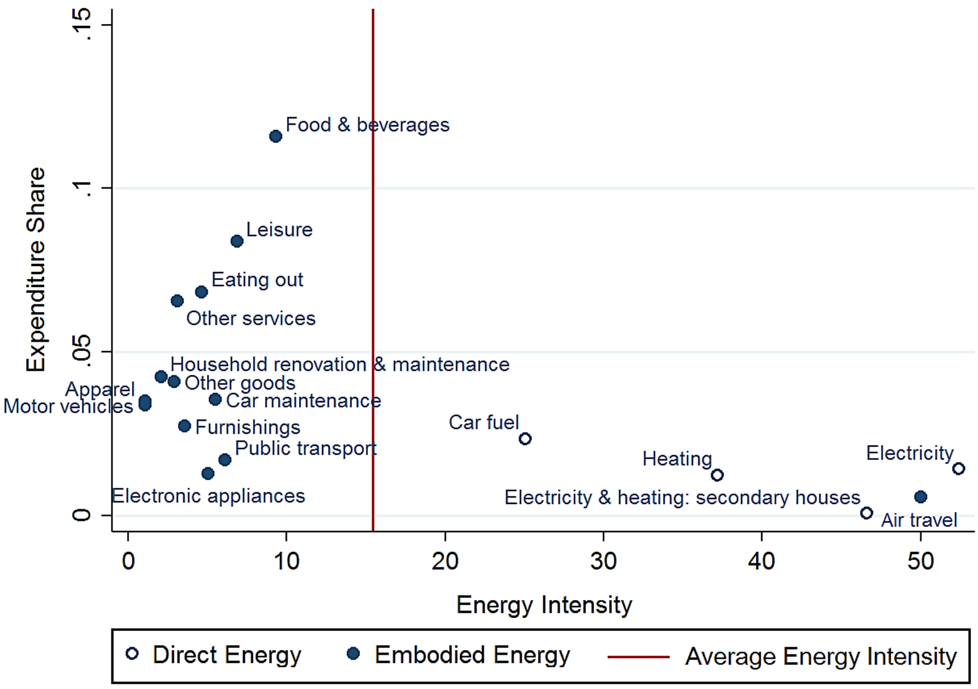
Based on the combination of datasets described in the previous section, *Table 2* presents basic descriptive statistics for our main dependent variables. They suggest that an average Swiss household uses about 37 gigajoules (GJ) of total energy per month. This value closely traces previous estimates for Switzerland (Dürrenberger et al., 2001) and falls well into the range of 20 GJ to 69 GJ estimated for other developed economies (Bin & Dowlatabadi, 2005; Park & Heo, 2007). Its spread is substantial with an inter-quartile range of 23 GJ, suggesting that energy requirements vary considerably across Swiss households. Results from *Table 2* also give a first impression on the relative importance of direct and embodied energy requirements.

Table 2: Descriptive statistics

	Mean	St. dev.	min	max	Median
Total energy demand (MJ)	36,797	20,095	3,266	283,923	33,129
Direct energy demand (MJ)	13,499	7,420	1,225	67,659	12,031
Embodied energy demand (MJ)	23,298	16,551	1,082	264,336	19,498
Energy int. per CHF (MJ/CHF)	4.18	1.47	0.54	17.55	3.97
Observations	3,066				

On average, Swiss households use 13.5 GJ of direct compared to 23.3 GJ of embodied energy, suggesting that almost two-thirds of their total energy use stems from the energy embodied in non-energy commodities and services they consume. Again, results almost perfectly resemble findings from previous studies likewise demonstrating that embodied energy makes up the lion share of total energy consumption in most developed economies, including Switzerland (Bin & Dowlatabadi, 2005; Dürrenberger et al., 2001). Hence, clearly household choices over non-energy commodities have a larger effect on their total energy demand and environmental impact than their use of primary fuels, commonly targeted by energy policies. The finding therefore underscores the policy relevance of studying common determinants for and interactions between these two energy domains. *Table 2* also summarizes the energy intensity of household expenditures as measured in MJ per CHF. It shows that an average Swiss Franc spent by a household buys roughly 4.2 MJ of energy. The household with least energy-intensive expenditure pattern obtains as little as 0.54 MJ per CHF, while the household with the most energy-intensive one buys as much as 17.55 MJ per CHF. Several reasons contribute to this considerable variation, namely the purchase of energy-consuming durables, seasonal purchases (e.g. heating oil or summer holidays by air travel) and the variation in energy intensities across categories. *Figure 1*, which plots these intensities for a group of 17 aggregate expenditure groups against their share in total/discretionary expenditures[15], shows indeed that one CHF buys as little as 1.05 MJ when purchasing personal apparel and as many as 52.42 MJ when spent on electricity. It also highlights that the overall impact of a category on a household's energy use is the product of its energy intensity and its expenditure share. Thus, even categories with a small proportion of expenditures can exhibit a major effect on total energy demand. For instance, air travel makes up less than 0.6% of discretionary expenditures but is responsible for approximately 5% of energy requirements due to its energy-intensity of 50 MJ/CHF. Conversely, food and beverages have an average energy intensity of 9.34 MJ/CHF, but are responsible for about 19 % of energy requirements due to their high share in expenditures (11.5 %).

Figure 1: Energy intensities (MJ/CHF) and expenditure shares per consumption category



The marked difference in energy intensities per CHF between energy and non-energy commodities also has important implications for energy policy. For one, it indicates that a reduction in expenditures on direct energy carriers decreases total energy demand of a household considerably more than an identical

[15] Discretionary expenditures are measured as total expenditures less mandatory expenditures such as health, unemployment and disability insurances, or payments to pension schemes. Due to the comprehensive welfare state in Switzerland, mandatory expenditures make up about 36% of total expenditures of the average household in the SHBS.

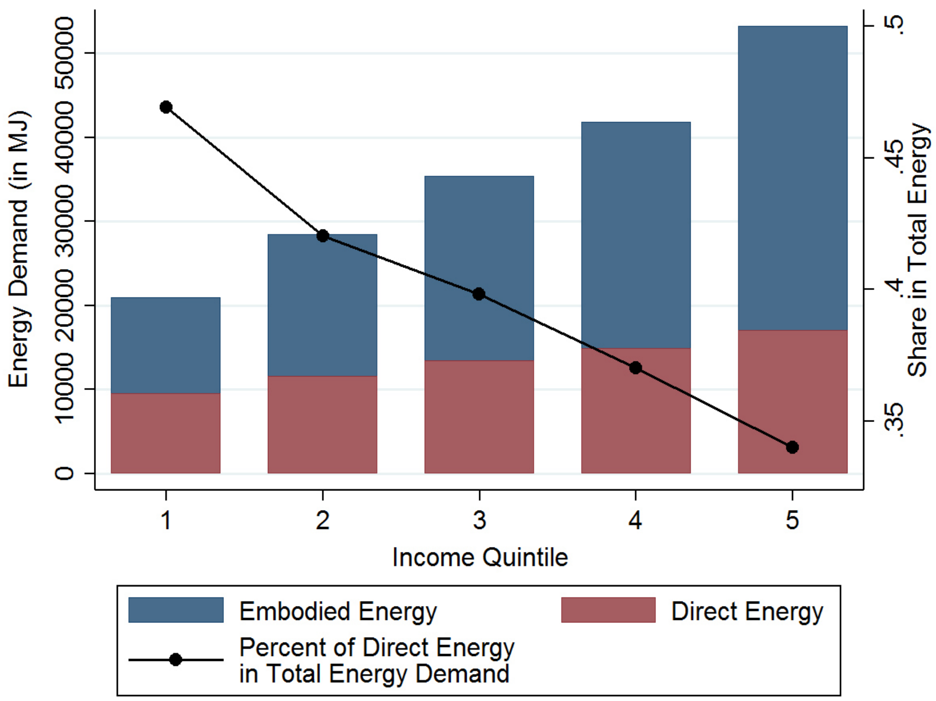
reduction in expenditures elsewhere. For instance, cutting expenditures on car fuels by 10 CHF would reduce household total energy demand by 250 MJ, whereas the same reduction in expenditures on personal apparel would decrease energy demand by only 10.5 MJ. This suggests that, despite the relative importance of embodied energy in total energy requirements, tax-based policies are likely to be most effective when targeting direct energy commodities. Second, due to the difference in energy intensities per CHF across expenditure categories, shifts in consumption patterns and changes in income can be predicted to have a substantial impact on total energy requirements. Both effects essentially depend on the sensitivity of household demand for individual commodities to changes in the budget constraint. Therefore, understanding how sensitive household energy requirements are with respect to changes in income, provides a ready way to judge the environmental effects of redistributive policy measures. Third, it also sheds some light on the risks associated with the implementation of policies that focus on improving the energy-efficiency in the domestic sector. Since such improvements imply monetary savings, they are tantamount to relaxing the budget constraint of the affected households. The subsequent increase in demand will inevitably affect energy requirements and thus yield a divergence between the technically possible energy savings from the efficiency improvement and the energy savings realized by the household, a phenomenon known as the *"rebound effect"* (Alcott, 2005; Binswanger, 2001; Sorrell & Dimitropoulos, 2008).[16] The major differences in energy intensities per CHF, evidenced in *Figure 1*, show that the net effect on household energy requirements depends on how arising savings are re-distributed over expenditure categories. In particular, it suggests that if households re-invest such savings into (other) energy commodities, efficiency improvements may completely fail to deliver the expected energy savings. Conversely, if households re-spent savings largely on non-energy commodities, total energy requirements may reduce substantially, despite rebound.[17] Thus, the net effect of any energy efficiency measure on total household energy demand depends on how corresponding

[16] For example, an average car-owning household in the SHBS spends about 125 CHF per month on gasoline. If this household would acquire a car with a 20% more efficient engine, technically possible energy savings would amount to 625 MJ. Yet, if these savings were completely re-spent using the new car, energy use before and after the efficiency-improvement would be identical (direct rebound of 100%). Alternatively, if all savings were spent on apparel, energy demand would drop by 600 MJ, implying a modest indirect rebound of 4 %.

[17] Rebound effects can not only be driven by the impact of efficiency improvements on income, but also by the implicit reduction in the relative price of the energy service in question (Binswanger, 2001; Sorrell & Dimitropoulos, 2008). Hence, focusing on income elasticities would lead to an underestimation of the increase in consumption of the cheaper energy service (i.e., the direct rebound effect). Nevertheless, focusing on income effects is common in studies simultaneously addressing direct and indirect rebound (for a review see Chitnis & Sorrell, 2015).

savings are re-spent. This, in turn, depends on how reactive demand for direct and embodied energy is with respect to changes in disposable income. *Figure 2* displays total household energy requirements by income quintile to obtain a first impression of this sensitivity. This figure shows that total energy demand rises substantially across the income range, more than doubling from about 21 GJ per month among the poorest 20% of households to more than 53 GJ among the richest quintile. Total energy demand in each successive quintile is larger than the demand of the previous poorer quintile. This suggests that, at least at this descriptive level, we do not find any indication for a reduction of environmental pressure among high income households as might have been expected based on the EKC literature. Moreover, there is no indication for such an abatement for any of the two components of total energy demand, i.e. the demand for both direct and embodied energy increases with household income, albeit at diverging rates. As a consequence the share of direct in total energy requirements decreases steadily from about 47% for households in the lowest income quintile to slightly less than 35% for the highest income households in our sample.

Figure 2: Direct and embodied energy demand for income quintiles



4. Econometric strategy

To further investigate the relationship between income and household energy demand, and to evaluate the impact of various controls on direct and embodied energy, we use the following model:

$$ln(E_i^\eta) = \beta_0^\eta + \sum_{k=1}^{m} \beta_k^\eta (\ln I_i)^m + \sum_{l=m+1}^{n} \beta_l^\eta \left(X_{li}^\eta\right) + \varepsilon_i^\eta \,, \quad (2)$$

where E_i^η with $\eta \in \{Direct, Embodied\}$ is the monthly direct or embodied energy consumption of household i $(i = 1, \ldots, 3{,}066)$. I_i^m represents its normalized disposable income for the same period to the power of the integer m. To allow for a possible non-linear relationship between energy demand and income (Ferrer-i-Carbonell & van den Bergh, 2004; Lenzen et al., 2006; Stern et al., 2017; Volland, 2017), we use a set of different specifications with m ranging from one to four, and evaluate whether increasing polynomials improve model fit by comparing information criteria. The double log form, which has been widely used in similar energy research (Pachauri, 2004), has the advantage of reducing the impact of outliers and heteroscedasticity, and allows to directly interpret regression coefficients as income elasticities. Hence, in all specifications, β_1 gives the income elasticity of energy demand, ϵ_{EI}^η. In the presence of non-linearity, this is valid only for median-income point. In this case, the income elasticity at income level I is given by:

$$\epsilon_{EI}^\eta = \frac{\partial\, ln(E^\eta)}{\partial lnI} = \beta_1 + \sum_{k=2}^{m} k\beta_k (ln\, I)^{k-1} \,. \quad (3)$$

X_{li}^η is a set of socio-demographic, geographical and temporal controls discussed above. In addition, estimations on direct energy include several controls aiming to capture household heterogeneity in terms of the stock of electronic durables, such as washing machines, computers or TV sets. To account for the fact that consumption decisions over direct and embodied energy may be taken jointly by the household, model (2) is estimated using a seemingly unrelated regression (SUR), as introduced by Zellner & Theil (1962). SUR allows the error terms, ε_i^η, of the two equations to be correlated, and thus provides a possibility to measure the existence and relevance of unobserved common determinants. This estimator has been widely used in the context of household energy demand (Bartels et al., 1996; Dubin et al., 1986; Fiebig et al., 1991; Henley & Peirson, 1994).[18]

Using the correlation between SUR residuals, we can also identify how the two demands shift in response to unobservables (such as prices). A positive correlation favors complementarity whereas a negative sign points to substitutability. We also analyze the relationship between the two demands by directly regressing one on the other simultaneously controlling for joint determinants namely, an extension of the equation system (2) that is estimated with SUR. The SUR estimates could be susceptible to endogeneity bias due to unobservables jointly affecting the two demands.[19] In order to check the robustness of these results to potential endogeneity, we also apply an instrumental variable (IV) approach. To evaluate whether endogeneity affects the results obtained by SUR, we instrument energy demand in each domain with that domain's demand of the neighboring households who filled in their expenditure diary during the same season.[20] The argument for using this instrument is that households living in the same region and completing the diary at the same time period are likely to face similar policy and price environments and thus show similar demand patterns. Also, household's energy demand in one domain should not influence energy demand of its neighbors in the other.[21]

5. Results

We discuss our findings in two steps. In *Section 5.1* we discuss the analysis of determinants including income effects, turning at the end to the EKC hypothesis. In *Section 5.2*, we focus on the trade-offs and interactions between direct and embodied energy.

5.1 Determinants of household direct and embodied energy demand

With respect to direct energy, findings across all specifications presented in *Table 3* reflect several well-documented phenomena (see, among others, Alberini et al., 2011; Baker et al., 1989; Meier & Rehdanz,

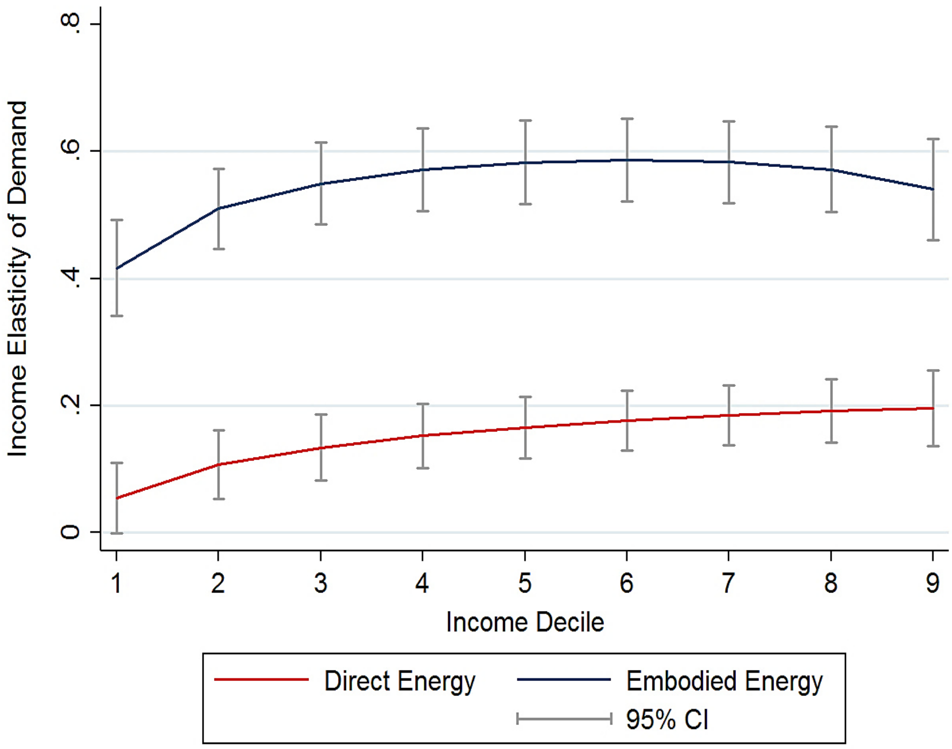
[18] When clustering standard errors over geographic regions or cantons, we obtain slightly smaller confidence intervals than the ones presented below. Yet, since the number of clusters is limited, these results may overstate precision (Cameron & Miller, 2015). Therefore, we have opted for a more conservative bootstrap approach.
[19] A similar endogeneity problem has been discussed by Leth-Petersen (2002), which is the only study explicitly addressing the interactions between sub-domains of household direct energy demand.
[20] Information on the household's location is derived by combining information on cantons, language regions and larger geographic regions. Thus, we obtain 16 geographical units that are similar, but not identical, to cantonal borders.
[21] Similar identification strategies have been applied by Miller & Alberini (2016) and Volland (2017).

2010). We find that direct energy demand increases under-proportionally with the number of individuals in the household, suggesting that co-habitation creates substantial scale economies (Ferrer-i-Carbonell & van den Bergh, 2004; Schröder et al., 2015). Results suggest that as household size increases, direct energy demand levels off with a 2-person household using only 14% more direct energy than a single household, and a 3-person household requiring just 3% more than a one with 2 members. We also find the common inverse U-shaped evolution of the semi-elasticity of energy demand with respect to age (Ferrer-i-Carbonell & van den Bergh, 2004). Also, direct energy demand increases up to an age of 44 years and then starts declining. Finally, our findings underline the importance of household possession of energy-consuming durables. Households owning more electronic devices, such as computers or dish washers show substantially higher direct energy use.[22] Likewise, car ownership increases direct energy demand substantially. Households owning a single car require about 47% more direct energy than an otherwise comparable household without a car, while households possessing two or more cars use even 76% more direct energy. A remarkable result is the evidence for a non-linear relationship between income and direct energy use, with higher-order polynomials being significantly different from zero up to the third order. The cubic specification of income also outperforms alternative specifications in terms of model fit, when judged by information criteria, McElroy's adjusted R squared values (McElroy, 1977), and standard log-likelihood ratio tests. For the best-fitting model M3, we obtain positive and significant coefficients of both disposable income and its squared term, while its cubic term displays a significant but negative coefficient, implying a sigmoid relationship between income and direct energy demand. Hence, direct energy requirements seem to react strongest to changes in income at medium income levels, while responses are less pronounced at (very) high and low values of disposable income. More precisely, coefficient estimates suggest that income elasticities are highest for incomes that exceed the median income in our sample by about 55 % (i.e., monthly disposable income of CHF 9'760), corresponding roughly to the 9th decile of the income distribution. *Figure 3* plots income elasticities for direct and embodied energy demand in different income deciles based on model M3.

[22] Data on the stock of electronic devices is collected only when they are *owned* by the household. Since most tenants live in multi-family buildings where those devices are shared, the previous coefficients should be interpreted cautiously.

Income elasticities for direct energy are below 0.3 across all deciles, demonstrating that direct energy is a staple good over the entire range of income. At median income (CHF 6'290 per month), elasticity is about 0.17 and thus in the range of results from previous studies on in-home energy demand (Berkhout et al., 2004; Filippini, 2011; Meier & Rehdanz, 2010; Volland, 2017), but smaller than income elasticities from studies on private mobility (see e.g., Espey, 1998; Graham & Glaister, 2002; Baranzini & Weber, 2013). The median income elasticity (0.17) is only slightly lower than the one estimated at the 9th decile (0.20), suggesting that despite the estimated functional form, income elasticities seem to be constant across the top half of the empirical income distribution. Conversely, elasticities increase markedly over the bottom half of the distribution. Households at the 1th decile have an estimated income elasticity of 0.055 and thus react three times less sensitively to changes in income than a median-income households.[23]

Figure 3: Direct and embodied income elasticities for income deciles (Model M3)



[23] Wald tests show that this difference is statistically significant at standard levels of error ($p < 0.0001$).

Table 3: Determinants of Swiss households' direct (D.) and embodied (E.) energy consumption

	M1		M2		M3		M4	
	D. (ln)	E. (ln)	D. (ln)	E. (ln)	D. (ln)	E. (ln)	D. (ln)	E. (ln)
Normalized disposable income (ln)	0.112***	0.465***	0.137***	0.497***	0.165***	0.583***	0.162***	0.589***
	(0.021)	(0.027)	(0.020)	(0.025)	(0.025)	(0.034)	(0.025)	(0.031)
Normalized disposable income (ln) ^{2}			0.061***	0.082***	0.043***	0.028	0.037	0.042
			(0.013)	(0.024)	(0.016)	(0.022)	(0.028)	(0.042)
Normalized disposable income (ln) ^{3}					-0.020**	-0.061***	-0.017	-0.067***
					(0.0088)	(0.019)	(0.011)	(0.018)
Normalized disposable income (ln) ^{4}							0.0022	-0.0051
							(0.0065)	(0.014)
Owner	0.0054	0.111***	0.0015	0.104***	0.0017	0.103***	0.0018	0.1028***
	(0.028)	(0.029)	(0.028)	(0.028)	(0.028)	(0.029)	(0.028)	(0.029)
Dwelling with shared energy costs	0.062**	0.011	0.064**	0.014	0.065**	0.016	0.065**	0.016
	(0.029)	(0.031)	(0.029)	(0.030)	(0.029)	(0.030)	(0.029)	(0.030)
Household with disaggregated data	0.087***	0.019	0.088***	0.020	0.087***	0.016	0.087***	0.015
	(0.032)	(0.033)	(0.032)	(0.033)	(0.032)	(0.033)	(0.032)	(0.033)
Household with 2 members	0.143***	0.257***	0.140***	0.252***	0.134***	0.231***	0.134***	0.231***
	(0.029)	(0.036)	(0.029)	(0.036)	(0.029)	(0.036)	(0.029)	(0.036)
Household with 3 members	0.176***	0.256***	0.170***	0.249***	0.162***	0.221***	0.162***	0.220***
	(0.034)	(0.047)	(0.034)	(0.046)	(0.035)	(0.047)	(0.035)	(0.047)
Household with more than 3 members	0.163***	0.384***	0.154***	0.371***	0.144***	0.339***	0.145***	0.337***
	(0.041)	(0.051)	(0.041)	(0.051)	(0.042)	(0.051)	(0.042)	(0.051)
Age of ref. person	0.0084*	0.026***	0.0078*	0.026***	0.0076*	0.025***	0.0075*	0.025***
	(0.0044)	(0.0046)	(0.0044)	(0.0045)	(0.0044)	(0.0045)	(0.0044)	(0.0045)
Age of ref. person ^{2}	-0.0001**	-0.0003***	-0.0001**	-0.0003***	-0.0001**	-0.0002***	-0.0001**	-0.0002***
	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)
Gender of ref. person: female	0.0045	0.043*	0.0058	0.045*	0.0089	0.055**	0.0092	0.054**
	(0.020)	(0.023)	(0.020)	(0.023)	(0.020)	(0.023)	(0.020)	(0.023)
Nationality of ref. person: foreign	0.044*	-0.015	0.044*	-0.014	0.046*	-0.0098	0.046*	-0.0097
	(0.024)	(0.031)	(0.024)	(0.031)	(0.024)	(0.030)	(0.024)	(0.030)
% of earning HH members	-0.0004	-0.0004	-0.0004	-0.0004	-0.0005	-0.0007*	-0.0005	-0.0007*
	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0004)
HH with more than one cell phone per person older than 12	0.049		0.045		0.045		0.045	
	(0.035)		(0.034)		(0.034)		(0.034)	
HH with more than one laptops per person older than 12	0.139***		0.132***		0.134***		0.134***	
	(0.048)		(0.048)		(0.048)		(0.048)	
HH with (at least one) desktop computer	0.021		0.021		0.020		0.020	
	(0.019)		(0.019)		(0.019)		(0.019)	
HH with (at least one) TV	0.013		0.012		0.010		0.010	
	(0.031)		(0.031)		(0.031)		(0.031)	
HH with (at least one) freezer	-0.013		-0.010		-0.010		-0.010	
	(0.020)		(0.020)		(0.020)		(0.020)	
HH with (at least one) washing machine	0.061***		0.057***		0.057***		0.057***	
	(0.020)		(0.020)		(0.020)		(0.020)	
HH with (at least one) dish washer	0.096***		0.097***		0.096***		0.096***	
	(0.024)		(0.024)		(0.024)		(0.024)	

HH with one car	0.381***		0.385***		0.384***		0.383***	
	(0.028)		(0.028)		(0.028)		(0.029)	
HH with two or more cars	0.564***		0.563***		0.561***		0.561***	
	(0.034)		(0.034)		(0.034)		(0.034)	
Pro-environmental attitude proxy	0.060**	0.107***	0.057**	0.102***	0.056**	0.099***	0.056**	0.099***
	(0.027)	(0.031)	(0.027)	(0.030)	(0.027)	(0.030)	(0.027)	(0.030)
Philanthropic attitude proxy	-0.016	0.083***	-0.017	0.082***	-0.018	0.079***	-0.018	0.079***
	(0.022)	(0.022)	(0.022)	(0.021)	(0.022)	(0.021)	(0.022)	(0.021)
Risk aversion proxy: legal protection insurance	0.060***	0.076***	0.061***	0.078***	0.060***	0.074***	0.060***	0.074***
	(0.018)	(0.019)	(0.018)	(0.019)	(0.018)	(0.019)	(0.018)	(0.019)
Constant	8.385***	8.873***	8.388***	8.875***	8.407***	8.929***	8.409***	8.926***
	(0.117)	(0.125)	(0.116)	(0.125)	(0.118)	(0.125)	(0.118)	(0.126)
Marital status	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,066		3,066		3,066		3,066	
AIC	8,332		8,297		8,274		8,277	
BIC	8,832		8,810		8,798		8,813	
McElroy's adj. R^2	0.369		0.374		0.378		0.377	
Cross-equation correlation of residuals	0.113		0.107		0.104		0.104	

Standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.010

Viewed over the entire income distribution, the results suggest that income elasticities tend to increase with income. This finding is in line with previous research by Volland (2017), who likewise finds increasing income elasticities for household energy demand in a British data set. As pointed out there, there are a number of potential explanations for this phenomenon. First, it is well-documented that households with similar levels of wealth tend to cluster in the same areas (Watson, 2009). A phenomenon that in Switzerland is additionally driven by heterogeneity in local taxation regimes (Morger et al., 2013; Schmidheiny, 2006). Correspondingly, it is perceivable that suppliers adjust their pricing schemes to neighbourhood wealth, such that wealthier households tend to pay higher prices.[24] An alternative explanation is that despite being a necessary good, there could be certain "luxury" features to energy. For instance, a rise in income may induce better-off households to spent more on activities that require higher direct energy input, such as purchasing bigger cars, driving them further, faster and more often, or heating up more spacious dwellings to higher temperatures. Since we compute energy requirements based mainly on expenditures rather than use, we cannot distinguish between these two hypotheses. An interesting avenue of future research would therefore be to investigate whether the income-increasing elasticities can be replicated in further data sets, and to what extent this variation can be traced to price differences.

With respect to embodied energy requirements, results from model M3 in *Table 3* are largely comparable to the ones for direct energy. In particular, we observe that the substantial scale economies reported for direct energy demand also extend to embodied energy requirements. Compared to a single household, a 2-person household consumes about 26 % more embodied energy, implying that per-capita requirements are about 37 % lower than that of the individual living in a single household. Similarly, a household consisting of more than three persons consumes only about 40 % more embodied energy than a single household, indicating that each person living in that household gets along with no more than a third of the embodied energy requirements of the single household resident. This suggests that Switzerland's

[24] Aside from issues of price discrimination, price differences across incomes may arise from differences in goods quality. That is, rich households may be more inclined to buy expensive high-quality commodities. Since differences in quality are not observable in the SHBS data, expenditures cannot be adjusted consequently. Thus, we may systematically overestimate energy use for wealthier households (Girod & De Haan, 2010). However quality variations can be conjectured to be limited for direct energy, this explanation pertains primarily to our results for embodied energy.

projected demographic transition towards smaller households will pose a substantial challenge to attaining the goals of the *Energy Strategy 2050*. In fact, official statistics predict that the share of single and 2-person households will each increase by 4% until 2030, while the share of 3-person households and households with more than three members will decline by 3% and 5%, respectively (Kohli et al., 2015). Simple calculations based on our results suggest that as an effect of this demographic transition alone, direct energy requirements will increase by about 2.6 %, while embodied energy requirements can be predicted to go up by roughly 1.5 %. We also observe a concave relationship between the age of the household's main respondent and its embodied energy use, peaking at age 50, slightly higher than the estimated peak for direct energy. Similarly, the functional relationship between income and embodied energy, closely resembles that of its direct energy counterpart. We observe positive coefficients for both disposable income and its square term (albeit statistically insignificant) and a negative and significant coefficient for the third-order term. Coefficient estimates indicate that income elasticities for embodied energy are highest at a disposable income of about CHF 7'300, corresponding roughly to the 6th decile of the income distribution. As shown in *Figure 3*, income elasticities for embodied energy change in a similar pattern across the income distribution as elasticities for direct energy. That is, income elasticity of embodied energy demand increases from 0.42 at the 1st decile of the income distribution to 0.59 at the 6th decile, and then declines to 0.54 at the 9th decile. Several Wald tests show that differences in elasticities are significant when comparing elasticity estimates for low and median incomes, but not when comparing high and median incomes. Thus, similarly to direct energy, income elasticities of embodied energy demand increase over the lower half of the income distribution and appear to remain constant over the top half.

Income elasticities of embodied energy requirements are substantially larger than elasticities for direct energy. This is not surprising as computations of embodied energy demand are based on expenditures on all non-energy commodities, and thus contain a substantial number of goods whose income elasticities of demand are larger than unity (Lenzen, 1998; Wiedenhofer et al., 2013). This also highlights that with rising income, the environmental impact of household consumption is increasingly determined by these latter type of goods and services.

The congruence in the effects of determinants across the two energy domains extends to the psychological controls. We find that, contrary to our expectations, households that donate to environmental organizations tend to use about 6% more direct and almost 10% more embodied energy. One reason for this finding could be that a large share of individuals who donate to environmental organizations do this not primarily because of environmental concern, but as a form of "warm-glow giving" (Andreoni, 1989). In support of this hypothesis, Menges et al. (2005) have demonstrated experimentally that actions which enhance self-image play an important role in donating to an environmentally relevant public good. Alternatively, households may perceive donations to environmental organizations as a form of indulgence for environmentally damaging behaviours. Girod & de Haan (2009) and Schütte & Gregory-Smith (2015) present cursory evidence that individuals indeed tend to engage such forms mental accounting and "neutralization" when justifying consumption behaviours with high environmental impacts. We proxy risk attitude by the possession of insurance covering legal expenses[25] and find that risk-averse households consume more direct energy. This is in line with previous studies showing that risk averse individuals are less likely to invest in energy efficient technologies (Christie et al., 2011; Farsi, 2010, Qiu et al 2014). Interestingly, we find a significant and positive relationship between risk aversion and embodied energy demand. Finally, we observe that philanthropic households tend to require insignificantly less direct but significantly more embodied energy. A negative impact of altruistic attitude on direct energy is also observed by Volland (2017) and Asensio & Delmas (2015), while Steg et al. (2005) fail to detect a significant relationship between altruistic attitude and the acceptability of energy policies.

Finally, as regards to the EKC hypothesis, the point estimates of model M3 (see *Table 3*) namely, the significantly negative coefficient of the cubic term, point to the possibility of negative income elasticities for both direct and embodied energy, beyond certain levels of income. However, the model's prediction shows a monotonously increasing effect of income at all levels of income within the range of our sample.

[25] Obtaining legal insurance may not only be motivated by preferences over risk in general (as measured in previous studies), but may also reflect one's perception of being subject to litigation risk. As both the likelihood of being involved in a legal dispute and the potential damage incurred from it tend to differ across different occupational groups (for anecdotical evidence see Ebeling (2012) and Sullivan (2012)) and to rise with wealth (McClellan et al., 2012), our proxy may capture the unobserved effect of wealth and occupational choice on energy demand. Results from a risk proxy using expenditures on optional health insurances are virtually identical.

If there is any curvature in the energy-income relationship, our demand estimates over the income deciles point to a slightly (but not significantly) convex and increasing curve rather than a concave inverse U-shaped curve. In fact, the turning point implied by the negative effect of the 3rd-order term exceeds the sample median income by a factor of 12.5 for direct energy and by a factor of 7 for embodied energy. These theoretical turning points correspond respectively to a monthly disposable income of CHF 78'400 and CHF 44'200. Noting that only 3 households in our sample report an income greater than CHF 44'000, we can easily conclude against the existence of an inverse U-shaped curve. The results therefore reject the EKC hypothesis in Swiss households. It is also important to note the results indicate a strong rate of increase in embodied energy over different income deciles, suggesting that economic growth brings about an increasing demand of non-energy goods.

5.2 Trade-offs between direct and embodied energy requirements

Overall, the results of the SUR models in *Table 3* indicate that direct and embodied energy demand in Switzerland are overwhelmingly driven by the same determinants, with effects being in the same direction. This suggests that energy use in both domains is highest among households with common socio-economic characteristics, in particular among high-income households, residing in owner-occupied single households. Consequently, they compose a natural target group for energy conservation policies. Moreover, it suggests that a policy measure, such as an environmental tax, could affect energy requirements in both domains similarly rather than inducing a substitution between them. It thus provides a first indication that and embodied energy demand are positively correlated among Swiss households. This is further supported by the correlation structure of the error terms, presented at the bottom of *Table 3*. The estimated cross-equation correlations are significant with values of about 0.11. While pointing to unobserved common determinants (e.g., energy prices),[26] the result also suggests that on average, these unobservables are likely to move embodied and direct energy demand in the same direction. A direct implication is that a household with high direct energy demand is likely to also have

[26] We have actually used all the demographic variables available in the SHBS data. The inclusion of other covariates relies on information criteria (BIC, AIC) and log-likelihood ratios, as indicated when we consider non-linearities in income effects.

high embodied demand (and vice versa), suggesting that energy consumption in the two domains can be considered complementary.

We also apply SUR and IV approach (3SLS) to the extended equation system in which demand in each domain is regressed on the other simultaneously controlling for joint determinants. The adopted IV approach is based on instrumental variables constructed from energy demand of the neighboring households.[27] One possible problem with these instruments is that variation of energy use within geographic units could be limited. Therefore, we replace regional fixed effects[28] by a set of region-specific averages encompassing average household size, average disposable income, the average number of cars owned by households, average age of the household reference person, average share of foreign households as well as average share of earning household members and female members. All socio-economic and socio-demographic determinants included in our preferred Model 3 in *Table 3* are included here as well. *Table 4* provides the estimation results for the interaction effects between embodied and direct energy for OLS, SUR and 3SLS models. As results for most remaining controls closely trace the findings presented in *Tables 3*, they are omitted from *Table 4*.

The SUR estimations (columns 3 and 4) suggest that single-equation OLS regressions (columns 1 and 2) are subject to a substantial bias. Both models confirm however a significant positive relationship between both energy domains, suggesting that all else being equal an average household with 1% higher requirements in one domain will have between 0.1% and 0.3% higher energy use in the other.

[27] Neighborhood energy demand can be considered as a relevant instrument in both energy domains for the F-statistic from the first-stage estimation largely exceeds the rule-of-thumb value of 10.
[28] The regressions with regional fixed effects show more or less similar results but with higher standard errors.

Table 4: Interactions between direct and embodied energy demand

	OLS		SUR		3SLS	
	(1)	(2)	(3)	(4)	(5)	(6)
	D. (ln)	E. (ln)	D. (ln)	E. (ln)	D. (ln)	E. (ln)
Direct (ln)		0.147***		0.272***		0.299***
		(0.019)		(0.019)		(0.052)
Embodied (ln)	0.093***		0.202***		0.036	
	(0.016)		(0.016)		(0.272)	
Household-specific socio-economic and socio-demographic factors	Yes	Yes	Yes	Yes	Yes	Yes
Average regional socio-economic and socio-demographic factors	Yes	Yes	Yes	Yes	Yes	Yes
Region	No	No	No	No	No	No
Month	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,066	3,066	3,066	3,066	3,066	3,066
R^2	0.36	0.46	0.35	0.45	0.36	0.45
AIC	3,703	4,534	.	.	.	.
BIC	3,999	4,775	.	.	.	.
First-stage regression F-statistic	.	.	.	.	35.61	52.17

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.010

As discussed earlier, we use an IV approach to assess whether the SUR estimates are impacted by endogeneity bias. The estimated IV results differ from those in SUR, with increases in embodied energy now no longer translating into adjustment in direct energy requirements. Conversely, a 1% change in direct energy use seems to trigger a slightly higher, but similar variation than SUR of about 0.3% in embodied energy requirements. Thus, the results suggest that, if at all, a positive relation, thus providing no indication that policies targeting direct energy demand will be (partially) offset by a compensatory increase of embodied energy demand; instead they might lead to a simultaneous decrease in the energy requirements in both domains.

6. Conclusions and limitations

This paper adopts a holistic approach to household energy demand by investigating the socio-economic and psychological drivers and the interactions between direct and embodied energy requirements. For this purpose it combines expenditures data from the Swiss household budget survey 2011 with data from life-cycle and input-output analyses. Using a seemingly-unrelated regression model (SUR), we observe that energy demand in both domains are largely driven by the same determinants. In particular, we find that the relationship between income and energy demand in both domains seems to follow a sigmoid relationship with changes in requirements tracing income changes most closely for medium to high income levels. However, the income-energy relationship remains positive over all income levels and there is no evidence of a turning point as in the EKC hypothesis.

In line with previous findings in the literature, our results show that income elasticities are well below unity across the entire range of observable incomes, suggesting that energy is a necessity as in staple goods. The income elasticity for embodied energy is however much greater than that of direct energy, suggesting that demand responses for non-energy goods are relevant for global energy policies. For both embodied and direct energy demand, we observe considerable scale economies arising from cohabitation, indicating that projected demographic changes in Switzerland pose a challenge to achieving the envisioned energy savings. Furthermore, our results underline previous findings suggesting that basic psychological characteristics like social and risk preferences, play a non-negligible role in determining household energy requirements (Fischbacher et al., 2015; Lange et al., 2014; Volland, 2017).

These findings, along with the positive cross-equation correlation of residuals from our SUR estimation, provide strong evidence that embodied and direct energy demand are driven by the same determinants, such that the environmental impact of a household in both domains can be derived from observable socio-economic variables. Moreover, when investigating the causal interactions between the two, we find no evidence for substitution. These results are important as they suggest that the wide-spread policies targeting direct energy use are unlikely to cause a substantial shift in household energy demand from the direct to the embodied domain. On the contrary, this article provides evidence of positive relationship between direct and embodied energy requirements, going from the former to the latter. This suggests that a demand response initiated for direct energy will trigger a complementarity response in embodied energy consumption. Hence, policies could not only help curbing the energy used in production of energy services, they could simultaneously reduce the complementary demand for non-energy commodities. From a policy perspective, this is a reason to more actively target direct energy demand due to the possibility of positive spill-overs to embodied energy requirement. Given the substantial part of non-energy goods in overall energy consumption, this should be coupled with interventions specific to embodied energy demand, such as carbon footprint taxes and labels.

A note of caution is warranted as our embodied estimations rely on a substantial number of assumptions. First and foremost, although we have information on the energy intensities for about 80% of final consumption items in the SHBS, these account for only 63% of discretionary and 44% of total expenditures. In particular, we were not able to obtain credible intensities for many economically important expenditure categories like taxes, fees and rents, which were therefore treated as if they did not imply energy use. While this is a common problem in the literature on household energy requirements (Herendeen, 1978; Randolph, 2008; Vringer & Blok, 1995), it suggests that additional investigations incorporating these categories may help to clarify the consequences of this treatment on our results. Another, potentially more critical caveat of our approach is that we use expenditures rather than physical units of consumption as the basis for computing energy requirements. As a consequence, we cannot distinguish between differences in the quality of consumption items purchased by households. This is problematic as previous literature has suggested that it may lead to an upward bias in estimated income elasticities (Girod & De Haan, 2010; Vringer & Blok, 1997). However, while this literature in general has found that estimated differences in income elasticities are significant they also tend to be small,[29] suggesting that all in all the problem may be limited. Moreover, since direct energy sources are a substantially more homogenous, problems regarding quality differences are likely to play a much smaller role here than for embodied energy demand.

[29] For instance, Vringer and Blok (1997) find that physical unit-based income elasticities decrease expenditure-based elasticities only slightly – from 0.63 to between 0.56 and 0.60. One reason could be – as pointed out by Girod & De Haan (2010) – that energy inputs into production may also increase with quality.

Appendix A: Matching procedures and additional data

In order to match expenditures from the SHBS 2011 with energy intensities from LCA, we use average prices form the Swiss Federal Office of Statistics (Rappo, 2015). However, prices are missing for the category *"622: Transport services"*. Therefore, we combine data on annual person-kilometers (pkm) from the *Microsensus on Mobility and Transports for 2010* (OFS, 2017a) with expenditures from the SHBS to obtain unit prices. Our estimations are close to the ones by Girod & De Haan (2010) for Switzerland.

Due to the different energy intensities of the sub-categories of *holiday packages*, we proceed to the disaggregation of this category. In order to do that, we use the *Swiss National Accounts on Tourism* (OFS, 2011) which provide information on tourism expenditures for Swiss residents. We estimate the shares of accommodation (19.03%), food (22.29%), transport (21.58%), airplane tickets (18.85) and leisure (18.25%) which we use to calculate their average expenditures, which are then multiplied by their corresponding energy intensities. We encounter a similar problem with the category *'secondary houses'*. The lack of any disaggregation criterion does not allow us to use a similar procedure. Therefore, we simply attribute a weighted average (electricity and heating) energy intensity to this category.

In order to estimate average prices per physical unit for furniture and various household appliances, we use an extensive list of average 2005 weights (e.g. in kilograms) established by the *Furniture Re-use Network*, UK, currently known as the *FRN Product Weight Protocol* (FRN, 2011).

According to the SHBS "*For an important number of tenants, a part of the energy costs (e.g. heating and hot water) is included in the category non-apportioned expenditures*." (SHBS, 2011, p.28). We apply the following disaggregation strategy in order to separate energy and non-energy costs: By calculating the average share of electricity, heating and shared expenditures of home-owners with non-nil expenditures in these categories (425 obs.), we obtain three *general* weights for these categories. Then, we estimate *individual* weights, which are defined as the part of shared expenditures in the household's total energy expenditures (including shared costs).

The product of the two previously calculated weights gives us a *final* weighting measure. Thus, the disaggregation is more important for households with a high proportion of shared costs (which is likely to capture a more important proportion of the direct energy expenditures). We use the final weights to separate actual electricity and heating costs from shared costs. Weights are applied to all households, except for the ones used for the disaggregation. The disaggregated expenditure amounts are then multiplied with their corresponding energy intensities. Shared expenditures, which now consist of non-energy services only, are attributed the same energy intensity as the category household reparation and maintenance (MJ per CHF=0.8317).

Appendix B: Descriptive statistics

Continuous variables	Mean	St. dev.	Min.	Max
Disposable income	7,091	4,234	290	61,753
Age of ref. person	53.07	15.21	19	95
% of earning HH members	53.77	39.61	0.00	100
Observations	3,066			

Binary variables	Mean
Owner	0.49
Dwelling with shared energy costs	0.77
Household with disaggregated data	0.14
Household with one member (reference category)	0.27
Household with two members	0.38
Household with three members	0.14
Household with more than three members	0.21
Gender of ref. person: female	0.30
Nationality of ref. person: foreign	0.13
Marital status: Single (reference category)	0.19
Marital status: Married	0.61
Marital status: Widowed	0.08
Marital status: Divorced	0.13
HH with more than one cell phone per person older than 12	0.05
HH with more than one laptops per person older than 12	0.02
HH with (at least one) desktop computer	0.57
HH with (at least one) TV	0.94
HH with (at least one) freezer	0.70
HH with (at least one) washing machine	0.62
HH with (at least one) dish washer	0.80
HH without a car (reference category)	0.17
HH with one car	0.57
HH with two or more cars	0.26
Pro-environmental attitude proxy	0.10
Philanthropic attitude proxy	0.20
Risk aversion proxy: legal protection insurance	0.34
Region: Zurich (reference category)	0.17
Region: Ticino	0.09
Region: Central Switzerland	0.10
Region: North-West Switzerland	0.13
Region: East Switzerland	0.12
Region: Leman	0.15
Region: Mittelland, French-speaking	0.06
Region: Region: Mittelland, German-speaking	0.17
Observations	3,066

Appendix C: Sensitivity analysis

Table C1: Sensitivity analysis for embodied energy requirements

	E. (ln)
Normalized disposable income (ln)	0.700***
	(0.028)
Normalized disposable income (ln) ^{2}	0.053***
	(0.020)
Normalized disposable income (ln) ^{3}	-0.077***
	(0.012)
Owner	0.101***
	(0.028)
Dwelling with shared energy costs	0.003
	(0.029)
Household with disaggregated data	0.042
	(0.034)
Household with 2 members	0.129***
	(0.033)
Household with 3 members	0.096**
	(0.043)
Household with more than 3 members	0.127***
	(0.047)
Age of ref. person	0.023***
	(0.0045)
Age of ref. person ^{2}	-0.0002***
	(0.00004)
Gender of ref. person: female	0.017
	(0.0242)
Nationality of ref. person: foreign	-0.045
	(0.029)
% of earning HH members	-0.0004
	(0.0004)
Pro-environmental attitude proxy	0.119***
	(0.031)
Philanthropic attitude proxy	0.120***
	(0.024)
Risk aversion proxy: legal protection insurance	0.105***
	(0.020)
Constant	9.090***
	(0.126)
Marital status	Yes
Region	Yes
Month	Yes
Observations	3,066

Chapter 2: Price and Income Elasticities of Swiss Household Electricity Demand: Differences between Frugal and Intensive Consumers

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1. Introduction

The notion of "average economic agent", "representative consumer" or "typical household" plays an essential role in applied economics. It is used to aggregate population attributes into a single representative entity in order to measure its sensitivity to changes in its characteristics or environment. Although bringing computational and interpretational convenience, and usually being related to lower policy-implementation costs, the focus on the "typical consumer" is nevertheless likely to conceal some important differences among sub-groups in the population under study. Yet, knowledge about how responsiveness varies between these sub-groups could be used to design specific instruments which achieve policy goals with a better investment-impact ratio, in shorter time periods and with less welfare distortions, compared to "one-size-fits-all" interventions based on the reactivity of the "average Joe". The study of population heterogeneity is thus a necessary first step in assessing the efficiency and the equity dimensions of policy interventions (Gillingham, 2014; Wadud et al., 2009).

In residential energy demand, the interest in the sensitivity of the *average* consumer to tax and wealth increases has triggered a vast body of scientific literature focusing mean price and income elasticities. This effort has been justified by the willingness of national governments to curb GHG pollution levels and to ensure energy independence, by simultaneously pursuing better life standards for their populations. However, previous estimations of average price and income elasticities have been found to vary dramatically across studies (Espey & Espey, 2004; Fan & Hyndman, 2011; Sanquist et al., 2012). Qualified as "mixed" and "inconclusive", these results have been attributed to differences in data aggregation levels, empirical methods and time horizons, but also to heterogeneity of responses across countries and within populations (Jessoe & Rapson, 2014; Miller & Alberini, 2016). Despite a general agreement that electricity consumption is indeed characterized by significant variability which might severely bias average estimations (Jaffe & Stavins, 1994; Lindén et al., 2006; Randolph, 2008), differences in the responsiveness of various population groups to changes in prices and income have hitherto received little attention from researchers.

The variation of electricity consumption within populations can be readily related to two major sources. Namely, households vary significantly both in their available electric appliances and in the way they use them. The first of these aspects captures not only the number and the type of electronic durables, but also their technical characteristics, such as efficiency. The second aspect is related to appliance-specific utilization behaviors, such as how often a given device operates or the frequency of leaving it on standby. Previous analyses (among others Frondel et al., 2017; Hendricks & Koenker, 1992; Reiss & White, 2005) indeed observe important heterogeneity in residential electricity demand originating from the ownership, type and usage of various appliances. In particular, Reiss & White (2005) find differences between household electricity price elasticities in terms of electric appliances and their usage, with owners of larger appliances being more price-sensitive compared to households with a regular set of electronic devices. These authors also address differences between price elasticities within the population directly, by focusing on tiers of electricity consumption. This method has the advantage of providing a more general picture of the intensity of electricity demand because it considers the global household stock and usage of electronic devices and does not focus on them individually. However, as outlined by Koenker & Hallock (2001), an unconditional "truncation of the dependent variable" suffers from sample selection problems (see p. 147). Their proposed quantile regression approach provides a solution to avoid this bias by defining different consumption quantiles (conditional on) various household characteristics. Quantile regressions also allow to account for unobservable differences related to energy intensity between households. For these two reasons, it is particularly well-suited for the analysis of the responsiveness of electricity consumption across population groups with different levels of electricity consumption. Despite the existence of prior research applying quantile analysis on residential electricity demand (Hendricks & Koenker, 1992; Huang, 2015; Kaza, 2010; Niu et al., 2016; Sardianou, 2008), panel data applications remain scarce, especially in relation with electricity price.

This paper contributes to the understanding of the heterogeneity in the price and income elasticities of electricity demand across various groups of Swiss households. For this purpose, we apply a panel quantile regression with correlated random effects (Wooldridge, 2010) in order to assess and compare the price and income sensitivities of the average electricity consumer ("average Joe"), the parsimonious one ("frugal Jane") and the intensive user ("wasteful John"). We find that while income does not have a significant impact across the spectrum of electricity demand, households at the lowest decile of the consumption spectrum or those who use electricity intensively do not react significantly to changes in prices, in contrast to households at the 25th and 50th conditional percentiles who exhibit price elasticities significantly different from zero. More generally, these findings suggest important heterogeneity between electricity consumers and could be used to draw some policy conclusions.

The rest of the paper is organized as follows. *Section 2* discusses prior findings on heterogeneous price and income elasticities and outlines the importance of investigating heterogeneity in the context of Switzerland's recent energy policies. The datasets we rely upon and related descriptive statistics are introduced in *Section 3*, while *Section 4* outlines our econometric strategy. The results from our estimations are presented and discussed in *Section 5*. *Section 6* concludes and provides policy recommendations.

2. Literature review and background

2.1 Literature review

Research in the domain of residential energy demand has repeatedly assessed the average effects of prices and income on household electricity demand. Although residential electricity consumption has been generally estimated to be price- and income-inelastic, previous findings have been described as "inconsistent" or exhibiting an important degree of variation (Espey & Espey, 2004; Fan & Hyndman, 2011; Labandeira et al., 2017; Sanquist et al., 2012). On average, in the case of developed countries,[1] income is found to have a null or small positive impact on electricity consumption, with income elasticities being lower than 0.10 in magnitude (Alberini et al., 2011; Bedir et al., 2013; Brounen et al., 2012; Grønhøj

[1] Zhou & Teng (2013) provide a list with prior estimation for developing countries, where not surprisingly price and income are overall higher. It could be expected that the price and income sensitivities in developed economies are lower due to the satiation of electricity demand in these countries.

& Thøgersen, 2011; Kavousian et al., 2013; Leahy & Lyons, 2010; O'Doherty et al., 2008; Sanquist et al., 2012), whereas the most frequent estimates of price elasticities for electricity demand are between -0.4 and -0.2 on the short, and -0.7 and -0.5 on the long run (Dennerlein & Fleig, 1987; Dennerlein, 1990; Fan & Hyndman, 2011; Reiss & White, 2005; Labandeira, et al., 2017). However, Espey & Espey (2004) observe that earlier research reports price elasticities in a wide interval of values spanning from -2.01 to 0.08 to in the short run, and from -2.5 to -0.07 on the long run. More recently, a meta-analysis on the price elasticities of electricity demand by Labandeira et al. (2017) finds an even more dramatic variation between -24.0 to 4.2. According to Miller & Alberini (2016) and Jessoe & Rapson (2014) this can be attributed not only to differences in data aggregation levels, empirical methods and time horizons, but also to heterogeneity of responses between and within populations.

Several prior studies examine the heterogeneity in different domains of household energy demand by applying a quantile regression method.[2] In her analysis of residential heating demand in Greece, Sardianou (2008) uses conditional quantile analysis among other standard regression techniques. Her results reveal that income plays a significant, albeit not different role for high and low heating consumers. Here, the effect of energy prices is measured indirectly through households' willingness to restrict heating fuel consumption in case of a fuel price increase. The author concludes that intensive heating consumers are less inclined to reduce their energy use, compared to more frugal households. Somewhat similarly, Frondel et al. (2012) and Gillingham (2014) observe that households who use intensively energy for private car transportation are significantly less price-reactive compared to their more frugal counterparts. This is explained by the possibility that more intensive energy consumers are more dependent on the services provided by the energy-using device, thus limiting their sensitivity to price variations. However, it is also conceivable that households with high levels of energy consumption exhibit higher price elasticities because of the important

[2] Other strategies for addressing heterogeneity in household energy consumption comprise the use of interaction terms, splitting population in tiers according to different household characteristics other than energy consumption (e.g., income levels, age) or cluster analysis (Gillingham, 2014; Romero-Jordán et al., 2016; Zhou & Teng, 2013).

amount of discretionary usage of durables, as suggested by Gillingham et al. (2015) and Wadud et al. (2010a).

If it concerns the heterogeneity in household electricity demand, an important point of reference for our analysis is the previously mentioned study by Reiss & White (2005) which uses two waves of a residential energy consumption survey covering 1,300 Californian households. This work estimates elasticities of income and prices in terms of appliance holdings and usage. Significant heterogeneity is observed in terms of price-, but not of income-responsiveness between households. More precisely, the authors find that while price variations have an insignificant effect on electricity usage, intensive electricity consumers (i.e., users with space or water electric heating systems) are more sensitive to changes in prices than frugal ones (owning only a set of universally owned electronic durables), with most price elasticities falling in the interval -0.4 and -0.2. Yet, their estimated empirical elasticity distribution shows that 44% of households are characterized by a nil price sensitivity on the short-run, while only about 13% are price-elastic. These authors also investigate price sensitivities across quartiles of income and electricity demand and find that wealthier households are less price-reactive than their poorer counterparts. Concerning price estimates for quartiles of electricity usage, Reiss & White (2005) notice that *"… elasticities are lower for households that use high amounts of electricity, despite the fact that households with energy-intensive electric space heating/cooling systems have much greater electricity price sensitivity ceteris paribus."* (p.871). They attempt to explain this by their previously obtained result that as income rises, households move to less price-elastic electricity uses, and by the weak correlation between income and the ownership of heating/cooling systems. Nevertheless, the difference between the point estimates in each quartile is not tested. Moreover, the works of Koenker & Hallock (2001) and Heckman (1979) show that such a procedure leads to a selection bias due to the simplistic segmentation of the response variable. Instead, they suggest that the estimation of the conditional quantiles of demand provides a better approach to assessing parameters at different parts the consumption distribution.

Hendricks & Koenker (1992) use a quantile regression to investigate the heterogeneity in electricity demand of about 340 households in Chicago, with a rather technical goal, i.e., testing the use of nonparametric hierarchical spline models for conditional quantiles. The authors use socio-demographic, dwelling and electronic durable attributes as explanatory variables, but do not control for price and income characteristics. They find that higher quantiles of demand are significantly influenced by household features and appliance ownership in contrast to lower ones. This leads them to suggest when using a "representative consumer" for estimating "baseload" electricity demand (i.e., low electricity consumption levels), demographic factors can be ignored, for electricity usage is supposed to be more influenced by behavioral characteristics.

Also by using a quantile regression method, Kaza (2010) addresses space heating and cooling, as well as the energy used by appliances and for warm water, where the use of electricity might be supposed predominant. The analysis shows that the housing type, size and neighborhood density have substantially different impacts at the tails of the distribution of household energy demand in the US, compared to the conditional average. Kaza (2010) also observes that energy prices have a stronger impact at the upper spectrum of energy demand for cooling and other uses (i.e., electricity). This result leads him to conclude that different increases in the energy prices in tiers of energy consumption are likely to be more efficient for reducing energy usage than uniform increases such as a single electricity tax. However, this work uses an aggregated price measure for all energy domains. The author also finds that low-income consumers exhibit lower income elasticities at lower conditional quantiles of electricity use. On the other hand, home owners, which can be supposed to be more affluent, consume more energy for heating, warm water and appliances. Kaza (2010) suggests that while wealthier households are more likely to have more energy efficient durables, they also probably own more devices.

Several more recent studies also address residential electricity consumption by applying a quantile regression analysis, but focus on the effects of non-price factors on conditional electricity quantiles (Huang, 2015; Niu et al., 2016; Schleich et al., 2013; Valenzuela et al., 2014). An exception is Niu et al. (2016) who surprisingly do not find a significant effect of prices across levels of electricity usage in China. None of the previously discussed studies has used household level panel data, with estimations being overwhelmingly based on household-level cross-sectional data. This is problematic for the identification of structural coefficients. Indeed, price elasticities for cross-sectional estimates reflect price-related differences in electricity consumption between households, rather than changes in electricity consumption by households facing changing prices.

In the face of these findings, our contribution to the existing literature is namely to focus on the price and income elasticities across different quantiles of household electricity consumption in Switzerland by using a panel dataset containing a rich set of covariates.

2.2 Background

Similarly to analyses applied to other countries, earlier studies for Switzerland have extensively focused on the estimation of average price and income impacts on electricity demand. These works have mainly relied on cross-sectional aggregated data (Boogen et al., 2017; Dennerlein & Fleig, 1987; Zweifel et al., 1997), with only few using household-level analysis (Boogen et al., 2014; Filippini, 1999, 2011). Most of these studies find average price elasticities of about -0.3 and insignificant effect of income on electricity demand. To our knowledge, no previous works address heterogeneous price and income elasticities across Swiss households.

Yet, such an investigation is important in the context of Switzerland's recent energy policies for two reasons. First, the government's long-term *Energy Strategy 2050* foresees the introduction of an energy tax in order to achieve a viable energy transition after the nuclear phase-out decision following the 2011 Fukushima nuclear power plant accident. With nuclear energy currently accounting for one-third in Swiss electricity production and private households being responsible for 60% of the increase in the national electricity consumption since 2000 (OFEN, 2017), it is necessary to assess the effectiveness of a price-based policy instrument. As argued in the introduction of this article, the analysis of the responsiveness of different household groups to variations in prices is a first step in this direction.

A second reason relates to the current liberalization of the electricity market in Switzerland.[3] The most recent development in this area consists of deregulating the electricity market for private households and small firms who will have the possibility of opting for the most attractive supplier or electricity mix. It is expected that the customers influence the development of electricity supply by enabling innovative products and services. The competition between electricity providers is likely to increase the interest in identifying heterogeneous segments of residential consumers.[4]

3. Data

3.1 Datasets

The analysis presented in this article relies on a panel dataset of Swiss households surveyed online in four consecutive years between 2015 and 2018. The dataset, known as the Swiss Household Energy Demand Survey (SHEDS), covers the entire geographical space of Switzerland, except the canton of Ticino, and is conceived as a rolling panel dataset consisting of about 5,000 respondents per wave. Its main objective is to collect rich information on Swiss household's energy consumption behaviors from a demographic, economic, sociological and psychological perspectives. Household members aged 18 years old or more, and at least partially responsible for the household, are interviewed about their electricity usage and behaviors during the one-year period prior to the survey.[5]

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[3] Since 2009, customers with large annual electricity consumption (more than 100 MWh) can freely choose their electricity provider. However, small-scale consumers are expected to be granted access to the free electricity market from 2023 onwards. For political reasons, the liberalization of the Swiss retail electricity market has been postponed several times so far.

[4] The Swiss electricity market is characterized by the presence of a large number (about 630) of electricity providers which nevertheless constitute monopolies on cantonal or regional levels. It is also heavily regulated, with the main legislation in this field being the Federal Electricity Supply Act (*StromVG*) and the Federal Electricity Supply Ordinance (*StromVV*), which introduce the partial liberalization of the Swiss electricity market mentioned earlier. In addition, the Federal Electricity Act (*EleG*) applies to legal issues related to grid construction and maintenance. Finally, the Federal Energy Act (*EnG*) addresses the general guidelines concerning the economic and environmental aspects of energy provision.

[5] These data have been used in previous research among others, by Hille et al. (2017) and Blasch et al. (2017). Further details about SHEDS are given in Weber et al. (2017).

In addition to SHEDS, we use price data from the Swiss Federal Electricity commission (ElCom) at the zip code level. These price data[6] are carefully extracted from the ElCom's price platform which allows comparisons between electricity prices across providers, household types and years.[7] Prices are given as weighted averages for each one of the eight household categories (consumption profiles) separately by zip code and two product types (green or standard). ElCom defines these eight price categories, referred to as "consumption profiles", based on dwelling attributes, such as the possession of specific electronic durables, the number of rooms in the dwelling, and the building type (an apartment or a house). Since these features are also available in the SHEDS, we are able to match households with their local electricity providers based on the zip codes and the specific survey year.[8] This helped us to create a unique dataset and achieve an excellent household-provider zip code matching: only 70 households (less than 2% of observations) in our datasets were not directly matched. We proceed by attributing to those the electricity prices of the closest zip-code neighbor within the same price category.[9] It is important to note that the price measures are partly selected by each individual household mainly because of their choice in the selection of multi-tariff (day/night) pricing as well as a range of "green" products generally available in Switzerland. However, the temporal variation remains largely exogenous.

3.2 Dependent variable

We use the logarithm of annual household electricity use (kWh) as response variable in our QR model. We exclude households who do not report electricity consumption from a bill and those who report an annual

[6] The price measure used in our analyses includes the entire set of components of electricity tariffs: network price, energy price, communal levies and feed-in tariffs. See https://www.prix-electricite.elcom.admin.ch/

[7] The ElCom's price platform is available at: https://www.prix-electricite.elcom.admin.ch/BaseDataSelection.aspx. The underlying database not directly available to us, we extracted the data using a Java code written by Crispin Kirchner. Compared to the data provided in spreadsheets publicly available at ElCom's website, the constructed data provide a better disaggregation level.

[8] The matching in terms of number of rooms is not perfect for 2 household types: those living in a 3-room apartment and those with more than 5 rooms, in which we used average prices of the corresponding categories matching in other variables that is, year, zip-code and product type (standard/green). Detailed information about the consumption profiles used by ElCom are provided at: https://www.prix-electricite.elcom.admin.ch/BaseDataSelection.aspx.

[9] We include a dummy variable to control for this imputation strategy. The effect of this dummy is invariably small and statistically insignificant across all regressions.

consumption below 200 kWh or above 30,000 kWh.[10] The final panel data set is a sample of 3,856 observations corresponding to a total of 1,483 households for which data is available for at least two waves of the SHEDS. *Table 1* displays descriptive statistics for this dataset.

As shown in the *Table 1*, the annual residential electricity use is characterized by substantial variation. The average values are slightly lower in comparison to official energy statistics from the Swiss Federal Office of Energy, which reports an average household annual residential electricity consumption of 5,096 kWh in 2015 to 5,311 kWh for 2018 (OFEN, 2019c). A possible explanation for this discrepancy with official statistics is that the SHEDS does not cover the canton of Ticino, situated in the south of Switzerland, characterized by a milder climate and by a generalized use of electrical resistance heaters by households, thus leading to about 30% more electricity consumption with respect to the rest of the country (Eymann et al., 2014).

3.3 Model specification

We consider three major sets of control variables: (1) socioeconomic and sociodemographic determinants (income, prices, household composition, age, gender, education), (2) dwelling characteristics (dwelling location, dwelling age), (3) weather-related controls (heating and cooling degree days), and (4) psychological factors (environmental, altruistic, egoistic and hedonic). In addition, we add canton fixed effects and year dummies in order to control for unobserved characteristics. Moreover, as explained later, we use econometric models that account for many time-invariant factors and omitted variables.

Our particular interest is on the impact of electricity prices and income. The measure of average electricity prices (and its components) obtained from the electricity regulator ElCom is a simplification of a complex construct of base prices, taxes and tariffs that change over time and across different areas and various users. Whether individuals are sufficiently aware of prices is an important empirical question. Prior research, both

[10] We follow Boogen et al.'s (2014) strategy for excluding extreme observations. Alternative strategies for excluding outliers (e.g., dropping observations with electricity consumption below 300kWh and above 20,000 kWh or Tukey's strategy for excluding data points standing further than 1.5 quartile ranges from the first and third quartiles) confirm our fundamental results.

within Switzerland and abroad, shows that differences in electricity consumption tend to be related to differences in electricity prices, and that changes in electricity prices are accompanied by changes in consumption in a way that is consistent with economic theory (Espey and Espey 2004; Labandeira et al. 2017), i.e., consumers behave as if they are aware of prices and price changes.[11]

Table 1: Descriptive statistics

Year:	2015		2016		2017		2018	
Continuous variables	*Mean*	St. dev.	*Mean*	St. dev.	*Mean*	St. dev.	*Mean*	St. dev.
Annual electricity demand (kWh)	4,367	4,135	4,028	3,938	4,061	4,117	4,012	4,115
Electricity price (in CHF/100)	20.34	3.15	20.22	3.37	19.93	3.56	20.41	3.53
Monthly gross income (CHF)	8,811	4,381	8,900	4,631.00	9,048	4,588	9,068	4,566
Age of ref. person	56.05	14.10	53.71	14.55	54.04	14.72	55.06	14.73
Number of household members	2.29	1.18	2.23	1.14	2.28	1.19	2.26	1.16
Vintage of dwelling (years)	44.42	36.89	46.62	43.85	48.16	44.95	48.30	43.97
Heating degree days (HDD)	3,235	574.32	3,432	553.41	3,375	517.04	3,024	517.45
Cooling degree days (CDD)	239.40	71.46	146.23	60.10	205.10	77.79	218.06	89.31
Binary variables	*Mean*		*Mean*		*Mean*		*Mean*	
Pro-environmental attitude: yes	0.89		0.86		0.86		0.88	
Altruistic attitude: yes	0.76		0.74		0.75		0.72	
Aspiring for social power: yes	0.13		0.10		0.10		0.10	
Hedonic attitude: yes	0.67		0.62		0.68		0.62	
Imputed electricity price: yes	0.03		0.01		0.01		0.01	
Gender: female	0.37		0.40		0.40		0.41	
Education: tertiary	0.40		0.45		0.50		0.49	
Location: city	0.44		0.47		0.46		0.46	
Location: agglomeration	0.33		0.30		0.31		0.31	
Location: countryside	0.23		0.23		0.24		0.23	
Canton: ZH	0.19		0.22		0.20		0.22	
Canton: BE	0.16		0.16		0.17		0.17	
Canton: LU	0.04		0.05		0.06		0.05	
Cantons: UR, SZ, OW, NW, GL, ZG	0.05		0.05		0.05		0.05	
Canton: FR	0.03		0.03		0.03		0.03	
Canton: SO	0.03		0.03		0.02		0.03	
Cantons: BS, BL	0.06		0.05		0.05		0.05	
Canton: SH, TG	0.04		0.03		0.04		0.04	
Cantons: AR, AI	0.00		0.01		0.01		0.01	
Canton: SG	0.03		0.02		0.03		0.03	
Canton: GR	0.08		0.08		0.08		0.09	
Canton: AG	0.10		0.10		0.11		0.10	
Canton: VD	0.03		0.04		0.03		0.03	
Canton: VS	0.04		0.03		0.03		0.02	
Cantons: NE, JU	0.04		0.04		0.04		0.04	
Canton: GE	0.07		0.06		0.06		0.06	
Observations	636		1,059		1,081		1,080	

Moreover, households obtain information on electricity prices regularly from grid operators, ElCom and Swiss media. Therefore, there are good reasons to assume that Swiss consumers have at least a general idea about the evolution of the electricity prices, which is an important topic of public discussion. There are no

[11] Although economic theory suggests that consumers respond to marginal prices, it has been recently shown that electricity consumers respond to average electricity prices and not to marginal or expected marginal prices (Ito, 2014).

reasons to believe that lack of awareness causes a delay between billing cycles and actual consumption. In fact, the art. 7 of the Federal Electricity Supply Ordinance sets a deadline (the 31st of August) for electricity providers to announce their new electricity tariffs (for the upcoming year) to the regulator and their customers. According to ElCom,[12] only about 8% of all grid operators do not meet this deadline, but this does not impact any overall price-related statistics and analyses given the small sizes of the areas served by these operators. Information about changes in the electricity prices (which occur on annual basis in Switzerland) are made public not only directly by the providers, but also by various media.[13] The majority of customers receive their electricity bills every 3 or 4 months, before receiving a final summary bill of their annual electricity consumption at the end of the year.[14] An analysis by Gilbert & Graff Zivin (2014) has recently shown that households respond to changes in prices within a week after the reception of their energy bill. It could be therefore supposed that Swiss households can make a timely adjustment in their consumption in reaction to price changes. These responses could however be limited to short and medium terms. Long-term responses might require investment in energy efficiency that could take longer periods.

Figure 1 provides a log-log plot of electricity consumption and price. However, the observed negative relationship between electricity demand and price could be due to omitted variables and endogeneity. For instance, households with higher consumption are probably more likely to adopt more economical double-tariff models and/or standard electricity as opposed to more expensive green products. However, to the extent that these selection patterns are stable over time, longitudinal variations can help overcome such biases. In this paper, we adopt econometric approaches to account for all time-invariant selection patterns.

Our second determinant - gross income - is obtained as the mid-point of the reported income interval. For open-ended income categories we use the Pareto-curve-based procedure suggested by Celeste et al. (2013). We also assume that the respondent's sociodemographic attributes, like gender, age and education provides

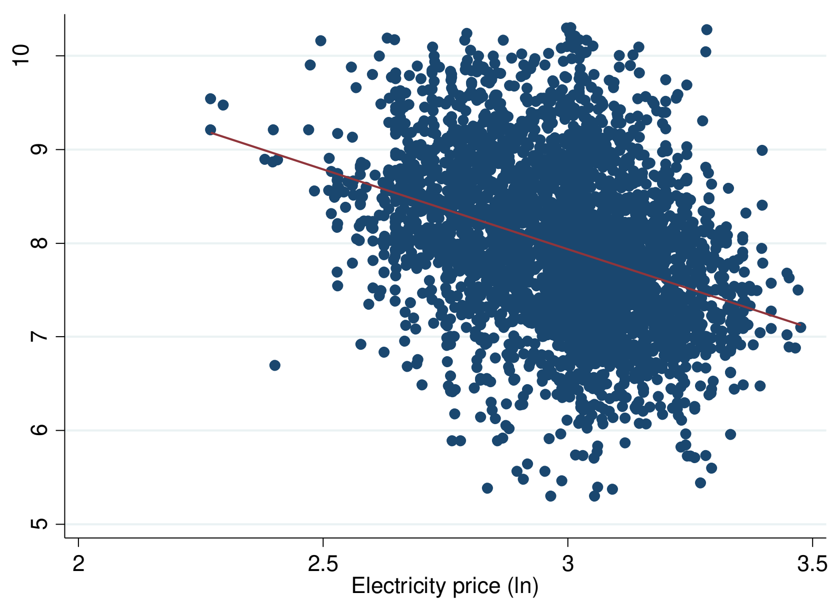
[12] This information is available on Elcom's website https://www.elcom.admin.ch/elcom/fr/home/documentation/medienmitteilungen.msg-id-72073.html

[13] For instance https://www.tdg.ch/suisse/electricite-facture-salee-2018/story/15794655 and https://www.24heures.ch/suisse/electricite-facture-salee-2018/story/15794655

[14] This information is available on the web pages of big electricity providers such as *SIG*, *BKW*, *Groupe E* and *Romande Énergie*.

information about the household's corresponding characteristics. A similar approach is adopted with respect to participants' individual attitudes towards various psychological factors, although more complex interactions between household members may determine distinguishable psychological characteristics of the household as an inseparable entity (Volland, 2017). Similar to prior analyses we include distinctive measures for hedonic, egoistic, altruistic, and biospheric values (Steg et al., 2014). These attributes are surveyed using various batteries of questions from the psychological module of the SHEDS. Given the available data, we control for the household's environmental, altruistic and hedonic attitude, as well as for its aspiration for social power. Using principal component analysis (PCA), we reduced the question batteries into four continuous variables. However, in order to provide a ready interpretation of the coefficients of our psychological variables, we prefer to use binary controls corresponding to the principal components with the highest loadings.[15]

Figure 1: Relationship between electricity demand and electricity prices



The third category of determinants considered in relation with annual electricity usage contains dwelling-related characteristics. Similar to income, a mid-point interval method is used to create a continuous

[15] Although the Kaiser–Meyer–Olkin statistic ($KMO \geq 0.7$) indicates a good quality of the continuous measures, the adopted single components seem to be sufficient. Our various analyses show that replacing the binary indicators with corresponding PCA continuous measures does not alter our fundamental results.

variable containing the construction year of the dwelling, from which its age is then calculated. Guided by several preliminary regressions, we decided to exclude other residence characteristics such as type (house or apartment), size and ownership status, as well as the number of electronic durables and the use of electricity for heating, cooling or warm water. As described in *Sub-section 3.2*, electricity prices for different household groups are defined on some dwelling and device characteristics and therefore adding them to our model could lead to multicollinearity.[16] Moreover, adding the set of various electronic durables could lead to an endogeneity problem due to omitted variable bias (Boogen et al., 2014).

Heating degree days (HDD) and cooling degree days (CDD) are obtained from MétéoSuisse - the Swiss Federal Office of Meteorology and Climatology - for 159 whether stations.[17] We could not have a one-to-one matching between zip code areas and weather stations. Given Switzerland's topography and the presence of strong temperature differentials in relatively small weather pools, we decided against linear interpolation. Thus, we consider that the closest station (in straight-line distance) to the household's zip code area provides the best measure of the aforementioned variables.[18]

Finally, we control for unobservable characteristics by including year dummies and canton fixed effects. Since for some cantons (e.g., Uri, Obwalden, Nidwalden) the proportion of observations in the SHEDS is too small for sound econometric analysis, we proceed by grouping households from the closest geographic areas together. A time dummy allows us to capture unobservable time-variant effects.

4. Econometric approach

In order to evaluate the effect of socio-economic factors on electricity demand, we use the following regression model:

[16] We are indebted to an anonymous reviewer for emphasizing this issue.
[17] HDD is defined as the annual sum of the daily difference between the threshold temperature of 20°C and the average outside daily temperature when it is below 12°C. Similarly, CDD is measured as the annual sum of the difference between the average daily temperature and the threshold of 18.3°C.
[18] The average distance between the household's zip code and the weather station's zip code is about 8 kilometers. Detailed information about the location of MétéoSuisse weather stations is available at https://www.meteosuisse.admin.ch/home/valeurs-mesurees.html?param=messnetz-automatisch.

$$ln(kWh_{it}) = \beta_0 + \beta_1 ln(P_{it}) + \beta_2 ln(I_{it}) + \sum_{l=3}^{n}(\beta_l X_{lit}) + a_i + \varepsilon_{it} , \quad (1)$$

where kWh_{it} is electricity consumption of household i in year t, P_{it} is the electricity price that household i is facing and I_{it} is its disposable income. Households' demographic and psychological characteristics, weather variables, as well as dwelling features, canton and year dummies are individually captured by $X_{3it}, \dots , X_{nit}$. a_i and ε_{it} are respectively time-invariant household-specific effects, and time-variant idiosyncratic errors.

We estimate the average impacts of the variables in equation (1) both by correlated random effect (CRE) and fixed effect (FE) models.[19] Both models allow us to use the available dataset to control for endogeneity of unobservable characteristics which do not vary across periods. The CRE provides simultaneously the FE estimates of controls with sufficient within variation (namely electricity prices, gross income, dwelling age, age of the reference person, HDD and CDD) and the coefficients of variables which do not vary between clusters, such as gender, or exhibit little within variation, such as education (Allison, 2009; Schunck, 2013). Because many of the variables included in (1) can be considered as time-invariant (e.g., education, environmental attitude), the CRE has the advantage of quantifying the impact of these variables as well.

In order to address the possibility of heterogeneous price and income elasticities, we apply the quantile regression (QR) method developed by Koenker & Bassett (1978). QR addresses namely the question of whether an explanatory variable has different impacts across conditional quantiles of consumption. Thus, it is an important complement to estimations of the price and income elasticities of the "average Joe" in the sense that it provides a more complete picture of the relationship between the dependent measure and the set of covariates under study.[20] In particular, we use QR models adapted for panel data analysis. In line with Bache et al. (2013) and Abrevaya & Dahl (2008), we operationalize a CRE quantile estimation by including the time averages of the basic time-variant covariates in (1), and by applying a pooled quantile regression

[19] These approaches lead to the same fixed effect estimates, as shown by Schunck (2013).
[20] A short discussion of a basic quantile regression model is provided in the appendix.

to this extended model specification (Wooldridge, 2010). In order to provide more robust estimation results, we cluster the error terms by household (Machado & Silva, 2013).

Despite the existence of alternative approaches to panel quantile regression with fixed effects (Machado & Silva, 2019; Canay, 2011; Koenker, 2004; Powell, 2016) , we do not rely on them because of their restrictive assumptions about individual fixed effects. In particular, as pointed out by Powell (2016), in order to interpret the marginal effects at various consumption quantiles, we need to keep the quantiles unconditional to individual fixed effects. This is only possible in Powell's model, which proved to be quite sensitive in our data.[21]

5. Empirical results

Table 2 presents results from two statistically equivalent linear regression models (CRE and FE). The two estimators differ negligibly in our case due to the slightly different specification of panel averages in the CRE model. The CRE model in column (2) includes the sample means of variables that represent genuine longitudinal variation. In particular, in order to avoid multicollinearity in the presence of year dummies, we exclude means of the temporal variables such as the two age variables. These models confirm several previously well-documented phenomena. First, an increase in electricity prices has a significant, negative impact of on electricity consumption. Our FE estimate of average price elasticity (-0.30), precisely in the middle of the interval of most frequent short- and medium-run estimates (-0.4 to -0.2) suggested by previous studies (Fan & Hyndman, 2011; Reiss & White, 2005). Our average price elasticity is practically the same as the elasticities reported in earlier studies for Switzerland (Boogen et al., 2017; Filippini, 1999). More generally, in line with previous findings, our results confirm that electricity demand is inelastic with respect to prices, at least in the short-run. This is consistent with the fact that electricity can be considered

[21] Another alternative is Machado & Silva (2019) but not appropriate for short panels. In order to allow for reliable inference even with moderate number of time periods, we implement the split-panel jackknife bias correction suggested by Dhaene & Jochmans (2015). The results confirm in general our findings especially concerning the pattern of estimated price elasticities. We are grateful to Joao Santos Silva for providing us with the code for the implementation of the jackknife correction bias. Results from these analyses are available in Appendix B.

as a basic good.[22] In line with previous works in similar set-ups (Alberini et al., 2011; Bedir et al., 2013; Grønhøj & Thøgersen, 2011; Kavousian et al., 2013; Leahy & Lyons, 2010; O'Doherty et al., 2008), we find an insignificant short-term impact of income on electricity consumption.

In agreement with other studies (e.g., Bartusch et al., 2012), we find that the vintage of the dwelling has a positive effect on the consumption of electricity. The age of the reference person is also related to higher electricity usage, probably due to more sedentary lifestyles at later stages of life, to increased need of thermal comfort, or to possession of different (less efficient, different type) electronic durables by the elderly (Bardazzi & Pazienza, 2017; McLoughlin et al., 2012; Meier & Rehdanz, 2010). It is important to note that a model, where both age variables are combined with household-specific means and time dummies, could represent a multicollinearity problem. However, alternative model specifications show that including both effects (average age of reference person and building) does not affect our results.

The average estimates listed in Column (1), also show that households living in non-urban locations consume significantly higher amounts of electricity compared to city-dwellers, namely about 27% and 45% more for people living in agglomerations and those residing in the countryside, respectively. One possible explanation for this is the urban heat-island effect, characterizing urban areas which are warmer compared to neighboring rural regions due to the higher concentration of human activities (Arnfield, 2003). Cities also benefit from public lighting and from district heating services, both of which could be related to lower personal use of electricity.

[22] It is also interesting to note that a substantial number of sampled households use electricity for heating: about 25% report to rely on electricity as a primary heating source, while 37% use electricity for generating hot water.

Table 2: CRE and FE linear regressions

	(1)	(2)
	Linear CRE	Linear FE
Electricity price (ln)	-0.312**	-0.296**
	(0.142)	(0.136)
Gross income (ln)	-0.023	-0.032
	(0.039)	(0.038)
Heating degree days (HDD)	-0.0000001	0.0001
	(0.0001)	(0.0001)
Cooling degree days (CDD)	0.00004	0.00002
	(0.0003)	(0.0004)
Year: 2016 (ref. 2015)	-0.012	-0.021
	(0.037)	(0.039)
Year: 2017 (ref. 2015)	-0.036	-0.029
	(0.025)	(0.026)
Year: 2018 (ref. 2015)	-0.057**	-0.013
	(0.029)	(0.026)
Age of ref. person	0.011***	
	(0.0012)	
Vintage of dwelling	0.001***	
	(0.0003)	
Number of household members	0.177***	
	(0.016)	
Gender: female	-0.117***	
	(0.039)	
Education: tertiary	-0.041	
	(0.029)	
Location: agglomeration (ref. city)	0.242***	
	(0.042)	
Location: countryside (ref. city)	0.375***	
	(0.047)	
Pro-environmental attitude: yes	-0.007	
	(0.028)	
Altruistic attitude: yes	-0.032	
	(0.021)	
Aspiring for social power: yes	0.009	
	(0.031)	
Hedonic attitude: yes	0.003	
	(0.017)	
Imputed electricity price: yes	Yes	No
Average electricity price (by id)	Yes	No
Average gross income (by id)	Yes	No
Average HDD (by id)	Yes	No
Average CDD (by id)	Yes	No
Canton dummies	Yes	No
Constant	Yes	Yes
Observations	3,856	3,856
Households	1,483	1,483
Observations per household:		
min	2	2
max	4	4
average	2.6	2.6
R^2:		
within	0.01	0.01
between	0.41	0.08
overall	0.38	0.08

Clustered standard errors (by id) in parentheses
** p<0.05, *** p<0.010

An additional household member increases the total electricity usage (by approximately 20%), whereas a households with a female head use consume (about 13%) less electricity than their male counterparts - findings similar to those of Brounen et al. (2012) and Grønhøj & Thøgersen (2011). With respect to gender, the latter authors explain that women report to do more efforts to save electricity than men. Yet, an earlier work by Karjalainen's (2007) suggests that women prefer higher heating temperatures which could lead to higher consumption of electricity, if for instance additional electric radiators are used.

The estimated coefficients of weather variables - HDD and CDD, are statistically insignificant. However, it is likely that year dummies and individual fixed effects (embedded in the CRE model) capture most of weather variations. Alternatively, the insignificant effect could be also explained by the fact that HDD and CDD are measured at the weather station and do not represent household-specific variations (as explained in *Section 3.3*).

Table 3 provides the correlated random effect quantile regression (CRE QR) results for five quantiles of the conditional distribution of electricity consumption. This analysis completes the picture of the "average Joe" covered by the CRE linear model. Our QR model uses the same set of variables as those previously discussed in the CRE setup. Exploring the heterogeneity among households, we observe that electricity prices play a statistically significant role only at the lower spectrum of the distribution of electricity demand, but an insignificant one at its upper part. That is, the estimated QR coefficients of prices become significant at generally accepted significance levels only at the median and the first quartile of the conditional distribution, where the estimated price elasticity is approximately -0.41 and -0.57. Yet, we find that households in the lowest decile do not react significantly to price changes. The same applies for intensive electricity consumers, situated namely at the third quartile and the 90^{th} percentile of the conditional distribution.

This finding corresponds to Reiss & White's (2005) observation that price elasticities are higher at the lower-end of the (unconditional) electricity distribution. Hence, a policy measure, which based on an average estimation establishes higher electricity prices (at a flat rate) for all consumers runs the risk of affecting disproportionately frugal and intensive users. Therefore, our analysis suggests that taxes should have different behavioral and welfare effects in different consumer groups. While showing an inelastic demand similar to other quantiles, parsimonious users are relatively responsive to price changes, hence a greater potential for reducing consumption. However, from an equity perspective, they should not be the focus of policies aiming at demand reduction, not only because they are frugal in the first place, but also because the undesired impact on their welfare could be greater. This is especially valid if reducing energy demand would require investment in efficiency with greater income effect for low-income households. These undesired effects could however be resolved by coupling taxes with subsidies targeting low-income households, and/or with additional non-price measures specifically designed for intensive users.[23]

We are however cautious about this interpretation of our results for policy guidance. In fact, *Table 3* shows that "frugal Janes" in the lowest conditional decile are also price-insensitive. The most parsimonious and most intensive consumers might be non-reactive to price variations for very different reasons though. It is conceivable that since the former already use as little electricity as possible, there is no further possibility (or willingness) to reduce electricity as prices increase. As soon as those households start having "less basic" uses of electricity perhaps they also become more sensitive to price variations. On the other hand, "wasteful Johns" might be characterized by non-discretionary electricity usage (for instance heat pumps) which does not allow them to decrease consumption at their will. Hence, our findings point more generally to heterogeneous price elasticities across the conditional electricity distribution, thereby calling for more targeted policy measures.

[23] Non-price measures could consist of recommendations, nudges, information labels, but also standards and stringent regulation. Utilities could for instance send messages to intensive users reminding them they are using too much electricity, by comparing them with a typical household or with their neighbors, by informing them about saving possibilities (electricity-related and financial) or by sending them targeted ads for efficient appliances.

Table 3: Quantile analysis (CRE QR)

	Correlated random effects quantile regressions				
	q0.10	q0.25	q0.50	q0.75	q0.90
Electricity price (ln)	-0.442	-0.571**	-0.409**	-0.322	-0.515
	(0.311)	(0.251)	(0.169)	(0.239)	(0.301)
Gross income (ln)	0.008	-0.013	0.026	-0.004	0.033
	(0.095)	(0.067)	(0.050)	(0.061)	(0.071)
Heating degree days (HDD)	0.0001	-0.0002	-0.0001	0.0002	0.0002
	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Cooling degree days (CDD)	-0.0006	-0.000001	-0.001	0.0002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year: 2016 (ref. 2015)	-0.086	0.017	-0.100	-0.089	-0.185
	(0.094)	(0.071)	(0.052)	(0.098)	(0.103)
Year: 2017 (ref. 2015)	-0.118**	-0.030	-0.089**	-0.132**	-0.122
	(0.058)	(0.050)	(0.035)	(0.0587)	(0.066)
Year: 2018 (ref. 2015)	-0.040	-0.091	-0.142***	-0.042	-0.071
	(0.057)	(0.062)	(0.047)	(0.059)	(0.079)
Age of ref. person	0.010***	0.010***	0.011***	0.012***	0.014***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)
Vintage of dwelling	0.0001	0.0005	0.0004	0.001	0.001
	(0.0006)	(0.0006)	(0.0004)	(0.001)	(0.001)
Number of household members	0.232***	0.233***	0.239***	0.234***	0.203***
	(0.021)	(0.022)	(0.019)	(0.022)	(0.030)
Gender: female	-0.121**	-0.127***	-0.097***	-0.099**	-0.044
	(0.049)	(0.047)	(0.033)	(0.044)	(0.072)
Education: tertiary	-0.073	-0.048	-0.028	0.004	-0.037
	(0.046)	(0.046)	(0.037)	(0.044)	(0.066)
Location: agglomeration (ref. city)	0.166***	0.147***	0.192***	0.313***	0.518***
	(0.058)	(0.052)	(0.041)	(0.063)	(0.126)
Location: countryside (ref. city)	0.212***	0.306***	0.431***	0.496***	0.543***
	(0.073)	(0.066)	(0.049)	(0.055)	(0.095)
Pro-environmental attitude: yes	-0.075	-0.051	-0.028	-0.083	0.006
	(0.051)	(0.042)	(0.041)	(0.061)	(0.083)
Altruistic attitude: yes	-0.056	-0.027	-0.072	-0.065	-0.128
	(0.048)	(0.041)	(0.037)	(0.039)	(0.068)
Aspiring for social power: yes	0.077	0.038	0.041	0.126	0.054
	(0.058)	(0.054)	(0.041)	(0.067)	(0.081)
Hedonic attitude: yes	0.030	0.030	0.024	0.037	0.084
	(0.041)	(0.033)	(0.028)	(0.037)	(0.057)
Imputed electricity price: yes	Yes	Yes	Yes	Yes	Yes
Average electricity price (by id)	Yes	Yes	Yes	Yes	Yes
Average gross income (by id)	Yes	Yes	Yes	Yes	Yes
Average HDD (by id)	Yes	Yes	Yes	Yes	Yes
Average CDD (by id)	Yes	Yes	Yes	Yes	Yes
Canton dummies	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes
Observations	3,856	3,856	3,856	3,856	3,856
Households	1,483	1,483	1,483	1,483	1,483
Observations per household:					
min	2	2	2	2	2
max	4	4	4	4	4
average	2.6	2.6	2.6	2.6	2.6
Pseudo R^2	0.36	0.38	0.38	0.38	0.36

Clustered standard errors (by id) in parentheses
** p<0.05, *** p<0.010

The results displayed in *Table 3* also indicate different impacts across the consumption spectrum for variables with little or no within variation such as gender and living area. For instance, households with a female reference person use significantly less electricity at low levels of electricity usage, whereas gender does not affect high consumption levels. If women are more energy-conscious than men, as suggested by Thøgersen & Grønhøj (2010), they could perform better at reducing energy when energy reduction is possible (discretionary electricity usage). However, it is also possible that the negative impact of the female dummy on electricity consumption suggests that the lower quantiles have a disproportionate share of single-member female households. It is also interesting to notice that in comparison to city-dwellers, non-urban households use much higher amounts of electricity at the upper-end of the conditional electricity distribution. As argued before, it is likely that areas outside cities are characterized by a more limited heating and lighting options and the increasing magnitude of the location coefficient could simply translate this decreasing level of discretionary electricity usage.

In order to test the robustness of the main results of the previous, we perform several additional robustness checks by dropping households who move across communal or cantonal borders in order to alleviate the effects of important life-style changes that cannot be accounted for, by restricting our sample to a balanced panel, or by imposing different restrictions for outliers. These results point to a slightly higher and statistically significant (at 5%) average price elasticities (between -0.4 and -0.5), and confirm our result that the estimated price elasticities are significant for lower quantiles of electricity usage (see Appendix B).

Caveats

Our analysis bears a number of caveats that can be addressed in further research. First, while our findings provide evidence of heterogeneity of price responses among consumption quantiles, the estimated pattern of variation across quantiles might be sensitive to model specification. In particular, our QR analyses with alternative conditioning on time-invariant factors especially individual fixed effects, suggest that the pattern of relatively high elasticity in lower quantiles might not live up to rigorous robustness tests. Such assessments require more flexible QR models that could provide a general framework for conditional quantiles without relying on fixed effects in line with Powell (2016).

Secondly, most Swiss households can choose their electricity product, with a usually low fraction opting for more expensive "green" electricity. Our estimates should not be affected to the extent that this is a time-invariant factor that does not influence our longitudinal price variation. However, given that over time some households might switch to different products (without necessarily adapting their consumption), our estimates of price effects could be biased. Third, due to the lack of price data on alternative heating fuels, we do not consider cross-price elasticities in our model specification. Since, most electricity-saving behaviors are by substitution with other energy sources, a complete picture of price responses requires a full analysis of alternative energy prices. Fourth, due to the limited longitudinal income variations in a relatively short panel data set, the analysis does not allow to identify long-term income effects.

Finally, we focus on the heterogeneity of price responses across different groups of consumers defined on their intensity of consumption. Alternative grouping methods could be used in order to investigate the heterogeneity in price and income responses, in particular different income groups and dwelling locations. These elements present possibilities for future research to provide better insights about the long-term effect of prices and income on household electricity demand across different groups of households.

6. Conclusion and policy implications

In this article, we analyze the heterogeneity in price and income elasticities of the residential demand for electricity in Switzerland. In particular, we are interested in price and income effects for different levels of usage intensity. For this purpose we use a four-year panel dataset obtained from the Swiss Household Energy Demand Survey (SHEDS). We combine these data with a unique price data set retrieved from the Swiss electricity regulator (ElCom) and weather data from the Swiss federal office of Meteorology and Climatology (MétéoSuisse). Our estimation strategy consists of applying correlated random effects (CRE) quantile regression models. The results show that for many covariates, average CRE represents only lower quantiles of electricity consumption, namely, "frugal" consumers. With respect to prices, the elasticities found in the linear CRE model mirrors the estimated influence of prices in the lower tail of the electricity distribution. In fact, our QR model shows that up to the sample median households react to changes in prices, but in upper quantiles, price-elasticities are statistically insignificant, with an expected negative sign. Concerning the income effect, our average estimations truthfully reflect the non-significant effect of this variable across the conditional distribution of household electricity demand. The CRE method also allows us to estimate the impact of time-invariant covariates, some of which also exhibit different effects across the electricity consumption spectrum. The main results concerning electricity prices and income hold when we use alternative control variables and sample restrictions.

Overall, our results suggest that the "average Joe" differs from the "frugal Jane" and the "wasteful John" in a variety of aspects. Understanding response heterogeneity between consumers could be used not only to assess the distributive effects of various policies but also for guiding policies targeting various groups of consumers. With respect to policy implications, our findings suggest that when designing policy measures price and income effects should be considered based on household heterogeneity. In particular, even the average inelastic response to price changes, mask some groups of consumers with negligible or little responsiveness to prices. This implies that for instance, if a tax can be used to curb the household's electricity consumption, the effect is probably limited in a selection of households. This not only limits the effectiveness of price measures, but might compromise the equity considerations of tax policies. As pointed out by our results, taxes could impact the frugal usage of electricity with a relatively high welfare impact, but could leave out the intensive electricity consumers, the very consumers that should be targeted. In order to overcome these undesired effects, policy makers could couple taxes with subsidies for potentially penalized groups and/or non-price measures for those that are less responsive to price changes.

Appendix A: Quantile regression

A starting point for quantile regression is the notion of conditional quantiles, as illustrated by Koenker & Hallock (2001) in their discussion of the determinants of infant birthweight. In order to generalize a linear model (adapted to sample means) to conditional quantiles, consider a generic matrix representation of equation (1),

$$y_i = \mathrm{X}_i'\beta + \varepsilon_i \,. \tag{2}$$

From (2), the estimated coefficients vector $\hat{\beta}$ at the q^{th} quantile of y_i ($q \in (0;1)$), hereafter expressed as $\hat{\beta}_q$, are obtained by minimizing the asymmetric loss function given as:

$$\sum_{i:\ y_i \geq \mathrm{X}_i'\beta}^{N} q\,|\,y_i - \mathrm{X}_i'\beta_q| \quad + \quad \sum_{i:\ y_i < \mathrm{X}_i'\beta}^{N} (1-q)\,|\,y_i - \mathrm{X}_i'\beta_q| \,. \tag{3}$$

Quantile regression allows a ready interpretation of the estimated coefficients $\hat{\beta}_q$ as marginal effects within their respective quantiles (Angrist & Pischke, 2009). Apart from characterizing the marginal effects over the entire conditional distribution of the dependent variable, QR provides a robust estimator. As opposed to OLS estimators, QR is more robust to outliers, and to the distribution of error terms.

As demonstrated by Bache et al. (2013) and Abrevaya, J., & Dahl (2008), panel data models such as fixed effects formulation and the correlated random effects (CRE) in line with Wooldridge (2010), can be applied to QR models. In particular using data simulations, Bache et al. (2013) demonstrate that similar to a linear model, a CRE-QR model can be implemented directly by including sample panel means of time-variant variables.

Appendix B: Robustness checks

Table B1: Fixed effects quantile regressions with a Jackknife correction bias (Machado & Silva, 2019) and excluding canton and location dummies

	Fixed effects quantile regressions				
	q.10	q.25	q.50	q.75	q.90
Electricity price (ln)	-0.568***	-0.497**	-0.359	-0.230	-0.162
	(0.198)	(0.205)	(0.196)	(0.162)	(0.158)
Gross income (ln)	-0.035	-0.038	-0.045	-0.051	-0.054
	(0.032)	(0.043)	(0.041)	(0.053)	(0.054)
Heating degree days (HDD)	0.000	0.000	0.000	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cooling degree days (CDD)	-0.000	0.000	0.000	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Year: 2016 (ref. 2015)	-0.003	-0.002	0.000	0.002	0.003
	(0.058)	(0.041)	(0.054)	(0.044)	(0.053)
Year: 2017 (ref. 2015)	-0.004	-0.012	-0.028	-0.044	-0.051
	(0.068)	(0.055)	(0.066)	(0.045)	(0.063)
Year: 2018 (ref. 2015)	0.008	0.010	0.014	0.018	0.020
	(0.109)	(0.086)	(0.092)	(0.073)	(0.099)
Age of ref. person	-0.011	-0.009	-0.005	-0.002	0.000
	(0.030)	(0.023)	(0.027)	(0.022)	(0.029)
Vintage of dwelling	0.001	0.001	0.001**	0.002***	0.002**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Number of household members	0.035	0.035	0.035	0.034	0.034
	(0.030)	(0.040)	(0.027)	(0.025)	(0.024)
Education: tertiary	-0.117	-0.117	-0.117***	-0.116	-0.116
	(0.061)	(0.087)	(0.045)	(0.088)	(0.099)
Pro-environmental attitude: yes	0.044	0.030	0.003	-0.023	-0.036
	(0.045)	(0.041)	(0.033)	(0.035)	(0.032)
Altruistic attitude: yes	-0.034	-0.028	-0.016	-0.004	0.002
	(0.030)	(0.018)	(0.029)	(0.024)	(0.022)
Aspiring for social power: yes	-0.000	0.004	0.011	0.018	0.022
	(0.035)	(0.047)	(0.038)	(0.027)	(0.029)
Hedonic attitude: yes	-0.004	-0.002	0.003	0.008	0.011
	(0.016)	(0.026)	(0.021)	(0.018)	(0.026)
Imputed electricity price: yes	Yes	Yes	Yes	Yes	Yes
Observations	3,882	3,882	3,882	3,882	3,882

Clustered standard errors in parentheses,

** p<0.05, *** p<0.010

Table B2: Fixed effects quantile regressions a Jackknife correction bias (Machado & Silva, 2019) and including canton and location dummies

	Fixed effects quantile regressions				
	q.10	q.25	q.50	q.75	q.90
Electricity price (ln)	-0.612***	-0.547**	-0.424**	-0.306	-0.251
	(0.217)	(0.263)	(0.190)	(0.198)	(0.135)
Gross income (ln)	-0.049	-0.049	-0.050	-0.050	-0.050
	(0.035)	(0.042)	(0.030)	(0.066)	(0.043)
Heating degree days (HDD)	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cooling degree days (CDD)	-0.000	-0.000	0.000	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Year: 2016 (ref. 2015)	-0.034	-0.023	-0.003	0.016	0.024
	(0.035)	(0.040)	(0.051)	(0.060)	(0.044)
Year: 2017 (ref. 2015)	-0.020	-0.024	-0.032	-0.039	-0.043
	(0.056)	(0.065)	(0.062)	(0.026)	(0.049)
Year: 2018 (ref. 2015)	0.018	0.019	0.019	0.020	0.021
	(0.098)	(0.113)	(0.084)	(0.067)	(0.083)
Age of ref. person	-0.013	-0.010	-0.006	-0.002	-0.000
	(0.026)	(0.030)	(0.021)	(0.014)	(0.024)
Vintage of dwelling	0.001	0.001	0.001**	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Number of household members	0.039	0.037	0.034	0.031	0.029
	(0.020)	(0.028)	(0.037)	(0.023)	(0.016)
Education: tertiary	-0.103	-0.104	-0.105***	-0.107	-0.107
	(0.090)	(0.083)	(0.033)	(0.101)	(0.088)
Location: agglomeration (ref. city)	0.155	0.125	0.067	0.013	-0.013
	(0.089)	(0.226)	(0.157)	(0.075)	(0.180)
Location: countryside (ref. city)	0.002	0.009	0.022	0.035	0.041
	(0.186)	(0.177)	(0.168)	(0.395)	(0.212)
Pro-environmental attitude: yes	0.045	0.030	0.001	-0.027	-0.039
	(0.041)	(0.044)	(0.037)	(0.038)	(0.030)
Altruistic attitude: yes	-0.039	-0.030	-0.015	0.000	0.007
	(0.028)	(0.026)	(0.035)	(0.023)	(0.009)
Aspiring for social power: yes	-0.005	-0.001	0.007	0.014	0.018
	(0.036)	(0.057)	(0.039)	(0.025)	(0.030)
Hedonic attitude: yes	-0.002	-0.000	0.004	0.007	0.009
	(0.013)	(0.019)	(0.011)	(0.017)	(0.025)
Imputed electricity price: yes	Yes	Yes	Yes	Yes	Yes
Canton Dummies	Yes	Yes	Yes	Yes	Yes
Observations	3,882	3,882	3,882	3,882	3,882

Clustered standard errors in parentheses, ** p<0.05, *** p<0.010

Table B3:CRE QR: excluding data points standing further than 1.5 IQR from the first and third quartiles of the distribution of electricity demand

	Correlated random effects quantile regressions				
	q.10	q.25	q.50	q.50	q.75
Electricity price (ln)	-0.719	-0.681**	-0.543***	-0.408	-0.125
	(0.415)	(0.282)	(0.200)	(0.239)	(0.307)
Gross income (ln)	-0.034	-0.030	0.025	-0.034	-0.006
	(0.111)	(0.084)	(0.050)	(0.038)	(0.060)
Heating degree days (HDD)	0.0004	-0.00003	-0.0001	0.0002**	0.0002
	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Cooling degree days (CDD)	-0.001	0.001	0.0001	0.0004	0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year: 2016 (ref. 2015)	-0.121	0.068	-0.035	-0.051	-0.032
	(0.106)	(0.070)	(0.053)	(0.066)	(0.085)
Year: 2017 (ref. 2015)	-0.198***	-0.001	-0.057	-0.095**	-0.077
	(0.067)	(0.053)	(0.038)	(0.039)	(0.058)
Year: 2018 (ref. 2015)	0.006	-0.016	-0.121***	-0.044	-0.029
	(0.072)	(0.054)	(0.045)	(0.047)	(0.050)
Age of ref. person	0.010***	0.010***	0.010***	0.009***	0.009***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Vintage of dwelling	-0.0001	0.0003	0.0004	0.001	0.001
	(0.0005)	(0.0004)	(0.0003)	(0.001)	(0.001)
Number of household members	0.255***	0.241***	0.224***	0.215***	0.163***
	(0.023)	(0.021)	(0.017)	(0.016)	(0.024)
Gender: female	-0.093	-0.126***	-0.086***	-0.103***	-0.055
	(0.058)	(0.049)	(0.032)	(0.037)	(0.050)
Education: tertiary	-0.086	-0.025	-0.027	-0.0069	-0.013
	(0.058)	(0.046)	(0.034)	(0.041)	(0.050)
Location: agglomeration (ref. city)	0.172***	0.128***	0.139***	0.133***	0.206***
	(0.065)	(0.049)	(0.038)	(0.048)	(0.066)
Location: countryside (ref. city)	0.230***	0.236***	0.373***	0.359***	0.363***
	(0.074)	(0.070)	(0.045)	(0.056)	(0.051)
Pro-environmental attitude: yes	-0.020	-0.035	-0.021	-0.028	-0.034
	(0.065)	(0.050)	(0.039)	(0.043)	(0.041)
Altruistic attitude: yes	-0.039	-0.026	-0.047	-0.046	-0.041
	(0.056)	(0.040)	(0.032)	(0.035)	(0.039)
Aspiring for social power: yes	0.031	0.029	0.008	0.036	0.058
	(0.086)	(0.051)	(0.038)	(0.061)	(0.069)
Hedonic attitude: yes	0.065	0.044	0.012	0.019	0.0004
	(0.049)	(0.035)	(0.026)	(0.032)	(0.040)
Imputed electricity price: yes	Yes	Yes	Yes	Yes	Yes
Average electricity price (by id)	Yes	Yes	Yes	Yes	Yes
Average gross income (by id)	Yes	Yes	Yes	Yes	Yes
Average HDD (by id)	Yes	Yes	Yes	Yes	Yes
Average CDD (by id)	Yes	Yes	Yes	Yes	Yes
Canton dummies	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes
Observations	3,586	3,586	3,586	3,586	3,586

Clustered standard errors in parentheses, ** p<0.05, *** p<0.010

Table B4: CRE QR: excluding data points standing further than 3 IQR from the first and third quartiles of the distribution of electricity demand

	Correlated random effects quantile regressions				
	q.10	q.25	q.50	q.75	q.90
Electricity price (ln)	-0.806	-0.594**	-0.470**	-0.381	-0.588
	(0.426)	(0.258)	(0.192)	(0.221)	(0.319)
Gross income (ln)	-0.019	-0.051	0.024	-0.003	0.062
	(0.126)	(0.081)	(0.052)	(0.057)	(0.073)
Heating degree days (HDD)	0.0003	-0.0001	-0.00003	0.0002	0.0001
	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Cooling degree days (CDD)	-0.0003	0.001	-0.0003	0.0003	-0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year: 2016 (ref. 2015)	-0.113	0.070	-0.096	-0.071	-0.052
	(0.102)	(0.073)	(0.052)	(0.077)	(0.111)
Year: 2017 (ref. 2015)	-0.181**	-0.003	-0.086**	-0.101**	-0.052
	(0.075)	(0.051)	(0.036)	(0.047)	(0.076)
Year: 2018 (ref. 2015)	-0.001	-0.039	-0.130***	-0.048	-0.024
	(0.067)	(0.059)	(0.048)	(0.053)	(0.064)
Age of ref. person	0.011***	0.010***	0.010***	0.010***	0.010***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Vintage of dwelling	-0.0001	0.0003	0.0003	0.001	0.001***
	(0.001)	(0.001)	(0.0004)	(0.001)	(0.0004)
Number of household members	0.257***	0.243***	0.233***	0.227***	0.189***
	(0.024)	(0.020)	(0.019)	(0.017)	(0.020)
Gender: female	-0.108**	-0.131***	-0.094***	-0.107**	-0.084
	(0.053)	(0.046)	(0.033)	(0.043)	(0.051)
Education: tertiary	-0.086	-0.021	-0.016	0.013	-0.035
	(0.055)	(0.044)	(0.036)	(0.043)	(0.049)
Location: agglomeration (ref. city)	0.179***	0.146***	0.172***	0.218***	0.338***
	(0.065)	(0.050)	(0.038)	(0.055)	(0.069)
Location: countryside (ref. city)	0.242***	0.288***	0.410***	0.467***	0.455***
	(0.067)	(0.070)	(0.050)	(0.054)	(0.057)
Pro-environmental attitude: yes	-0.036	-0.038	-0.021	-0.026	0.062
	(0.068)	(0.044)	(0.041)	(0.048)	(0.051)
Altruistic attitude: yes	-0.036	-0.031	-0.056	-0.071	-0.138**
	(0.056)	(0.039)	(0.034)	(0.037)	(0.054)
Aspiring for social power: yes	0.014	0.032	0.042	0.060	0.131
	(0.082)	(0.049)	(0.039)	(0.061)	(0.082)
Hedonic attitude: yes	0.078	0.045	0.031	0.038	0.053
	(0.048)	(0.035)	(0.028)	(0.034)	(0.035)
Imputed electricity price: yes	Yes	Yes	Yes	Yes	Yes
Average electricity price (by id)	Yes	Yes	Yes	Yes	Yes
Average gross income (by id)	Yes	Yes	Yes	Yes	Yes
Average HDD (by id)	Yes	Yes	Yes	Yes	Yes
Average CDD (by id)	Yes	Yes	Yes	Yes	Yes
Canton dummies	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes
Observations	3,795	3,795	3,795	3,795	3,795

Clustered standard errors in parentheses, ** p<0.05, *** p<0.010

Table B5: CRE QR: excluding HHs who have changed their canton of residence

	Correlated random effects quantile regressions				
	q.10	q.25	q.50	q.75	q.90
Electricity price (ln)	-0.341	-0.299	-0.388**	-0.476*	-0.323
	(0.387)	(0.268)	(0.178)	(0.244)	(0.346)
Gross income (ln)	0.004	-0.017	0.005	-0.036	0.008
	(0.084)	(0.058)	(0.048)	(0.060)	(0.068)
Heating degree days (HDD)	0.000	0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cooling degree days (CDD)	-0.001	0.000	-0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year: 2016 (ref. 2015)	-0.129	-0.032	-0.105*	-0.114	-0.180*
	(0.098)	(0.086)	(0.057)	(0.108)	(0.098)
Year: 2017 (ref. 2015)	-0.133**	-0.056	-0.082**	-0.150**	-0.138*
	(0.060)	(0.056)	(0.038)	(0.063)	(0.076)
Year: 2018 (ref. 2015)	-0.045	-0.057	-0.131***	-0.037	-0.091
	(0.067)	(0.065)	(0.048)	(0.061)	(0.088)
Age of ref. person	0.010***	0.010***	0.011***	0.012***	0.013***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)
Vintage of dwelling	0.000	0.001	0.000	0.001**	0.002
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Number of household members	0.222***	0.227***	0.246***	0.238***	0.203***
	(0.023)	(0.023)	(0.021)	(0.021)	(0.039)
Gender: female	-0.103*	-0.130***	-0.100***	-0.095**	-0.055
	(0.054)	(0.047)	(0.035)	(0.047)	(0.072)
Education: tertiary	-0.045	-0.030	-0.027	0.006	-0.050
	(0.051)	(0.046)	(0.038)	(0.048)	(0.069)
Location: agglomeration (ref. city)	0.151**	0.153***	0.189***	0.303***	0.580***
	(0.060)	(0.051)	(0.043)	(0.064)	(0.153)
Location: countryside (ref. city)	0.232***	0.334***	0.454***	0.512***	0.590***
	(0.074)	(0.066)	(0.051)	(0.057)	(0.107)
Pro-environmental attitude: yes	-0.067	-0.038	-0.034	-0.073	-0.001
	(0.060)	(0.045)	(0.044)	(0.065)	(0.093)
Altruistic attitude: yes	-0.071	-0.031	-0.076**	-0.082*	-0.130*
	(0.052)	(0.040)	(0.037)	(0.042)	(0.072)
Aspiring for social power: yes	0.042	0.020	0.048	0.110	0.038
	(0.061)	(0.052)	(0.043)	(0.070)	(0.089)
Hedonic attitude: yes	0.037	0.042	0.028	0.055	0.094
	(0.044)	(0.034)	(0.029)	(0.040)	(0.058)
Imputed electricity price: yes	0.097	-0.004	-0.140	-0.098	0.195
Average electricity price (by id)	-0.730*	-0.994***	-0.997***	-1.055***	-1.641***
Average gross income (by id)	0.202*	0.101	0.096	0.228***	0.190**
Average HDD (by id)	-0.000	-0.000	-0.000	-0.000*	-0.000
Average CDD (by id)	0.000	-0.001*	-0.001	-0.001	-0.000
Canton dummies	0.151	0.199***	0.159**	0.235**	0.374***
Constant	7.490***	9.972***	10.614***	10.322***	12.012***
Observations	3,712	3,712	3,712	3,712	3,712

Clustered standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.010

Table B6: CRE QR: excluding HHs who have changed their zip code of residence

	Correlated random effects quantile regressions				
	q.10	q.25	q.50	q.75	q.90
Electricity price (ln)	-0.814*	-0.614*	-0.261	-0.385	-0.336
	(0.419)	(0.355)	(0.229)	(0.267)	(0.339)
Gross income (ln)	0.056	0.011	0.033	-0.003	0.028
	(0.120)	(0.081)	(0.057)	(0.052)	(0.083)
Heating degree days (HDD)	0.000	0.000	-0.000	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cooling degree days (CDD)	-0.001	0.000	-0.001	-0.000	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year: 2016 (ref. 2015)	-0.078	-0.023	-0.126*	-0.182*	-0.245*
	(0.120)	(0.095)	(0.073)	(0.107)	(0.126)
Year: 2017 (ref. 2015)	-0.146*	-0.071	-0.098**	-0.179***	-0.160*
	(0.085)	(0.063)	(0.049)	(0.065)	(0.089)
Year: 2018 (ref. 2015)	-0.023	-0.045	-0.152***	-0.024	-0.032
	(0.075)	(0.075)	(0.051)	(0.060)	(0.068)
Age of ref. person	0.010***	0.011***	0.011***	0.011***	0.013***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)
Vintage of dwelling	-0.000	0.000	0.000	0.001	0.002**
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Number of household members	0.245***	0.231***	0.243***	0.232***	0.189***
	(0.029)	(0.025)	(0.022)	(0.021)	(0.028)
Gender: female	-0.080	-0.119**	-0.090**	-0.093**	-0.039
	(0.054)	(0.047)	(0.036)	(0.046)	(0.061)
Education: tertiary	-0.028	0.011	-0.022	0.010	-0.033
	(0.062)	(0.050)	(0.039)	(0.046)	(0.068)
Location: agglomeration (ref. city)	0.209***	0.167***	0.206***	0.329***	0.551***
	(0.065)	(0.054)	(0.044)	(0.071)	(0.116)
Location: countryside (ref. city)	0.258***	0.321***	0.446***	0.514***	0.553***
	(0.073)	(0.072)	(0.053)	(0.055)	(0.092)
Pro-environmental attitude: yes	-0.013	-0.042	-0.027	-0.062	0.018
	(0.072)	(0.048)	(0.044)	(0.055)	(0.079)
Altruistic attitude: yes	0.010	-0.017	-0.061	-0.062	-0.161**
	(0.062)	(0.041)	(0.037)	(0.040)	(0.063)
Aspiring for social power: yes	0.070	0.023	0.050	0.144**	0.103
	(0.080)	(0.060)	(0.044)	(0.068)	(0.078)
Hedonic attitude: yes	0.084	0.078**	0.041	0.052	0.096
	Yes	Yes	Yes	Yes	Yes
Imputed electricity price: yes	Yes	Yes	Yes	Yes	Yes
Average electricity price (by id)	Yes	Yes	Yes	Yes	Yes
Average gross income (by id)	Yes	Yes	Yes	Yes	Yes
Average HDD (by id)	Yes	Yes	Yes	Yes	Yes
Average CDD (by id)	Yes	Yes	Yes	Yes	Yes
Canton dummies	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes
Observations	3,715	3,715	3,715	3,715	3,715

Clustered standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.010

Table B7: CRE QR for a 4-year balanced panel

	Correlated random effects quantile regressions				
	q.10	q.25	q.50	q.75	q.90
Electricity price (ln)	-0.823*	-0.972*	-0.575	-0.224	-0.136
	(0.498)	(0.512)	(0.403)	(0.458)	(0.498)
Gross income (ln)	0.016	0.004	0.154	0.039	-0.020
	(0.152)	(0.144)	(0.105)	(0.104)	(0.224)
Heating degree days (HDD)	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Cooling degree days (CDD)	-0.000	-0.000	0.000	0.000	-0.002
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Year: 2016 (ref. 2015)	-0.026	-0.047	-0.120	-0.056	-0.143
	(0.152)	(0.329)	(0.135)	(0.086)	(0.127)
Year: 2017 (ref. 2015)	-0.093	-0.051	-0.154*	-0.070	-0.071
	(0.096)	(0.216)	(0.093)	(0.046)	(0.085)
Year: 2018 (ref. 2015)	-0.074	-0.029	0.060	0.058	-0.038
	(0.101)	(0.158)	(0.096)	(0.071)	(0.120)
Age of ref. person	0.009**	0.012***	0.012**	0.012***	0.010*
	(0.004)	(0.004)	(0.005)	(0.004)	(0.006)
Vintage of dwelling	-0.002**	-0.003	-0.002	-0.001	-0.000
	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)
Number of household members	0.095**	0.110**	0.120	0.113*	0.080
	(0.048)	(0.047)	(0.077)	(0.066)	(0.077)
Gender: female	-0.113	-0.097	-0.067	-0.131	0.092
	(0.129)	(0.164)	(0.148)	(0.107)	(0.161)
Education: tertiary	-0.177	-0.093	-0.125	-0.092	0.023
	(0.132)	(0.112)	(0.127)	(0.095)	(0.129)
Location: agglomeration (ref. city)	-0.008	-0.087	-0.231	-0.092	-0.082
	(0.078)	(0.104)	(0.156)	(0.099)	(0.182)
Location: countryside (ref. city)	0.053	-0.093	-0.099	-0.029	-0.169
	(0.100)	(0.115)	(0.105)	(0.074)	(0.177)
Pro-environmental attitude: yes	0.079	0.095	0.188	0.092	-0.014
	(0.102)	(0.105)	(0.141)	(0.072)	(0.141)
Altruistic attitude: yes	-0.057	-0.048	0.040	0.068	0.132*
	(0.080)	(0.080)	(0.101)	(0.071)	(0.076)
Aspiring for social power: yes	0.107	0.102	0.135	0.345**	0.475***
	(0.103)	(0.165)	(0.154)	(0.158)	(0.132)
Hedonic attitude: yes	0.455***	0.454***	0.505**	0.563***	0.640***
	(0.143)	(0.162)	(0.200)	(0.155)	(0.142)
Imputed electricity price: yes	Yes	Yes	Yes	Yes	Yes
Average electricity price (by id)	Yes	Yes	Yes	Yes	Yes
Average gross income (by id)	Yes	Yes	Yes	Yes	Yes
Average HDD (by id)	Yes	Yes	Yes	Yes	Yes
Average CDD (by id)	Yes	Yes	Yes	Yes	Yes
Canton dummies	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes
Observations	884	884	884	884	884

Clustered standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.010

Chapter 3: Heterogeneity in Price Elasticity of Vehicle Kilometers Traveled: Evidence from Micro-Level Panel Data

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1. Introduction

To what extent do fuel price rises induce people to drive less? The answer to this question is crucial in the context of climate change, where fuel taxes are considered as an important instrument to curb GHG emissions. If price elasticity is weak, such an instrument will not be effective. Distributional impacts are also of primary concern. If reactions differ across individuals and households, some will be more deeply affected than others. Heterogeneous responses to fuel prices may therefore be at the root of serious social questions.

A large body of scientific research is dedicated to the estimation of price elasticities of vehicle kilometers traveled (VKT). Most studies analyze aggregate demand and point to rather low price elasticities of roughly -0.1 in the short run and about -0.3 in the long run (Barla et al., 2009; de Jong & Gunn, 2001; Goodwin et al., 2004; Graham & Glaister, 2004; Johansson & Schipper, 1997), thus suggesting that price-based policy measures are unlikely to significantly reduce mileage, fuel consumption and GHG emissions. When household-level demand is investigated, however, average price elasticities exhibit considerably greater magnitudes (e.g., Frondel & Vance, 2009; Sevigny, 1998; West, 2004). Specific segments of consumers seem particularly reactive to price variations because of their mobility behaviors and the presence of transportation alternatives. For instance, households living in urban areas are likely to switch to public transport as a response to higher motor fuel prices, whereas households based in remote areas such as agglomerations or in the countryside cannot easily avoid using their cars even when fuel becomes more expensive. An increase in fuel prices can affect low-income drivers disproportionally, pushing them to opt for cheaper means of travel such as public transportation, car sharing or soft mobility. Also, as a response to higher gasoline prices, intensive drivers could more easily reduce mileage if they engage in a substantial share of discretionary driving, i.e., driving through choice rather than by necessity (see Handy et al., 2005).

The identification of heterogeneous segments of households is essential to assess the distributional and ethical consequences of price interventions, which would obviously affect their acceptability by the population (Mattioli et al., 2018).[1] The heterogeneity in fuel price elasticities has previously been investigated for groups of drivers defined mainly on *observed* socio-demographic segmentation criteria such as income level (e.g., Santos & Catchesides, 2005; Wadud et al., 2009; West, 2004), location (e.g., Gillingham & Munk-Nielsen, 2019; Spiller et al., 2017), multiple-car ownership or household lifecycle (among others Bento et al., 2009; De Borger et al., 2016a; Schmalensee & Stoker, 1999). This literature shows that various driver groups exhibit statistically different price elasticities, so that careful policy design is essential to achieve GHG and energy-reduction goals efficiently and with the least social welfare distortion. However, there are significant discrepancies between the findings of different studies, while the majority focuses on the US. While different empirical methods, temporal horizons and data types might explain such differences, Wadud et al. (2010a) illustrate how plausible real-world scenarios might explain contrasting findings. This provides a motivation for addressing the heterogeneity of price responsiveness in other countries. In Europe, the organization of motorized transportation is very different from that in North America.[2] European countries, and Switzerland in particular, thereby constitute interesting case studies for extending and generalizing knowledge in this domain.[3] Therefore, we follow Gillingham (2014) and Wadud et al.'s (2009) call for further research in this area.

In addition to observed segmentation criteria, *unobserved* grouping characteristics can be used to investigate heterogeneity in the price elasticity of car-travel demand. VKT can indeed be affected by behaviors or habits, which are often not observed by researchers and of which car drivers themselves might

[1] The violent strikes of the so-called "yellow vests" in France at the end of 2018, which originated after the announcement of an increase in diesel taxes, illustrates dramatically how heterogeneous impacts may matter for the acceptability of policy measures. The discontent originated mainly from rural regions, which often face lower economic development but have to bear a disproportionate fuel tax burden in comparison with large urban centers because the latter are less dependent on private motorized transportation (for anecdotal evidence see *The Economist*, 2018).

[2] For instance, the share of taxes in gasoline prices is particularly important in most European countries (European Commission, 2020; AvenergySuisse, 2021), real fuel prices are significantly higher (World Bannk, 2020) and vehicle fleets consist of cars with notably better motor fuel efficiency (ICCT, 2020). In addition, public transport networks are characterized by a particularly high density not least because of significantly shorter travel distances. National mobility surveys also point to differences in car-travel behaviors: UK and Swiss households use their private cars mainly for leisure trips (NTS, 2018; OFS, 2017b), while the main purpose of vehicle usage in the US is related to professional, non-recreational activities NHTS (2017). More detailed comparisons between the US and European mobility contexts are provided by Buehler (2011), Giuliano & Dargay (2006) and Sprei et al. (2019). Such differences certainly affect price elasticities of driving demand: estimations of price elasticities in European countries are generally higher than in the US (Frondel et al., 2017; Graham & Glaister, 2002).

[3] The number of studies examining heterogeneity of fuel price elasticities in European countries is still limited (e.g., Blow & Crawford, 1997; De Borger et al., 2016a; Frondel et al., 2012; Gillingham & Munk-Nielsen, 2019; West, 2004).

not necessarily be aware. For instance, drivers might not always select the most efficient route, or purposefully drive longer distances to arrive at a certain destination in order to avoid areas with heavy traffic jams, bad road quality, poor weather conditions or dangerous neighborhoods. It is also possible that some car owners enjoy driving per se. Alternatively, discretionary driving might be related to leisure activities taking place further away from the dwelling or the living region. Other unobserved factors include the driver's (or a family member's) health, work and household duties, or proximity to facilities, such as a gym or a commercial center. Previous analyses suggest that such factors, which we assume to affect driving intensity, play an important role in private travel demand (Gardner & Abraham, 2007; Sun et al., 2014; Zhao et al., 2020).

Quantile regression (QR; see Koenker & Bassett, 1978) offers the possibility of investigating the impact of such unobserved factors. In such models, conditional quantiles can be interpreted as different levels of intensity of car-travel demand. Several authors (Frondel et al., 2012; Gillingham, 2014; Gillingham et al., 2015) have used QR to investigate price elasticities of groups of consumers defined on the basis of their driving intensity and have found evidence for statistically significant differences between driver groups. To our knowledge, only Gillingham et al. (2015) use a QR method adapted for panel data.[4]

Most analyzes on heterogeneity of price elasticities of VKT rely on cross-section data, and therefore obtain estimates from geographical differences rather than temporal variations. This distinction is crucial because the concept of price elasticity is inherently related to *temporal* variations. Nevertheless, panel data applications in this field remain scarce. Also, in the absence of micro-level data, many studies use aggregate fuel prices (e.g., Gillingham & Munk-Nielsen, 2019; Mattioli et al., 2018) and prices imputed or assigned on the basis of geographical location (e.g., Kayser, 2000). Yet, as mentioned by Oum et al., (1992) *"Aggregation 'averages out' some of the underlying variabilities of price sensitivity"* (p. 153), suggesting

[4] However, this study uses the panel QR method suggested by Canay (2011), which is affected by a severe estimation bias, as outlined by Besstremyannaya & Golovan (2019).

that the differences between the price elasticities of groups of drivers could be also more easily dismissed as statistically insignificant.[5]

The present chapter contributes to the understanding of heterogeneity in gasoline price elasticity of private car-travel demand. In order to examine the price elasticities of segments of drivers with different levels of driving intensity, we use the panel-data quantile regression approach suggested by Wooldridge (2010) and previously applied in other fields of empirical economic research (Abrevaya & Dahl, 2008; Bache et al., 2013; Tilov et al., 2020). Heterogeneity in price responses is also addressed by using observed socio-demographic and vehicle segmentation criteria and analyzed by including interaction terms in a fixed-effect regression model. We use longitudinal data, which are better suited for the estimation of structural coefficients than cross-section data (see Hsiao, 2007). Also, in contrast to most prior works that consider rather old time periods, aggregate demographic and price data, or complex price constructs from different sources in the absence of individual prices, the present article uses household-level data and disaggregate gasoline prices between 2018 and 2020. To the best of our knowledge, this analysis is the first to rely on micro-level revealed behavior to address the effect of price on VKT for different household segments in Switzerland.[6]

The remainder of this article is organized as follows. The related literature is reviewed in *Section 2*. The dataset is introduced in *Section 3*, while our econometric approach is discussed in *Section 4*. *Section 5* presents the empirical findings and *Section 6* presents our conclusions.

[5] Estimating average price elasticities using macro-level city-, county-, or state-level price data might lead to an important downward bias, as discussed by Levin et al. (2017) and Wadud et al. (2010a). The effect of aggregation in empirical works is also discussed by Blundell & Stoker (2005), Halvorsen & Larsen (2013), Miller & Alberini (2016).

[6] Erath & Axhausen (2010) also investigate heterogeneity for private mobility in Switzerland. Their results show that frequent users of public transportation, the elderly and people living in remote areas are more sensitive to variations in fuel prices. Households owning larger vehicles, with a greater number of adults and with a male respondent are in contrast less price sensitive. The authors also observe that households with high income have larger price elasticities. However, these analyses rely on stated preferences, thus relying on hypothetical responses to price variations (Tanner, 2012).

2. Literature review

Our article relates to the wide literature on price elasticities in transportation. In this section, we focus on the contributions that investigate heterogeneity in price elasticity. *Table 1* provides an overview of the literature's findings with respect to heterogeneity in the price responsiveness of car-travel demand.

Table 1: Price elasticity heterogeneity in previous studies

References	**Country, observation period**	**High income**	**Urban area**	**> 1 car**	**Fuel-efficient car**	**High travel intensity**	**Other segmentation criteria considered**
Articles using driving distance or vehicle kilometers (or miles) traveled as dependent variable							
Blow & Crawford (1997)	UK, 1988-1993	-	+				
De Borger et al. (2016a)	Denmark, 2004-2008			+			
Frondel et al. (2012)	Germany, 1997-2009	o	o	o		-	
Gillingham (2014)	US, 2001-2003	+	+			-	
Gillingham et al. (2015)	US, 2000-2010		+		-	+	vehicle buyer type
Gillingham & Munk-Nielsen (2019)	Denmark, 1998-2011		U				distance to work
Santos & Catchesides (2005)	UK, 1988-1993	-	+				
Wang & Chen (2014)	US, 2009	U					
West (2004)	US, 1997	-	+				
Articles using car fuel demand as dependent variable							
Kayser (2000)	US, 1981	+					
Liu (2015)	US, 1997-2002	-	+	-	-		family size
Mattioli et al. (2018)	UK, 2006-2012	-					
Spiller et al. (2017)	US, 2009	+	-	+	-		distance to urban area
Wadud et al. (2009)	US, 1984-2003	U					
Wadud et al. (2010a)	US, 1997-2002	-	+	+			# of wage earners
Wadud et al., (2010b)	US, 1997-2002	-	+	+			# of wage earners

Notes: "+/-" indicate higher/lower magnitudes of price elasticity for the specific segment (e.g., high income); "o" indicates insignificant differences between the price elasticities; "U" indicates a U-shaped evolution of the magnitude of price elasticities along the distribution of the variable. Cells are left empty whenever the relationship was not investigated.

Most often, earlier research defines categories of car drivers on the basis of income levels and location. Among others, Blow & Crawford (1997), Wadud et al. (2010a) and West (2004) observe that wealthier households are less reactive to fuel price changes. These studies explain their findings by the possibility that poorer households, which already allocate an important part of their income to car-travel, may respond to increasing gasoline taxes by simply driving less, or by switching to public transportation. Conversely, high-income drivers are less sensitive to price increases because, proportionally, such changes affect their income only marginally (Wadud et al., 2010a).

In contrast, Gillingham (2014), Hughes et al. (2006), Kayser (2000) and Spiller et al. (2017) reach the opposite conclusion, namely that price elasticity of VKT (or gasoline demand) increases with income. Their analyses suggest it is also conceivable that lower income households that possess a private car do so because they hardly have any cheaper or more convenient mobility alternatives, and as a result might instead reduce other expenditures when fuel prices increase. Likewise, when a drop in motor fuel prices occurs, the first reaction of poorer families might not be to invest in more travel, but rather to acquire basic commodities. On the other hand, more affluent households may be more sensitive to price rises because they have the option of reducing discretionary driving (i.e., leisure or non-work-related trips) or because prices are more salient to drivers with higher motor fuel bills. Yet other studies observe a U-shaped relationship between price elasticity and income (Wadud et al., 2009; West, 2004) or insignificant patterns (Archibald & Gillingham, 1981; Frondel et al., 2012; Yatchew & No, 2001).

Concerning location, there is general agreement that rural households are less price-reactive than city-dwellers because the former often have little choice over their daily travel distance or the means of transport for commuting (e.g., Gillingham, 2014; Santos & Catchesides, 2005; Wadud et al., 2009). However, Spiller et al. (2017) find the car fuel demand of urban households in the US to be less price-elastic than that of rural households. These authors argue that, due to congestion in cities, urban drivers might have optimized their amount of driving, which would make their motor fuel demand less responsive to price variations. Gillingham & Munk-Nielsen (2019) draw a somewhat mixed conclusion with respect to consumer groups defined on living location. They find that both households living in the outskirts of cities (long commutes to work) and city-dwellers (short commutes to work) are particularly responsive to fuel price variations when compared with households with intermediate travel distances. The authors assume that drivers in the former category have stronger incentives to consider substitutes because small increases in fuel prices affect driving expenditures substantially, whereas city-dwellers have more alternatives for commuting.

More recently, the concept of driving intensity has been considered in the analysis of heterogeneity in fuel price elasticity of car-travel/gasoline demand. Using quantile regressions, Gillingham (2014) investigates the case of Californian drivers, and finds that the lowest conditional quantiles (low driving intensity) of VKT are more price-elastic than the highest conditional quantiles (high driving intensity). Frondel et al.

(2012) obtain similar findings for Germany and notice that higher conditional quantiles reflect greater dependency on private mobility and, hence, a lower price elasticity.[7] However, more driving may also be related to non-essential (or discretionary) car travel, as suggested by Gillingham et al. (2015). Their study for the state of Pennsylvania shows price elasticities of greater magnitude at the third conditional quartile than at the first one (where elasticity is non-significantly different from zero). The authors explain the difference when compared with the California study by the fact that the latter focuses only on new car registrations rather than on the entire vehicle fleet. It is however not clear how this data difference affects the findings of the two studies. Also, in contrast to the two previously mentioned studies,[8] Gillingham et al. (2015) use the panel-data quantile regression approach suggested by Canay (2011). Besstremyannaya & Golovan (2019) criticize this method because it could lead to a severely biased inference in applied works with a large number of observations and a small number of time periods, as is the case in Gillingham et al. (2015). Moreover, this technique conditions quantiles on fixed effects, thus making their interpretation difficult (see Powell, 2016).

Most studies in this literature continue to use aggregate price data and rely on cross-section datasets. The application of macro-level price data is likely to be problematic not only for estimating average price elasticities (De Borger et al., 2016a; Levin et al., 2017; Oum et al., 1992), but also for identifying differences in the price reactivities of various segments of drivers, since most of the existing variability in prices is leveled out in such datasets. The interpretation of the temporal dimension of cross-sectional data might moreover be problematic. Results based on cross-section data are most commonly considered as medium- to long-run responses because they are obtained by comparing different households in different (long-run) equilibria (e.g., Bento et al., 2009; Baltagi & Griffin, 1984; Graham & Glaister, 2002; Wadud et al., 2010a). However, there is continuing debate, and some authors such as Espey (1998), Kayser (2000), Mattioli et al.

[7] National household travel surveys show indeed that the main purpose of vehicle usage in the US and in Germany is related to professional and non-recreational activities (MOP, 2018; NHTS, 2017).
[8] Despite having panel data at hand, Frondel et al. (2012) prefer to use a pooled quantile regression in their analysis because *"panel quantile methods are fairly new"* (p. 466).

(2018) interpret analyses relying on cross-section data as providing short-run reactions whenever the technology used by individual households (i.e., their car) is controlled for. Moreover, price elasticities estimated with cross-section datasets might be biased because, more price sensitive households might be more selective in where they choose to refuel. However, the estimates of gasoline price elasticities should not be affected by self-selection in longitudinal analyses with short panels because in the short run, the choice of a gas station is likely to be determined by routines (see BCG, 2014; GasBuddy, 2021; Kitamura & Sperling, 1987). In contrast, the temporal horizon is clearly defined in panel datasets as the interval between two time periods. The inclusion of time-fixed effects also contributes to mitigate potential biases related to factors affecting households' driving demand.[9]

3. Dataset and descriptive statistics

Our empirical analysis is based on data from the Swiss Household Energy Demand Survey (SHEDS) (Weber et al., 2017), which covers the whole of Switzerland (except the canton of Ticino) and is a rolling panel of 5,000 respondents per wave. We focus on the 2018-2020 waves of the survey, excluding 2016-2017 because information on individual motor fuel prices was not collected in these waves.[10] We consider only gasoline cars, which represent approximately two thirds of the overall car fleet in Switzerland (OFS, 2020c), and exclude all other types of vehicles (in particular diesel, electric, hybrid and plug-in hybrid cars) because fuel prices and technologies are difficult to compare.

[9] A direct approach to distinguish between the short- and the long-run effects of price variations in the field of car travel is the one used by Batley et al. (2011), Dargay (2007) and Goodwin et al. (2004). These authors use lagged prices in order to exploit the dynamics of price elasticities. Their research also shows that asymmetric model specifications (in which the main explanatory variables are split into monotonic "sub-variables" capturing for instance the cumulating series of income/price rises and falls) can be used if drivers react differently to price increases and price reductions. These methods require nevertheless an important number of observations. In the case of the dynamics of price elasticities in particular, longer panels, usually with data covering more than 5 time periods, as also noted by Wadud et al. (2010a), are necessary in order to be able to apply these models.

[10] SHEDS takes place in the second quarter of each year, so that the survey period does not correspond to a calendar year. It is also important to note that we account for the fact that the number of days between two SHEDS waves is not exactly the same from one wave to the next and across respondents. This is done by calculating the number of days between the dates at which respondents filled in two consecutive waves of the survey, so as to obtain an average daily driving distance, and then by multiplying this number by 365.

The dependent variable in our analysis is the annual driving distance (or VKT) of the most used car in the household. It is obtained as the difference in odometer readings reported in two consecutive waves of SHEDS. We therefore exclude observations from households that change their car between two survey waves. Considering cars purchased less than a year ago would force us to extrapolate annual distances from distances traveled during part of the year, which would require compelling assumptions, since distance traveled is affected by seasonal factors. We moreover consider annual driving distances below 100 or above 70,000 kilometers[11] as unlikely and exclude these observations (about 4% of the sample) from the analysis.

Figure 1 shows the distribution of driving distances in our final dataset. Kernel densities are superimposed to illustrate the evolution of VKT for each year in our observation window. As expected, the density is strongly skewed to the right, with a peak of about 10,000 kilometers a year.[12] While the Kernel densities for 2018 and 2019 are similar, it is interesting to note that the distribution shifts to the left in 2020, presumably because of the Covid-19 lockdown.[13] Additional information about VKT is displayed in *Table A.1* in the *Appendix* of this chapter, which provides descriptive statistics for our sample, separately for each of the three years covered in our dataset. On average, distance traveled is between 12,000 and 15,000 km/year, but it is characterized by important variability between households. Our values are consistent with statistics from the 2015 *Mobility and Transport Microcensus* (OFS, 2017c), which show that the "first" car in a typical Swiss household is driven, on average 13,880 kilometers per year. In addition, *Touring Club Switzerland* – Switzerland's largest mobility association – uses an annual total of 15,000 kilometers for the calculation of the average costs related to a private car in 2020. *Table A.1* also reveals the important drop in average VKT related to the Covid-19 lockdown, with a decline of around 1,500 kilometers between 2019 and 2020.

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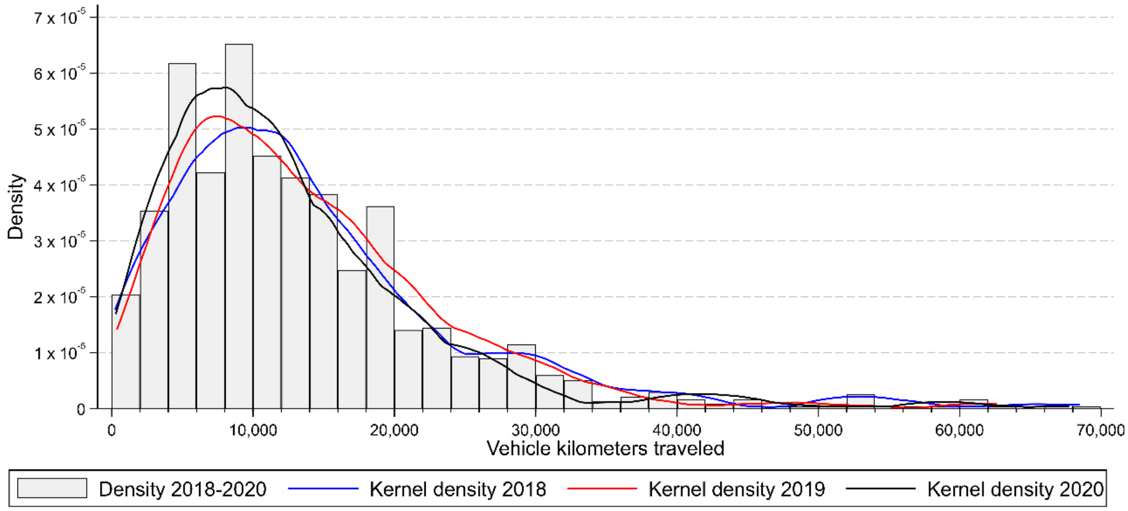
[11] Setting these limits allows to exclude likely mistakes in odometer readings and also eliminates observations for drivers who have faced very specific circumstances, such as long periods of time spent abroad or health issues, causing very small and unusual observed VKT.
[12] In our models, we take the natural logarithm of the dependent measure (VKT), which makes its distribution close to a Bell curve.
[13] The Swiss government imposed a strict national lockdown from March 16 to June 8, 2020. Given that SHEDS respondents are interviewed from April to June, the lockdown affected distances measured in the 2020 wave.

Figure 1: Annual driving distance



Note: Epanechnikov kernel with optimal width.

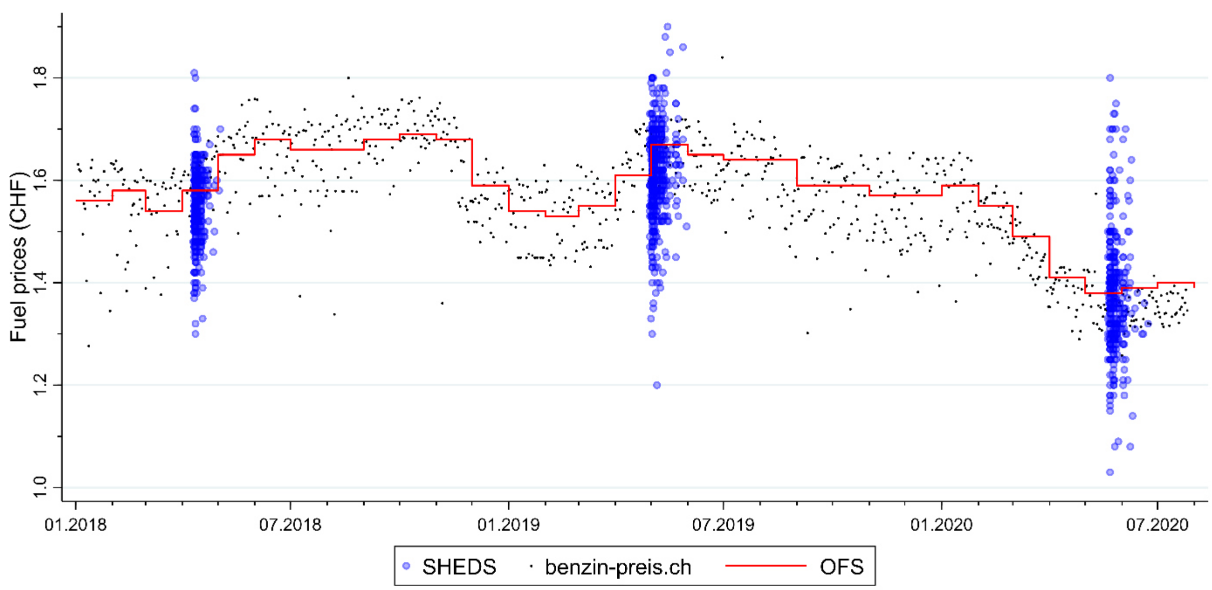
Gasoline price, the key independent variable in this article, is obtained directly from respondents, who are asked the price they paid when they last filled up the tank.[14] We emphasize the originality and the importance of how this information is collected. We observe a specific price for each household and each year, while most of the existing literature uses regional, or even national, average prices. Two major forces determine the price of car fuel in Switzerland: taxes and other non-energy related costs. Fuel taxation being defined at the federal level, it explains little of the within-country variations in car fuel prices. Conversely, the Swiss oil importers association (*AvenergySuisse*) points out that the main differences in car fuel prices originate from the costs of storage, transport, logistics, marketing, building depreciation or non-fuel-related local taxation regimes faced by gas stations (AvenergySuisse, 2021). In 2019, ABE (2019) found that the price of the most common gasoline type (unleaded with 95 RON) could differ by up to 65 Swiss Cents between gas stations in the French-speaking part of Switzerland. This once again demonstrates the importance of factors such as the storage capacity of retailers or the distribution costs they pay. For instance, gas stations located close to the sole Swiss oil refinery (Cressier, canton of Neuchâtel) benefit from low

[14] We apply Tukey's (1977) method to identify outliers: for each wave, observations with prices farther than three times the inter-quartile range below the first or above the third quartile of the price distribution are discarded (21 additional observations).

distribution costs. On the other hand, in large cities such as Geneva, high rental costs are associated with higher fuel prices.[15]

Figure 2 shows the individual fuel prices reported by SHEDS respondents, and compares them with price data from two other sources: (1) the Swiss Federal Statistical Office, which provides national average monthly prices (OFS, 2020d) and (2) the private consumer website www.benzin-preis.ch, where drivers can enter daily information about the type of fuel they use, its price, as well as the location of the gas station where they filled the tank. *Figure 2* shows there is considerable variability across prices collected during the survey as well as in prices available from www.benzin-preis.ch, but the averages and their evolution are close in all sources. A moderate increase is observed between 2018 and 2019, before a substantial decrease in 2020.

Figure 2: Gasoline prices, from different sources



In addition to gasoline price, we account for various socio-demographic and vehicle-related factors expected to influence distance traveled. Household annual gross income is calculated as the mid-point of income intervals and using the Pareto-curve-based procedure for open-ended income categories, as

[15] *ABE*'s investigation does not cover the German-speaking (eastern) part of Switzerland and does not consider gas stations located on highways, where prices are generally higher and consumers more captive.

suggested by Celeste et al. (2013). Engine efficiency and car vintage constitute the subset of vehicle-related determinants. The coefficient of car-related variables may be affected by endogeneity, because drivers who (intend to) travel more might choose to buy newer, more efficient cars, or alternatively larger and more comfortable cars. This issue has been addressed in various ways in the existing literature: (1) instrumental variable approaches, although finding relevant and strong instruments has proven challenging;[16] (2) simultaneous equations models (Mannering, 1986; Small & Dender, 2007; Weber & Farsi, 2014); (3) excluding engine efficiency from the set of determinants based on theoretical considerations relating to consumer behavior.[17] In this article, however, we consider only households that have not changed cars during the observation period.

Various socio-demographic attributes are also included in our model specifications. The respondent's age, considered as representative for the household as a whole, is expected to affect VKT because mobility patterns and needs vary according to life stages. The number of general (GA) travel cards held by the household members is included, as these indicate the extent of substitutability between private and public transportation for each household. With respect to the necessity of using private transportation, we use a set of dummy variables designating if the household lives in an urban, agglomeration or countryside area. Finally, we include year dummies to control for unobserved time-varying factors. The final sample consists of 1,172 observations from 501 unique households, among which 331 are observed twice and 170 are observed three times.

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[16] Such instruments could be the characteristics of the replaced car relative to the average car in the economy (De Borger et al., 2016b) or the fuel price at the time a vehicle was bought (Linn, 2016).

[17] According to economic theory, a rational consumer should consider a variation in the cost of driving in the same manner, whether it results from a change in fuel prices or from a change in fuel economy (De Borger et al., 2016a; Gillingham, 2014; Sorrell et al., 2009). This has led some authors to exclude engine efficiency from the set of determinants of fuel demand and to interpret (the negative of) price elasticities as a rebound effect instead (e.g. Frondel et al., 2012; Gillingham et al., 2015). However, it is unlikely that households react in the same manner to the two sources of variation in driving costs: price changes are usually unexpected and temporary, while improvements in engine fuel efficiency are permanent (Linn, 2016), and consumers might have different levels of awareness of these two measures (Gillingham et al., 2016). In addition, excluding important vehicle characteristics from modelling fuel demand might lead to an omitted variable bias, as outlined by Spiller et al. (2017). For further discussion of the theoretical non-equivalence between the cost effect of fuel prices and fuel efficiency, see Weber & Farsi (2014).

4. Econometric approach

In order to evaluate the effect of fuel prices, socio-demographic, and vehicle factors on households' VKT, we use the following multivariate regression model:

$$ln(VKT_{it}) = \alpha + \beta \cdot ln(P_{it}) + \sum_{k=1}^{K}(\delta_k \cdot X_{kit}) + \nu_i + \varepsilon_{it} \quad (1)$$

where VKT_{it} is vehicle kilometers traveled by household i in year t using the main car and P_{it} is the self-reported fuel price that household i paid the last time it filled the tank. Because both VKT_{it} and P_{it} are in logarithmic form, coefficient β can be directly interpreted as a price elasticity. Other socio-demographic and vehicle characteristics are denoted $X_{1it}, \dots, X_{Kit}$.[18] The terms ν_i capture household-specific stochastic residuals and ε_{it} are idiosyncratic residuals.

With panel data, random effects (RE) and fixed effects (FE) methods can be used to estimate equation (1). Technically, the choice between a RE and a FE model is essentially a *"choice about how to balance variance and bias"* (Clark & Linzer, 2015). Some analyses in the field of car-travel demand have favored RE for short panel datasets (e.g., Filippini & Heimsch, 2016; Frondel et al., 2012). Yet, FE models have the advantage of relying on within- rather than between-observations variation, thereby providing a clearer interpretation of the estimated gasoline price coefficients as short-run price elasticities and controlling for endogeneity related to the existence of unobserved time-invariant determinants. In addition to RE and FE, we also estimate correlated random-effects (CRE) models (Mundlak, 1978), in which coefficients of independent variables with sufficient within-variation (e.g., gasoline price) are estimated using the within-variation in the data, while the coefficients of controls with no or little within-variation (e.g., fuel efficiency) are estimated from between-variation. CRE is implemented by adding the time averages of the time-varying covariates in equation (1), and by applying a random-effect regression to this extended model specification (Schunck, 2013).The investigation of heterogeneity in the sensitivity to fuel price is first addressed by

[18] Binary variable coefficients represent semi-elasticities after the transformation $exp(\delta_k) - 1$ (Halvorsen & Palmquist, 1980).

introducing a series of interactions between gasoline prices and observable characteristics in equation (1). To obtain clearly defined consumer segments, we dichotomize the continuous variables and create binary controls (as in Wadud et al., 2010a; Gillingham, 2014; Gillingham et al., 2015). We use the median to separate households, unless there is a natural threshold.[19] Thus, equation (1) is modified as follows (considering income in this example):

$$ln(VKT_{it}) = \alpha + \beta_1 \cdot ln(P_{it}) \cdot \mathbf{1}\{I_{it} < \overline{I_{it}}\} + \beta_2 \cdot ln(P_{it}) \cdot \mathbf{1}\{I_{it} \geq \overline{I_{it}}\} + \gamma \cdot ln(I_{it}) + \sum_{k=1}^{K} (\delta_k X_{kit}) + \nu_i + \varepsilon_{it} \quad (2)$$

where $\mathbf{1}\{\cdot\}$ is an indicator function taking the value 1 when the condition in brackets is true and $\overline{I_{it}}$ denotes the threshold value used to split the sample according to income I_{it}. This procedure allows us to obtain two separate price elasticities β_1 and β_2, for households respectively below and above the median. When the continuous variable used to split the sample is time invariant (e.g., fuel efficiency), the variable itself is understanfably dropped from equation (2). For each segmentation variable, we run a separate estimation in order to avoid multicollinearity issues and a critical loss of degrees of freedom.[20]

[19] For age, we use 65 years as the natural threshold, as this corresponds to retirement age. For the number of GA travel cards, we use 0 as the threshold, since most households do not have any.

[20] In this context, different authors argue that in the presence of multiple hypotheses, p-values associated with testing the statistical difference between coefficients should be adjusted (Chen et al., 2017). The reason for this correction is that implementing multiple tests leads to a higher probability of incidentally finding statistically significant results. This makes it difficult to tell which differences between groups are actually true, and which are merely due to chance. This problem has given rise to a specific field in the econometric literature focusing on various adjustment procedures. Such methods include the classical Bonferroni correction, which in presence of many tests can be rather conservative (Nakagawa, 2004), or the increasingky popular sharpened False Discovery Rate (FDR) q-values (Anderson, 2008). However, as noted by Streiner (2015), *"The discussion of how to correct for multiplicity has made the implicit assumption that we should correct for it, but this is by no means a position accepted by everyone."* (p. 724). The uncertainty of how many and which tests should be chosen, and whether reducing Type I error should come at the expense of increasing Type II error, are arguments against such adjustments (Perneger, 1998). For instance, a researcher could choose the type and the number of hypotheses to be finally tested and presented in a final analysis based on the result of *an ex-ante* FDR correction. Thus, instead of solving it, this could perpetuate the "p-value fiddling" problem. Rothman (1990) even argues that the *"...theoretical basis for advocating a routine adjustment for multiple comparisons [...] undermines the basic premises of empirical research, which holds that nature follows regular laws that may be studied through observations."* (p. 43). Other arguments against such adjustments, which we do not address here, are provided by Schulz & Grimes (2005), Moran (2003), O'Keefe (2003) and most recently by Parker & Weir (2020). Perhaps partly for such reasons none of the earlier studies on households' driving demand corrects for multiple hypothesis testing (e.g., Gillingham et al., 2015; Spiller et al., 2017; Wadud et al., 2010a). Based on these considerations and following prior analyses, in this article we also refrain from adjustments for multiple hypotheses testing.

Second, we use conditional quantile regressions (QR) to further investigate the presence of heterogeneous price responses. Initially developed by Koenker & Bassett (1978), QR is an important complement to the estimation of the *average* price elasticity of a *typical* car fuel consumer, in the sense that it provides a broader picture of the relationship between the dependent measure and the set of covariates. More precisely, the regression coefficients of the q^{th} conditional percentile of the dependent variable ($q \in (0;1)$), are estimated by minimizing the function $\sum_i^N q|\theta_{it}| + \sum_i^N (1-q)|\theta_{it}|$, where q are penalties attributed to observations, depending on their position with respect to the best line of fit, and θ_{it} are model residuals. Quantiles are defined with respect to residuals, so that QR also constitutes an important complement to the previously discussed method based on *observed* segmentation characteristics. Unobserved behaviors, such as driving behaviors or route choices, will then be captured by different quantiles.

We follow Wooldridge (2010) and implement QR for panel data by including the time averages of the basic time-varying covariates in equation (1), and by then applying a pooled quantile regression to this extended model specification. Although various extensions of QR for longitudinal data exist in the literature, we use a CRE QR method for three reasons. First, this model is adapted to datasets with a limited number of periods (T), but a large number of observations (N), unlike the models suggested by Canay (2011) and Machado & Santos Silva (2019). Second, in contrast to these QR techniques for longitudinal data, quantiles are not estimated conditional on fixed effects, thereby allowing their direct interpretation as “driving intensities”. Third, Powell's (2016) model with non-additive fixed effects and valid with a small T proved extremely sensitive to our model specifications, whereas CRE QR is robust to alternative model specifications.

5. Results and discussion

We present our empirical findings in two parts. First, we discuss the estimations of average price elasticity of VKT. The picture of the average household is in fact a useful starting point for the later analysis of heterogeneity in price elasticities. These results also allow us to discuss the role of the determinants of

VKT. Second, and most importantly, we present and discuss our analyses of heterogeneity in price elasticities.

Table 2 displays the estimations obtained with random effects (RE), fixed effects (FE) and correlated random effects (CRE). The first column of each of the three estimation blocks presents a basic model, whereas the second column encompasses a larger set of determinants.[21]

Table 2: Determinants of VKT: random effects (RE), fixed effects (FE) and correlated random effects (CRE) models

	RE1	RE2	FE1	FE2	CRE1	CRE2
Gasoline price (ln)	-1.050***	-0.926***	-0.866**	-0.882**	-0.932**	-0.973**
	(0.361)	(0.354)	(0.429)	(0.429)	(0.408)	(0.409)
HH gross income (ln)	0.130***	0.041	0.149*	0.137*	0.141*	0.134
	(0.049)	(0.051)	(0.081)	(0.082)	(0.081)	(0.082)
Fuel efficiency (ln)	0.301**	0.169			0.295**	0.145
	(0.126)	(0.123)			(0.125)	(0.122)
SHEDS year: 2019	0.059	0.070	0.048	0.045	0.053	0.062
	(0.046)	(0.046)	(0.048)	(0.048)	(0.047)	(0.047)
SHEDS year: 2020	-0.201***	-0.158**	-0.182**	-0.185**	-0.191***	-0.171**
	(0.066)	(0.066)	(0.072)	(0.072)	(0.068)	(0.067)
HH with a single car	-0.165**	-0.074	-0.064	-0.058	-0.086	-0.069
	(0.065)	(0.066)	(0.144)	(0.151)	(0.145)	(0.151)
Age of car (years)		-0.006				-0.005
		(0.006)				(0.006)
# HH members		0.084***		-0.086		-0.086
		(0.027)		(0.262)		(0.263)
Age of reference person (years)		-0.011***				-0.012***
		(0.002)				(0.002)
# GA travel cards per HH member		-0.240***		0.208		0.209
		(0.076)		(0.162)		(0.164)
Living location: agglomeration		0.078		-0.071		-0.068
		(0.065)		(0.162)		(0.162)
Living location: countryside		0.120*		-0.001		-0.007
		(0.071)		(0.196)		(0.200)
Av. gasoline price (by HH)	No	No	No	No	Yes	Yes
Av. HH gross income (by HH)	No	No	No	No	Yes	Yes
Av. # HH members (by HH)	No	No	No	No	No	Yes
Av. # GA travel cards per HH member (by HH)	No	No	No	No	No	Yes
Av. single car (by HH)	No	No	No	No	Yes	Yes
Av. living location: agglomeration (by HH)	No	No	No	No	No	Yes
Av. living location: countryside (by HH)	No	No	No	No	No	Yes
Observations	1,172	1,172	1,172	1,172	1,172	1,172
Households	501	501	501	501	501	501
R^2 within	0.016	0.008	0.017	0.020	0.016	0.020
AIC	2,603	2,555	1,341	1,346	2,608	2,556

Clustered standard errors (by household id) in parentheses
* p<0.10, ** p<0.05, *** p<0.01

In all models, the estimated price elasticities are significant (at least at the 10% level) and are of non-negligible magnitude. RE models yield estimates close to unity and slightly larger (in absolute value) than

[21] We also tried out specifications including additional sets of covariates, e.g. psychological factors, number of vehicles owned by the household, or region fixed effects. The inclusion of these variables does not affect the estimated price elasticities, even though it yields higher information criteria (AIC). Therefore, we display only two specifications: a “basic” and a “preferred” one.

those obtained through FE and CRE models. A Hausman test (Arellano, 1993) shows that FE estimations are preferable to RE estimations (Sargan-Hansen statistic: 16.35; χ^2=10; p-value = 0.09). FE and CRE models yield price elasticities of approximately -0.9, implying that a 1% change in fuel price would lead to a 0.9% decrease in VKT. Considering that VKT is generally less responsive than fuel consumption (Frondel et al., 2012; Graham & Glaister, 2004), the magnitude of our estimates appears particularly great. This finding suggests that price-based policies trying to reduce GHG emissions and energy consumption might have a much more considerable impact than previously thought. Former studies on car fuel demand for Switzerland indeed estimate much lower price responsiveness in the interval from -0.25 to -0.4 (see Baranzini & Weber, 2013; Carlevaro et al., 1992; Filippini & Heimsch, 2016; Peter et al., 2002; Schleiniger, 1995; Wasserfallen & Güntensperger, 1988). However, we note that these studies examine fuel demand rather than travel demand and consider country-level time-series data, and are thus likely to be characterized by a downward bias in the estimated price coefficients (Levin et al., 2017).[22] De Borger et al. (2016a), Frondel et al. (2012) and Santos & Catchesides (2005) who use disaggregate data for the UK, Germany and Denmark, respectively, find price elasticities of household driving demand between -0.6 and -0.9.

Several reasons may explain the relatively strong elasticities of VKT in the Swiss case. First, the public transport network of this country is characterized by a particularly high density and quality, thus providing a very good substitute for private transportation. The relatively high fuel prices (at least compared with US prices, where the price of gasolines are about half those in Switzerland[23]) may themselves contribute to increase consumers' reactions. An additional reason relates to the use of vehicles, which appears to differ from country to country. National car-travel surveys indeed show that Swiss and UK households use their private cars principally for leisure trips, while the main purpose of vehicle usage in the US and Germany relates to professional and non-recreational activities.[24] Nevertheless, we acknowledge that if more price-

[22] Potential sources of bias relate to the weighting of city-specific price responses, the omission of time and location fixed effects, and correlations between within-month variations in nationwide gasoline usage and national average prices. According to Levin et al. (2017, p. 344), such price elasticities might *"differ by magnitudes large enough to substantially impact subsequent policy evaluation or market analysis."*

[23] For instance, see Bloomberg (2021).

[24] MTMC for Switzerland (OFS, 2017a), NHTS (2017) for the US, NTS (2018) in the UK, and MOP (2018) for Germany.

sensitive drivers or households with higher gasoline bills are better informed about the gasoline price they face, this would lead to a measurement error in the price variable that is correlated with price sensitivity.

The results in *Table 2* also show that income elasticity of VKT is about 0.14. This is in line with previous estimations by Frondel et al. (2012) for Germany and Weber & Farsi (2014) for Switzerland. Car travel therefore classifies as a necessity good. This estimate is however much lower in comparison with the existing literature, where income elasticities are most often positioned between 0.3 and 0.8. A possible explanation for the low income elasticity observed in *Table 2* lies in the way income is measured. Because households report their income by interval, we derive income as the mid-point of each interval and this measure captures only limited variations in households revenues. Nevertheless, we expect income elasticities in Switzerland to be low because of the high standard of living that make fuel costs easily affordable. TCS (2020) reports that expenditures for motor fuel represent on average only 15% of the total annual car spending (120 CHF per month), with a substantial share being attributable to insurances and garage costs. The most recent available Swiss household budget survey, from 2017 (OFS, 2020e), reveals monthly gasoline expenditures of about 100 CHF per month, which represents less than 2% of monthly household disposable income.

Another remarkable result obtained in *Table 2* is that the distance traveled by the respondents of the 2020 wave of SHEDS is some 20% lower than in the reference year 2018. The strict national lockdown related to the Covid-19 pandemic between mid-March and June is included in the period covered by wave 2020 of the survey, which was fielded in May-June 2020. While the FE and CRE show that the impact of socio-demographic and vehicle characteristics[25] on driving distance is statistically insignificant (as should be expected in the short run),[26] we obtain the expected coefficients for most covariates in RE1 and RE2.

[25] In our cross-sectional estimation of the impact of fuel efficiency on VKT, we find evidence of a direct rebound effect, the coefficient of fuel efficiency being approximately 0.30 and statistically significant.
[26] Age of the respondent and car vintage are excluded from FE, whereas the panel-means of those two covariates are excluded from the CRE models. As in Tilov et al. (2020), this is in order to avoid collinearity with year dummies.

The picture of the "typical", or "average" consumer discussed so far may conceal important differences between households. To examine the possibility of heterogeneous price elasticities between various groups of drivers, we interact socio-demographic and car characteristics with gasoline price. The results of these interactions are displayed in *Table 3*. Each model estimated through FE and p-values related to Wald tests of the difference between the gasoline price coefficients is displayed at the bottom of the table.

We find evidence of statistically different price elasticities for households of different sizes. Single-member households are characterized by a significantly higher price elasticity compared with multiple-member households, probably because the latter group consists mostly of families with children. These households are likely to be more dependent on private car transportation, while single-member households can more easily adapt to higher gasoline prices by switching to public transportation or carpooling. This result is important regarding the expected increase of the number of single-member households by 30% in the next 30 years in Switzerland (OFS, 2020f). It is likely that this demographic evolution will be accompanied by an increase in the private vehicle stock. On the other hand, the demand for VKT will also become more price-reactive because of the higher price-reactivity of single-member households, other things being equal. From a policy perspective, the increase of gasoline price might lead to important decreases in the demand for car travel stemming from single-member households. However, such a policy would affect households that rely on their vehicles because of family-related constraints, such as the presence of children of a young age. To alleviate the tax burden, these households might be offered special conditions or financial incentives for using car-sharing schemes or public transportation.

Even though our test of differences between living locations is not conclusive (p-value is 0.26), our point estimates indicate a much stronger price elasticity in cities than in rural regions. This result is in line with previous findings in the existing literature (e.g., Blow & Crawford, 1997; Gillingham et al., 2015; West, 2004) and is usually explained by the less developed public transportation system in rural regions and because of the longer distance to various facilities such as grocery stores. This makes rural households, who are also more dependent on private mobility, more vulnerable to gasoline price variations. The development

Table 3: Price elasticities of various sub-groups (FE estimation)

	Income	Fuel efficiency	Car age	Single car	# HH members	GA cards per HH member	Age of ref. person	Living location
Low-income HH	-0.943*							
	(0.493)							
High-income HH	-0.865**							
	(0.435)							
HH with fuel-inefficient car		-0.913**						
		(0.433)						
HH with fuel-efficient car		-0.853*						
		(0.455)						
HH with new car			-0.863*					
			(0.478)					
HH with old car			-0.888**					
			(0.432)					
HH with single car				-0.961*				
				(0.531)				
HH with multiple cars				-0.853*				
				(0.457)				
Single-member HH					-1.492***			
					(0.507)			
Multiple-member HH					-0.708			
					(0.448)			
HH with 0 GA travel cards per HH member						-0.842*		
						(0.435)		
HH with >0 GA travel cards per HH member						-1.011		
						(0.629)		
HH of working age (≤65 y.o)							-0.880**	
							(0.428)	
HH of retirement age (>65 y.o)							-0.888	
							(0.578)	
Living location: city								-1.159**
								(0.498)
Living location: out of city								-0.664
								(0.463)
Observations	1,172	1,172	1,172	1,172	1,172	1,172	1,172	1,172
Households	501	501	501	501	501	501	501	501
Adjusted R^2	0.011	0.011	0.011	0.011	0.015	0.012	0.011	0.013
R^2 within	0.020	0.020	0.020	0.020	0.024	0.020	0.020	0.021
p-value	0.801	0.792	0.926	0.822	0.055	0.753	0.986	0.255

Clustered standard errors (by household id) in parentheses
* p<0.10, ** p<0.05, *** p<0.01

In each model, we also control for the same set of covariates as in FE2 but omit these results from the output presented here.

of public transportation in rural regions, the encouragement of car-sharing schemes or the acquisiotion of efficient vehicles via subsidies could therefore be used as complementary policy instruments in order to limit the impacts of fuel taxation on non-urban residents.

We further examine heterogeneity in gasoline price elasticity of VKT in *Table 4*, by using a quantile regression approach, adapted for panel data (CRE QR). This strategy allows us to focus on segments of drivers defined on unobserved factors, which we interpret as translating households' driving intensity. Our estimations show that only the upper end of the conditional car-travel demand, i.e., travel-intensive households, reacts significantly to changes in gasoline prices, while less intensive drivers do not exhibit statistically significant price elasticities. It is most likely that households situated at the seventh and ninth conditional deciles do a considerable amount of discretionary driving (e.g., driving related to leisure activities), which they can adjust easily whenever gasoline prices increase. This effect is desirable for price-based policies since it suggests that higher gasoline prices lead to a reduction in car usage among the most travel-intensive drivers. This finding is similar to that of Gillingham et al. (2015), who rely on an alternative panel QR method, but contrasts with findings in Frondel et al. (2012) and Gillingham (2014), who apply QR to pooled datasets.

Table 4: Quantile regression with correlated random effects (QR CRE)

	Q10	Q30	Q50	Q70	Q90
Gasoline price (ln)	-0.522	-0.957	-0.772	-1.061*	-1.786***
	(1.134)	(0.710)	(0.556)	(0.599)	(0.538)
HH gross income (ln)	0.129	0.022	0.123	0.228*	0.128
	(0.225)	(0.196)	(0.122)	(0.117)	(0.110)
Fuel efficiency (ln)	0.441**	0.171	0.049	0.054	0.073
	(0.193)	(0.156)	(0.161)	(0.155)	(0.181)
SHEDS year: 2019	0.172	0.015	0.016	0.022	0.001
	(0.108)	(0.067)	(0.054)	(0.062)	(0.071)
SHEDS year: 2020	-0.051	-0.211*	-0.240**	-0.262***	-0.320***
	(0.174)	(0.108)	(0.094)	(0.091)	(0.103)
Age of car (years)	-0.009	-0.007	-0.001	-0.001	0.003
	(0.015)	(0.007)	(0.009)	(0.007)	(0.007)
HH with single car	0.232	-0.017	-0.199	-0.084	0.039
	(0.277)	(0.288)	(0.181)	(0.188)	(0.187)
# HH members	-0.033	-0.625***	-0.831***	0.361	0.421
	(0.234)	(0.234)	(0.288)	(0.315)	(1.295)
Age of reference person (years)	-0.013***	-0.010***	-0.010***	-0.011***	-0.012***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
# GA travel cards per HH member	-0.364	0.408	0.045	0.054	0.401**
	(0.287)	(0.330)	(0.319)	(0.253)	(0.185)
Living location: agglomeration	-0.018	0.118	-0.096	-0.271	0.022
	(0.749)	(0.155)	(0.227)	(0.257)	(0.676)
Living location: countryside	-0.838	0.027	0.066	-0.447*	-0.242
	(0.706)	(1.393)	(0.291)	(0.233)	(0.366)
Av. gasoline price (by HH)	Yes	Yes	Yes	Yes	Yes
Av. HH gross income (by HH)	Yes	Yes	Yes	Yes	Yes
Av. single car (by HH)	Yes	Yes	Yes	Yes	Yes
Av. # HH members (by HH)	Yes	Yes	Yes	Yes	Yes
Av. # GA travel cards per HH member (by HH)	Yes	Yes	Yes	Yes	Yes
Av. living location: agglomeration (by HH)	Yes	Yes	Yes	Yes	Yes
Av. living location: countryside (by HH)	Yes	Yes	Yes	Yes	Yes
Observations	1,172	1,172	1,172	1,172	1,172
Households	501	501	501	501	501
R^2	0.114	0.120	0.119	0.118	0.116
Pseudo-R^2	0.109	0.086	0.060	0.063	0.088

Clustered standard errors (by household id) in parentheses
* p<0.10, ** p<0.05, *** p<0.01

We investigate the robustness of our findings by first setting alternative threshold limits for the definition of binary segments of drivers. Instead of taking the median of the distribution of the continuous variables income, fuel efficiency and car age to split the sample, we define household segments with respect to the first and the last quartiles of their distributions. As with the similar findings reported in *Table 3*, we do not observe any significant differences between segments of households defined by their income levels and the age of their vehicles. However, when driver segments are defined on the basis of the first quartile of fuel efficiency, households with (very) low fuel efficiency (below the 25th percentile of fuel efficiency) appear more price reactive, whereas the opposite is true when we use the third quartile (75th percentile) as a threshold. The finding that owners of (the most) fuel-inefficient cars are more price-sensitive is in line with previous studies (e.g., Liu, 2015; Spiller et al., 2017). Gillingham et al. (2015) argues that, because drivers of fuel-inefficient vehicles face a higher burden at the pump, they should be more price-reactive. However, we also observe that households with "very" fuel-efficient cars (above the 75th percentile of the fuel efficiency distribution) are more price-elastic than the rest of the households, which reveals that some households acquire more efficient cars precisely because they are more sensitive to fluctuations in gasoline prices (Liu, 2015). Drivers of less efficient vehicles might also continue using them despite higher operating costs, simply because they do not have cheaper or more convenient mobility options. Indeed, Turrentine & Kurani (2007) discuss that consumers' attitude towards fuel efficiency is likely to be more complex than economic assumptions suggest. Overall, our results indicate that drivers of the "most" and the "least" efficient cars are both particularly sensitive to price variations. This finding implies that drivers of cars with middle-range fuel efficiency would bear most of the cost of fuel taxation. In order to limit an undesired welfare impact on the drivers of "average" cars, alongside the introduction of a gasoline tax, special rebates or subsidies could be offered when cars below a certain efficiency level are replaced with more efficient ones.

As a second robustness check, we estimate price elasticities in different model specifications, such as FE1 in *Table 2*, which include only gasoline price, household income and year dummies as independent variables. Third, we define alternative limits for excluding extreme observations for VKT and gasoline prices. The findings presented earlier in this article are robust to these sensitivity checks.[31]

6. Conclusion

This article examines the fuel price elasticity of Swiss households' vehicle kilometers traveled (VKT). In particular, we investigate the differences in price responsiveness for various segments of households, defined using both observed and unobserved characteristics. One important strength of our study is its relainace on longitudinal household-level data, not only for vehicle kilometers traveled – measured as the difference between two odometer readings – but also and more originally for gasoline prices, as observed at the gas station by each household on its last fill-up. A series of panel regression models including interaction terms are estimated using 1,172 observations from waves 2018-2020 of the Swiss Household Energy Demand Survey (SHEDS). Results show a considerably higher price elasticity in comparison to prior estimates for Switzerland (or elsewhere), thus suggesting that fuel taxes may have a more substantial effect on driving than previously assumed.

Several reasons may well explain why gasoline price elasticities are higher in Switzerland compared with the majority of earlier research focusing on the US: distances driven are much shorter, and the extremely well-developed public transport system provides an excellent substitute for private transportation. Much higher fuel prices could also contribute to the stronger reactions. We acknowledge that the elasticity we estimate seems particularly strong, considering that it is a short- to medium-run elasticity and that VKT elasticity is generally lower than fuel demand elasticity. The household-level gasoline price data we use may explain the magnitude of this elasticity. In comparison, most prior analyses in this field use prices averaged at the regional or even national level, which may lead to a downward bias in the estimation of price elasticities (e.g., Levin et al., 2017). Overall, this finding can be seen as a reminder that the low price elasticities obtained in the literature might not necessarily apply to all countries, even those where income

[31] These, in addition to the results discussed in the previous paragraph, are presented in Appendix B.

levels are high. Policymakers should therefore keep considering the possibility of increasing gasoline prices via taxation in order to reduce GHG emission and household energy consumption.

Furthermore, we observe that the average elasticity conceals heterogeneity between households. Our findings from a conditional quantile regression model for panel data reveal that the highest conditional quantiles of travel demand are the most price-elastic. Because the highest portion of the distribution of driving demand is likely to represent higher amounts of leisure-related travel, an increase of gasoline prices would have a policy-desirable effect, by reducing discretionary driving of the most travel-intensive groups of households. In addition, we observe that single-member households and (with a lower statistical significance) city-dwellers are characterized by higher price elasticities. From a policy perspective, these results suggest that non-price measures could be considered in combination with gasoline taxes to reduce welfare distortions between different consumer groups. This is particularly significant in the context of Switzerland's *Energy Strategy 2050*, which clearly states that one of its main goals is to "… *compensate to the extent possible, any negative consequences of the tax on energy*" (OFEN, 2019a, p. 6813). For instance, the development of specific financial incentives for using public transport or car-sharing could be considered for multiple-member households and inhabitants of rural regions, who rely more heavily on private transportation. Since an important share of households have a moderate or low intensity of driving and are price-inelastic, they could be targeted by information campaigns promoting the financial and environmental advantages of fuel efficient cars, or could be offered special car-swap conditions, rebates, or subsidies for acquiring vehicles consuming less motor fuel.

We acknowledge that our analysis faces some caveats. First, we use a panel dataset that does not consider changes in vehicle ownership and is too short to capture variation related to socio-demographic variables such as the number of household members or household age. Datasets with longer panels would make it possible to investigate the effect of evolving technology, for instance using the continuous-discrete framework suggested by Dubin & McFadden (1984) and Mannering (1986) to correct for endogeneity related to vehicle characteristics such as fuel efficiency or vehicle age. Second, it is possible that travel price elasticities are asymmetric. For instance, Frondel & Vance (2013) find that, on average household driving demand is more sensitive to increases, rather than to decreases in price, and an interesting topic for future research would be to explore whether different segments of households react differently to price increases or decreases. It is conceivable that low-income households exhibit greater price elasticity when gasoline prices decrease because their car-travel demand is probably not satiated. On the other hand, when fuel prices increase, it might be more difficult for poorer households to reduce their already minimal driving demand, if it is mostly related to essential travel. In comparison, high-income households could more easily cut off their greater amount of leisure-related driving. Such questions could be addressed through the asymmetric model specifications applied by Batley et al. (2011) and Giuliano & Dargay (2006), but large datasets with more time periods and observations would be necessary for this. Finally, future research could also focus on various combinations of segmentation criteria, such as rural households with different income levels, or households with intensive VKT and inefficient vehicles. As shown by Gillingham & Munk-Nielsen (2019) and Mattioli et al. (2018), the study of more precise segments of drivers can provide further details about the effects of car fuel taxation across the population.

Appendix A: Descriptive statistics, per year

	SHEDS 2018		SHEDS 2019		SHEDS 2020	
Continuous variables	Average	Std. dev.	Average	Std. dev.	Average	Std. dev.
Vehicle kilometers driven	14,112.02	11,101.23	13,686.24	9,609.55	12,646.44	9,925.27
Gasoline price (CHF)	1.55	0.07	1.61	0.09	1.38	0.12
HH Gross income (CHF)	9,151.19	4,401.357	9,115.09	4,494.45	9,025.84	4,514.02
Fuel efficiency (km/L)	14.25	3.40	14.61	3.77	14.49	3.75
Age of car (years)	7.53	4.64	8.01	4.82	8.87	4.95
# HH members	2.16	1.04	2.17	1.08	2.20	1.06
Age of reference person (years)	52.65	15.28	53.32	15.21	54.33	15.19
# GA travel cards per HH member	0.17	0.34	0.15	0.32	0.15	0.32
Binary variables	Average		Average		Average	
Living location: city	0.44		0.44		0.45	
Living location: agglomeration	0.33		0.34		0.32	
Living location: countryside	0.23		0.22		0.23	
Observations	353		466		353	

Appendix B: Robustness checks

Table B1: FE models with interaction terms: basic model specifications: prices, income and year dummies

	Income	Fuel efficiency	Car age	Single car	# HH members	GA cards per HH member	Age of ref. person	Living location
Low-income HH	-0.914*							
	(0.489)							
High-income HH	-0.850*							
	(0.435)							
HH with fuel-inefficient car		-0.901**						
		(0.435)						
HH with fuel-efficient car		-0.826*						
		(0.455)						
HH with new car			-0.845*					
			(0.476)					
HH with old car			-0.868**					
			(0.433)					
HH with single car				-0.796*				
				(0.480)				
HH with multiple cars				-0.890**				
				(0.435)				
Single-member HH					-1.358***			
					(0.469)			
Multiple-member HH					-0.725			
					(0.449)			
HH with 0 GA cards per capita						-0.910**		
						(0.430)		
HH with >0 GA cards per capita						-0.746		
						(0.467)		
HH of working age (≤65 y.o)							-0.860**	
							(0.430)	
HH of retirement age (>65 y.o)							-0.873	
							(0.577)	
Living location: city								-0.916**
								(0.465)
Living location: out of city								-0.820*
								(0.442)
Observations	1,172	1,172	1,172	1,172	1,172	1,172	1,172	1,172
Households	501	501	501	501	501	501	501	501
Adjusted R^2	0.013	0.013	0.012	0.013	0.015	0.013	0.012	0.013
R^2 within	0.017	0.017	0.017	0.017	0.020	0.017	0.017	0.017
p-value	0.831	0.745	0.929	0.734	0.070	0.489	0.976	0.737

Clustered standard errors in parentheses
*p<0.10, ** p<0.05, *** p<0.010

In each model, we also control for the same set of covariates as in FE2, but omit these results from the output presented here.

Table B2: FE models with interaction terms and with alternative thresholds for several variables:[32]

	Income	Fuel efficiency	Car age	Single car	# HH members	GA travel cards per HH member	Age of ref. person	Living location
Low-income HH	-1.302***							
	(0.502)							
High-income HH	-0.807*							
	(0.433)							
HH with fuel-inefficient car		-1.196***						
		(0.456)						
HH with fuel-efficient car		-0.723						
		(0.440)						
HH with new car			-0.945**					
			(0.474)					
HH with old car			-0.882**					
			(0.429)					
HH with single car				-0.961*				
				(0.531)				
HH with multiple cars				-0.853*				
				(0.457)				
Single-member HH					-1.492***			
					(0.507)			
Multiple-member HH					-0.708			
					(0.448)			
HH with 0 GA cards per capita						-0.842*		
						(0.435)		
HH with >0 GA cards per capita						-1.011		
						(0.629)		
HH of working age (≤65 y.o)							-0.880**	
							(0.428)	
HH of retirement age (>65 y.o)							-0.888	
							(0.578)	
Living location: city								-1.159**
								(0.498)
Living location: out of city								-0.664
								(0.463)
Observations	1,172	1,172	1,172	1,172	1,172	1,172	1,172	1,172
Households	501	501	501	501	501	501	501	501
Adjusted R^2	0.015	0.019	0.011	0.011	0.015	0.012	0.011	0.013
R^2 within	0.023	0.027	0.020	0.020	0.024	0.020	0.020	0.021
p-value	0.124	0.039	0.723	0.822	0.055	0.753	0.986	0.255

Clustered standard errors in parentheses
*p<0.10, ** p<0.05, *** p<0.010

In each model, we also control for the same set of covariates as in FE2, but omit these results from the output presented here.

[32] First quartile of the distributions of income, fuel efficiency and car age.

Table B3: FE models with interaction terms and with alternative thresholds for several variables:[33]

	Income	Fuel efficiency	Car age	Single car	# HH members	GA travel cards per HH member	Age of ref. person	Living location
Low-income HH	-0.932**							
	(0.437)							
High-income HH	-0.776*							
	(0.455)							
HH with fuel-inefficient car		-0.809*						
		(0.436)						
HH with fuel-efficient car		-1.109**						
		(0.436)						
HH with new car			-0.848*					
			(0.443)					
HH with old car			-0.934**					
			(0.467)					
HH with single car				-0.961*				
				(0.531)				
HH with multiple cars				-0.853*				
				(0.457)				
Single-member HH					-1.492***			
					(0.507)			
Multiple-member HH					-0.708			
					(0.448)			
HH with 0 GA cards per capita						-0.842*		
						(0.435)		
HH with >0 GA cards per capita						-1.011		
						(0.629)		
HH of working age (≤65 y.o)							-0.880**	
							(0.428)	
HH of retirement age (>65 y.o)							-0.888	
							(0.578)	
Living location: city								-1.159**
								(0.498)
Living location: out of city								-0.664
								(0.463)
Observations	1,172	1,172	1,172	1,172	1,172	1,172	1,172	1,172
Households	501	501	501	501	501	501	501	501
Adjusted R2	0.012	0.015	0.011	0.011	0.015	0.012	0.011	0.013
R2 within	0.020	0.023	0.020	0.020	0.024	0.020	0.020	0.021
p-value	0.464	0.076	0.781	0.822	0.055	0.753	0.986	0.255

Clustered standard errors in parentheses
*p<0.10, ** p<0.05, *** p<0.010

In each model, we also control for the same set of covariates as in FE2, but omit these results from the output presented here.

[33] Third quartile of the distributions of income, fuel efficiency and car age.

Table B4: excluding observations with VMT below 500 km and 80,000km

	Income	Fuel efficiency	Car age	Single car	# HH members	GA cards per HH member	Age of ref. person	Living location
Low-income HH	-1.059**							
	(0.498)							
High-income HH	-0.924**							
	(0.438)							
HH with fuel-inefficient car		-1.001**						
		(0.428)						
HH with fuel-efficient car		-0.917**						
		(0.466)						
HH with new car			-0.872*					
			(0.481)					
HH with old car			-0.981**					
			(0.437)					
HH with single car				-0.987*				
				(0.538)				
HH with multiple cars				-0.942**				
				(0.456)				
Single-member HH					-1.437***			
					(0.503)			
Multiple-member HH					-0.819*			
					(0.451)			
HH with 0 GA cards per capita						-1.007**		
						(0.441)		
HH with >0 GA cards per capita						-0.777		
						(0.538)		
HH of working age (≤65 y.o)							-0.968**	
							(0.425)	
HH of retirement age (>65 y.o)							-0.907	
							(0.592)	
Living location: city								-1.202**
								(0.502)
Living location: out of city								-0.762
								(0.464)
Observations	1,167	1,167	1,167	1,167	1,167	1,167	1,167	1,167
Households	499	499	499	499	499	499	499	499
Adjusted R^2	0.014	0.014	0.014	0.014	0.017	0.015	0.014	0.016
R^2 within	0.023	0.023	0.023	0.023	0.025	0.023	0.023	0.024
p-value	0.660	0.715	0.679	0.924	0.114	0.582	0.884	0.296

Clustered standard errors in parentheses
*p<0.10, ** p<0.05, *** p<0.010

In each model, we also control for the same set of covariates as in FE2, but omit these results from the output presented here.

Table B5: CRE QR: basic model specifications: prices, income and year dummies

	Q10	Q30	Q50	Q70	Q90
Gasoline price (ln)	-0.466	-1.039	-0.903*	-1.100**	-1.741***
	(1.083)	(0.710)	(0.523)	(0.541)	(0.481)
HH gross income (ln)	0.155	0.152	0.111	0.191	0.339***
	(0.233)	(0.199)	(0.118)	(0.120)	(0.131)
Fuel efficiency (ln)	0.459**	0.200	-0.001	0.078	0.170
	(0.193)	(0.165)	(0.147)	(0.157)	(0.179)
SHEDS year: 2019	0.163	0.039	0.006	0.043	-0.020
	(0.104)	(0.065)	(0.053)	(0.058)	(0.082)
SHEDS year: 2020	-0.048	-0.212*	-0.272***	-0.265***	-0.344***
	(0.146)	(0.112)	(0.094)	(0.084)	(0.096)
Age of car (years)	-0.009	-0.004	-0.006	-0.002	0.004
	(0.014)	(0.007)	(0.008)	(0.007)	(0.008)
HH with single car	-0.009	0.052	-0.051	-0.112	-0.125
	(0.129)	(0.090)	(0.094)	(0.074)	(0.093)
# HH members	0.116*	0.118***	0.058	0.042	0.114***
	(0.069)	(0.038)	(0.036)	(0.031)	(0.034)
Age of reference person (years)	-0.012***	-0.010***	-0.009***	-0.010***	-0.012***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
# GA travel cards per HH member	-0.531***	-0.376***	-0.364***	-0.278***	-0.290***
	(0.172)	(0.128)	(0.105)	(0.092)	(0.103)
Living location: agglomeration	0.119	0.093	0.069	0.036	0.105
	(0.134)	(0.095)	(0.084)	(0.077)	(0.116)
Living location: countryside	0.180	0.198**	0.130	0.054	0.011
	(0.159)	(0.101)	(0.094)	(0.079)	(0.081)
Av. gasoline price (by HH)	Yes	Yes	Yes	Yes	Yes
Av. HH gross income (by HH)	Yes	Yes	Yes	Yes	Yes
Observations	1,172	1,172	1,172	1,172	1,172
Households	501	501	501	501	501
R^2	0.115	0.118	0.116	0.116	0.111
pseudo-R^2	0.108	0.080	0.058	0.062	0.077

Clustered standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table B6: CRE QR: excluding observations with VMT below 500 km and 80,000km

	Q10	Q30	Q50	Q70	Q90
Gasoline price (ln)	-0.435	-0.995	-0.723	-1.082*	-2.017***
	(0.906)	(0.774)	(0.557)	(0.620)	(0.646)
HH gross income (ln)	0.292	0.089	0.100	0.111	0.180
	(0.229)	(0.207)	(0.126)	(0.154)	(0.125)
Fuel efficiency (ln)	0.331*	0.245	0.036	0.066	0.188
	(0.174)	(0.153)	(0.156)	(0.189)	(0.191)
SHEDS year: 2019	0.142	0.005	0.003	0.042	-0.003
	(0.097)	(0.067)	(0.054)	(0.067)	(0.082)
SHEDS year: 2020	-0.037	-0.216*	-0.256***	-0.282***	-0.406***
	(0.139)	(0.130)	(0.095)	(0.097)	(0.117)
Age of car (years)	-0.007	0.000	0.003	0.002	0.004
	(0.011)	(0.008)	(0.009)	(0.007)	(0.007)
HH with single car	0.503*	-0.014	-0.205	-0.089	0.065
	(0.292)	(0.182)	(0.187)	(0.221)	(0.187)
# HH members	0.042	-0.674**	-0.897***	0.257	0.291
	(0.149)	(0.295)	(0.288)	(0.395)	(1.340)
Age of reference person (years)	-0.013***	-0.010***	-0.009***	-0.011***	-0.011***
	(0.004)	(0.002)	(0.003)	(0.002)	(0.002)
# GA travel cards per HH member	-0.071	0.252	0.014	-0.089	0.373**
	(0.312)	(0.291)	(0.311)	(0.182)	(0.151)
Living location: agglomeration	0.057	0.205	-0.057	-0.140	0.119
	(0.898)	(0.165)	(0.231)	(0.396)	(0.460)
Living location: countryside	-0.631	-0.046	0.067	-0.315	-0.183
	(0.823)	(0.377)	(0.299)	(0.656)	(0.270)
Av. gasoline price (by HH)	Yes	Yes	Yes	Yes	Yes
Av. HH gross income (by HH)	Yes	Yes	Yes	Yes	Yes
Av. single car (by HH)	Yes	Yes	Yes	Yes	Yes
Av. # HH members (by HH)	Yes	Yes	Yes	Yes	Yes
Av. # GA travel cards per HH member (by HH)	Yes	Yes	Yes	Yes	Yes
Av. living location: agglomeration (by HH)	Yes	Yes	Yes	Yes	Yes
Av. living location: countryside (by HH)	Yes	Yes	Yes	Yes	Yes
Observations	1,167	1,167	1,167	1,167	1,167
Households	499	499	499	499	499
R^2	0.128	0.136	0.132	0.126	0.124
pseudo-R^2	0.124	0.091	0.063	0.066	0.093

Clustered standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Conclusion

a. Summary of results and contributions to existing research

The three chapters of this dissertation contribute in several ways to the literature in the field of household energy demand. To begin with, Chapter 1 discusses the theoretical possibility of undesired interactions between direct and embodied energy demand, which could lead to a transfer of the energy burden to other countries, or sectors of the national economy, as a result of the reduction of energy consumption in one energy domain. For instance, a possible scenario is that energy policies achieve their goal of reducing the demand for electricity, heating or mobility, at the expense of an increase in the consumption of goods and services with a higher energy content. This could be considered as a sort of indirect "rebound effect", even though in this context reduction in energy requirements may not be necessarily related to efficiency improvements. More generally, the relationship between embodied and direct energy requirements could be characterized by trade-offs, complementarity or independence between them, and it is precisely by focusing on the dynamics between these two domains that Chapter 1 contributed to the existing literature in the field of total energy requirements. It addresses the "separability" hypothesis formulated by Leth-Petersen (2002) and follows the call of this author for future research in this field. From a methodological perspective, its added value consists in the use of a three-step procedure in investigating the relationship between separate domains of energy consumption: (1) by focusing on the effects of common determinants and on the simultaneity of embodied and direct energy demand: for this purpose, and in contrast to the majority of prior studies on total energy requirements, embodied and direct energy were examined separately, yet in a system of seemingly unrelated regression (SUR) equations; (2) by examining the cross-equation correlation of residuals of the SUR estimations, which also provides valuable information about how unobserved factors affect energy demand in each energy domain; (3) by addressing the substitution elasticity between direct and embodied energy consumption and controlling for endogeneity related to omitted factors – again, in a system of equations setup (3SLS). In addition, Chapter 1 contributes to the existing literature by relaxing the assumption of the linear effect of income across the income spectrum – a hypothesis adopted by the earlier studies, except that of Lenzen et al. (2006). The study of the existence of an energy Kuznets curve is of particular importance for the assessment of the effect of economic growth on the different domains of energy consumption. The results of the analyses of Chapter 1 show that direct and embodied energy requirements are influenced in the same manner by the same set of covariates; that there is a positive and significant, but rather small, cross-equation correlation between the residuals of the direct and the embodied energy demand equation, meaning that unobserved factors influence the energy demand in each of those two domains in a similar way; and that there is no evidence for substitution between direct (embodied) and embodied (direct) energy requirements. In other words, the analyses presented in Chapter 1 shows that there is no risk of undesired energy leakages between the two aforementioned energy sectors. On the other hand, its findings reveal that both energy domains are characterized by non-linear income effects, which are particularly pronounced for embodied energy, meaning that further economic development in Switzerland would bring about significant increases in the consumption of grey energy. However, we did not observe a turning point necessary for the identification of an energy Kuznets curve.

In contrast to Chapter 1, which uses cross-sectional data and does not include controls for energy (or non-energy) prices, Chapters 2 and 3 exploit longitudinal datasets and examine in detail the price elasticities of electricity and car travel demand, respectively. More precisely, those two chapters start where Chapter 1 ends: at the analysis of heterogeneity in energy consumption behaviors. Indeed, the last part of Chapter 1 focuses on the estimation of income elasticities at different levels of income – in essence, a discussion of the heterogeneity of income elasticity of energy demand. Chapter 2 concentrates on heterogeneous household behaviors in the field of direct energy consumption, by examining the research question as to whether segments of consumers defined on the basis of the intensity of their electricity demand exhibit different price and income elasticities of electricity demand. It contributes to the vast body of literature focusing on the average price and income elasticities of residential electricity consumption by examining the differences potentially concealed by the concept of the average, representative or typical consumer.

Given the limited number of studies in this domain, Chapter 2 can be also seen as an added value to this more specific field of analysis. The major difference when compared with previous works on price heterogeneity is that our segmentation strategy relies on the observation that households differ mainly in terms of their ownership (number, type, efficiency) and usage (stand by, frequency of usage) of electronic devices. Previously, Reiss & White (2005) outlined the importance of these two dimensions, but their econometric analysis was hindered by selection bias due to a simplistic truncation of the dependent variable (see Heckman, 1976). This led us to choose an alternative methodological approach, which had not been previously used in the study of heterogeneity of the price and income elasticities of residential electricity demand: a conditional quantile regression (Koenker & Bassett, 1978). Since conditional quantiles are defined with respect to the distance between the best line of fit and residuals, we interpreted the latter as readily capturing the amount of electronic devices within the dwelling and their usage by household members, thus forming what we refer to as "the intensity of electricity demand". Another novelty in comparison with previous studies applying quantile regression in the field of energy demand (e.g., Kaza, 2010; Sardianou, 2008) is that Chapter 2 uses a quantile regression approach adapted for panel data, i.e., a quantile regression with correlated random-effects (see Wooldridge, 2010). Notable applications of quantile regression with correlated-random effects can be found in the domains of the effects of birth inputs on birthweight (Abrevaya & Dahl, 2008) and of tobacco usage on birthweight outcomes (Bache et al., 2013), but to the best of our knowledge, this econometric technique has not been used in the field of residential electricity consumption. The findings of the second part of this thesis indicate that, while there are no statistically significant differences between the income elasticities of households with different levels of consumption intensity, different price elasticities across the consumption spectrum can be observed: households in the first and second conditional quartiles are significantly price-elastic as opposed to consumers at the very ends of the conditional distribution, probably due to the incapacity (or unwillingness) of the latter to reduce their usage of electricity as prices increase. We assumed that frugal electricity users owned only a basic set of electronic durables and that their electricity consumption was likely to be restricted, whereas intensive consumers probably relied on large amounts of non-discretionary electricity usage, such as from an electric heat pump.

The topic of price heterogeneity is continued in Chapter 3, but this final part of the dissertation focuses on the principal field of energy consumption outside of the dwelling – car travel. Unlike Chapter 2, Chapter 3 is part of a substantially larger body of literature, yet it followed the call for more research in the area of car travel/fuel demand launched by Gillingham et al. (2015) and Wadud et al. (2010a). Although its contribution to the existing literature might be seen as more modest in comparison with those of the first two chapters, several of its aspects present important added value with respect to earlier analyses. First, we deploy a household-level dataset with individual gasoline prices. As clearly outlined by Kirman (1992) and Oum et al. (1992) among others, the disadvantage of using aggregate measures is that it "averages out" important variation in the data. In the case of the study of private mobility, this may lead to an important bias in the empirical estimation of price elasticities, as shown by Levin et al. (2017). Yet, the majority of works on household car travel/fuel demand use gasoline prices, or socio-demographic features, aggregated at the country, region or city levels (e.g., Gillingham & Munk-Nielsen, 2019; Mattioli et al., 2018), or apply complex price constructs from various data sources (e.g., Kayser, 2000) in the absence of disaggregated data. Second, Chapter 3 addresses the question of heterogeneity in the price elasticities of car travel demand by using a longitudinal dataset and econometric techniques for the analysis of panel data. The majority of the earlier works in this domain apply overwhelmingly cross-sectional or pooled datasets (e.g., Gillingham, 2014). This affects the price elasticities of car travel demand in two major ways, as discussed in the first two sections of Chapter 3: (1) comparisons based on cross-sectional variations reflect differences between locations, rather than structural coefficients; (2) they do not allow a straightforward interpretation of the time horizon (i.e., short run versus long run) reflected by price elasticities. Finally, as in Chapter 2, the third chapter of this work employs a quantile regression analysis adapted for longitudinal data by applying the correlated random-effect approach described by Wooldridge (2010). Previously, only Gillingham et al. (2015) use the estimation method for panel data suggested by Canay (2011). However, a recent study by

Besstremyannaya & Golovan (2019) shows that in the case of a small number of time periods and important number observations, as in Gillingham et al. (2015), this can lead to a critical bias in estimation.

In addition, Chapter 3 examines the question of heterogeneity through the study of the price elasticities of various binary groups of households defined on observed socio-economic, socio-demographic and vehicle characteristics, such as income, living location, household composition, car vintage and engine efficiency. The majority of works in this domain use interaction terms between the price of car fuel and other covariates included in their model specifications (Frondel et al., 2012; Kayser, 2000; Wadud et al., 2010a), or split their samples into distinct groups (Gillingham, 2014; Gillingham et al., 2015) whose price elasticities are then compared. Our methodological approach is somewhat different, in that we dichotomize continuous variables into binary controls in order to identify groups of drivers, thereby followung Wadud et al. (2010a). While this does not solve the issue of multicollinearity discussed by those authors, it allows us to specify clearly defined groups of consumers, as well as to use the totality of our sample in order directly to compare whether estimated price coefficient of consumer segments are statistically different from each other. The empirical analyses of heterogeneity showed that multiple-member households households are significantly more price-elastic in comparison to single-member households, and we also observed some indicative evidence for differences between drivers located in urban and non-urban areas, as well as between drivers with different car efficiencies.

As noted above, both Chapters 2 and 3 target the empirical estimation of price elasticities and their heterogeneity, albeit for different domains of household energy demand. Therefore, their findings can be briefly compared. To begin with, we discover important differences in the average price elasticities in both domains, although the majority of earlier analysis in each fields find an inelastic short-run response of demand to price variations (price elasticities are situated generally in the interval -0.20 to -0.40). More precisely, in Chapter 3 we note a substantially higher average price elasticity of car travel demand (-0.85) compared with prior studies in this field, whereas in Chapter 2 we identified a price-elasticity of more conventional magnitude (-0.30). This result indicates that a policy-induced increase of gasoline prices will have a more important average impact on private car travel demand than an increase in electricity tariffs on the residential consumption of electricity. There are two main reasons that can explain this difference. First, electricity has fewer substitutes than car mobility. Second, the Swiss National Mobility Microsensus (OFS, 2017c) shows that Swiss drivers use their cars mainly for leisure activities, while electricity is likely to be characterized mostly by non-discretionary usage. Although we assumed that electricity and gasoline prices in our analyses are not affected by endogeneity, we briefly discuss the issue of price endogeneity further in the present conclusion, because this is an essential topic for studies using longitudinal data with long panels.

Another major difference between the second and third chapters of this dissertation, apart from the use of additional socio-economic and socio-demographic segmentation criteria for segments' definition in Chapter 3, concerns the interpretation and the results of quantile regression analysis with correlated random effects. As with Chapter 2, we interpret conditional quantiles as different levels of intensity of energy demand in Chapter 3. In contrast, however, the model specifications of Chapter 3 concentrates on a single energy-using device – the household's main car, and control for the device's efficiency (engine efficiency) in our model specifications. This means that the intensity of demand does not reflect the ownership and characteristics of energy-using appliances as in the second chapter of this work, but rather specific energy-related behaviors, such as driving longer distances in order to avoid areas with significant traffic jams, bad road quality, poor weather conditions or high crime levels. Interestingly, in each energy domain, the price elasticities estimated via quantile regression followed opposite paths across the energy demand spectrum. In the domain of residential electricity usage, frugal electricity consumers were significantly price-elastic compared with more intensive ones, whereas the opposite was true for the demand for mileage. This could be explained by the reason behind being an intensive energy user: if intensive energy demand is mainly characterized by non-essential consumption (e.g., heating via an electric heat pump), it will be less (or non) price-elastic than if it related to discretionary usage (e.g., driving for leisure purposes).

The empirical findings of the three chapters of this dissertation can be regarded as a general call for more, and more diversified, policy actions in the field of household energy consumption in Switzerland. As shown in Chapter 1, the large share of embodied energy in total energy requirements, combined with the possibility of important increases in grey energy demand due to economic growth, are good reasons to implement specific energy-reduction measures in this domain, which has hitherto received little attention from policymakers. However, given the wide range of consumption categories, non-price policy interventions, such as recommendations, nudges, information labels, standards and stringent regulation, might well be preferable to taxation. Alternatively, interventions could be limited to specific expenditure classes, such as electronic durables or air travel, the energy content of which is higher in comparison with other categories of embodied energy demand. In contrast, direct energy categories, which are characterized by higher energy content per physical and/or monetary unit of consumption and represent more homogeneous purchases, could be addressed by combining price- and non-price policy instruments, as suggested by the empirical results of Chapter 2 and Chapter 3. From a policy perspective, the key findings of these chapters indicate the efficiency and the equity of energy taxes in each of those two domains can be improved by carefully diversifying and tailoring policy interventions to household segments with different price elasticities. Detailed discussion of the distributional effects and the acceptability of energy taxation spreads nevertheless to the field of fiscal policy, however Chapters 2 and 3 do not venture into this domain. Although future research could thoroughly address these topics, the remainder of the conclusion will focus on other possibilities to extend the analyses presented in this thesis.

b. Future research

To begin with, future works can build upon Chapter 1 in two ways. First, by examining the interactions between more specific consumption categories. Chapter 1 adopted a holistic approach to energy requirements by aggregating a multitude of consumption categories into two separate domains – direct and embodied energy consumption. Thereby, it followed the remark of Leth-Petersen (2002) that *"…it is relevant also to test for separability between demand for energy and demand for non-energy goods, for example, food.* […] *To test for separability between energy and other goods one needs more detailed information about the consumption of other goods. This is a subject for future research."* (p.66). However, the aggregation in energy and non-energy goods makes interpretation of the exact interactions between categories of direct and embodied energy demand anything but straightforward. For instance, a drop in the use of car fuel (e.g., due to a price increase) could lead to an increase of the demand in electricity and heating, because consumers might opt to stay at home more. This could lead to an overall increase in direct energy requirements if savings were entirely reinvested in (inefficient) electricity and heating consumption. At the same time, consumers might also purchase more non-energy goods, such as furniture, but buy fewer cars. Those reactions would in turn affect the demand for embodied energy. While such scenarios are conceivable, the particular interaction mechanisms are likely to remain hidden when many energy categories are reduced to two main energy domains. Therefore, similarly to the aforementioned analysis by Leth-Petersen (2002) on the dependence between electricity and natural gas demand, a possible extension of Chapter 1 could be to investigate on the interactions between individual categories such as car travel and air travel demand or, alternatively, between electricity and motor fuel consumption. Previously, Wadud et al. (2010a) suggested that *"Wealthier households* […] *may switch to air travel if the price of motor fuel increases relative to jet fuel prices (as the latter are not taxed in most countries)."* (p.48). Also, in Switzerland, demand for electricity is expected to increase in the long run owing to policies encouraging households to replace space heating systems and vehicles using fossil fuels with electric heat pumps and electric mobility, respectively. Moreover, using single, clearly defined consumption categories is more suitable for investigating the effect of domain-specific energy prices, and allow us to examine the interactions between energy domains through the study of cross-price elasticities. Of course, the direct estimation of substitution elasticities, as in Leth-Petersen (2002) and in Chapter 1 of the present thesis, also remains a valid approach for the study of interactions. In this context, a challenge would be to find relevant and strong instruments in order to control for endogeneity of the conditional energy category. In addition, in the study of the interactions between car fuel demand and other categories such as air travel, electricity or dwelling energy consumption (electricity and heating), a Heckman selection model (see Heckman, 1976) could be used in order to consider all households, i.e., even those without a private vehicle. This analysis could be carried out in the SUR framework used in Chapter 1, by applying, for instance, the mixed-process models discussed by Roodman (2011).

A second possibility for improving Chapter 1 relates to the data used in the empirical analyses. Here, two main elements should be recognized. First, Chapter 1 uses expenditure data, thereby not decoupling more (quantity) from better (quality) consumption. Yet, this difference could affect the empirical estimation of model coefficients. Notably, in the context of the EKC hypothesis, high-income households are likely to consume goods and services of better quality, compared with poorer households. This suggests that the estimations related to the non-linear effect of income could be improved, especially with respect to embodied energy. Previously, Vringer & Blok (1997) make use of both expenditures and physical units of consumption as the basis for computing energy requirements in the Netherlands. Their physical unit-based estimations decrease average expenditure-based income elasticities only slightly. A reason for this, as pointed out by Girod & De Haan (2010), is that the energy inputs into production may also increase with better quality.[1] However, existing research has so far not investigated whether the alternative calculations of energy requirements affect the estimation of income elasticities across the income spectrum.

Concerning the data used in Chapter 1, it is important to mention that we use a rather old version of the SHBS (for the year 2011),, although during the process of writing, more recent versions of the SHBS became available. The reason for focusing on the SHBS 2011 is that it allowed us to match the expenditures for this particular year with the most recent available datasets (at that time) containing energy intensities from life-cycle analysis and energy-extended input-output analysis. In other words, in order to calculate total household energy requirements, it is necessary to obtain a coherent match between expenditure and energy intensity datasets.[2] Despite the more recent versions of the SHBS, the data used for analysis remains "static". Indeed, Chapter 1 addresses direct and embodied energy by focusing on a "snapshot" of

[1] In the context of the study of total GHG emissions in Switzerland, these authors nevertheless find important differences in the average income elasticities calculated by using expenditures and quantities.
[2] For instance, at the time of writing of Chapter 1, the most recent *Ecoinvent* life-cycle inventory was the 2.2 version. Currently, the most recent available version of the dataset and the related software is 3.7.1.

consumption in these two domains. Following prior studies, this chapter uses cross-sectional data from an expenditure survey. National budget surveys are not designed as rolling panels, as opposed to data sources such as the German Mobility Panel (MOP) or the Swiss Household Panel Survey (FORS), but are available on an annual basis for different observations. Since panel data presents various advantages over simple cross-sections (see Hsiao, 2007), a pseudo-panel obtained from repeated cross sections could also be a possible extension of the analyses presented in Chapter 1. This approach relies on comparisons between "cohorts" of observations, which share common socio-demographic, socio-economic, or other features which permit their identification as "similar". The averages of these cohorts are then treated as individual observations for panel data analysis. To the best of our knowledge, pseudo-panel techniques have not been used in this particular field, although many earlier works use panel data in energy domains such as the demand for car travel and ownership (e.g., Cornut, 2016; Dargay, 2007, 2002; Weis & Axhausen, 2009), electricity demand, or natural gas consumption (e.g., Bernard et al., 2011; Kostakis et al., 2021). Constructing a pseudo-panel from the SHBS would be a rather technical challenge, which would require dealing with the fact that energy intensity datasets are not available on an annual basis,[3] that price inflation affects expenditures in the different editions of the SHBS, and that changes regarding consumption categories occur from year to year. The general advantages and drawbacks of constructing pseudo-panels, applying panel data techniques to those datasets, and the interpretation of the estimated coefficients should also be carefully considered (Guillerm, 2017; Inoue, 2008; Kirman, 1992; Moffitt, 1993; Verbeek, 1996).[4]

The analyses presented in Chapters 2 and 3 can be also extended in several ways through future research. In both chapters, the study of heterogeneity in the price elasticities of electricity and car travel demand assumed that price variations are treated the same way, regardless of whether prices increase or decrease. That is, the effect of energy prices on demand was assumed to be symmetric.

[3] It is also possible to proceed like Volland (2017) and focus directly on energy expenditures as dependent variable.
[4] Despite the aforementioned interest of using pseudo-panels, this method has also been strongly criticized, owing to the aggregation of observations and to the underlying assumptions concerning unobserved heterogeneity (László & Sevestre, 2013; Kirman, 1992).

However, there are reasons to believe that the same consumer group might react differently when prices rise or fall. For instance, in the field of car travel/gasoline demand, it is conceivable that low-income households are more price-elastic than wealthy drivers when fuel prices decrease, because their car-travel/fuel demand is probably not satiated. On the other hand, when fuel prices increase, it might be more difficult for poorer households to reduce their already frugal driving/fuel demand, if it is related to essential travel. In this case, high-income households could more easily cut out leisure-related mileage. Similar scenarios could apply in the domain of residential electricity consumption.[5] For these reasons, research focusing on heterogeneous price elasticities of car travel/fuel demand should take into account the possibility of asymmetric price responses. Although earlier works often find evidence for asymmetry when examining the impacts of average energy prices,[6] this topic has not been addressed in the context of price heterogeneity.[7]

Another particularity of the analyses presented in Chapter 2 and 3 is the way energy-consuming durables are taken into account in our model specifications. In Chapter 2, the price of electricity already reflected the stock of appliances – a reason we did not include any controls for the possession of electronic devices in our regressions. Chapter 3 excluded a small proportion of car drivers from our econometric analyses, namely those who changed their cars during the three-year timespan covered by the dataset, in order to avoid unrealistic assumption about the mileage of those drivers. Both chapters used very short panels (of between 3 and 4 years) – a period of time during which capital could be considered fixed. Thus, our focus was on the differences between the price elasticities of segments of consumers *in the short run*. On the long term, however, the differences that exist between the elasticities of two given segments of consumers might contrast with those differences in the short run. For instance, in the long run, the price elasticity of gasoline

[5] When electricity tariffs decrease, poorer households might use their basic electronic appliances more often, or for longer periods of time. Comparatively, the electricity demand of richer households could be less price-reactive, if in addition to basic electronic devices, they only disposed of an electric heat pump (it would be the opposite if they dispose of private swimming pools or saunas heated by electricity). In the case of a price increase, low-income consumers may not be willing or able to reduce consumption, whereas high-income consumers might be willing to cut off non-essential electricity consumption.
[6] For electricity demand, see for instance Gupta et al. (2017) and Young et al. (1983). In the field of private mobility see Dargay (2001), Frondel & Vance (2013) or Sentenac-Chemin (2012).
[7] The study of asymmetry will however require large datasets with many time periods (see Giuliano & Dargay, 2006).

demand of intensive drivers might be higher than the price elasticity of less-intensive ones. When gasoline prices rise, the replacement of an internal combustion engined car with an electric (or a more efficient) vehicle is indeed a probable solution for households with a substantial amount of gasoline expenditure Households with low mileage may nevertheless be less price-responsive in the long run, since their already small fuel expenditures will grow only marginally as a consequence of a price increase. These drivers might also prefer to pay a higher fuel price instead of investing in a new vehicle.[8] The opposite could be true in the short run: households that intensely depend on their cars might marginally reduce their demand for fuel, because they might have hardly any alternative mobility option. Hence, it is possible that in the short run the price elasticity of gasoline demand of intensive drivers is actually lower than the price of less-intensive ones.[9] Briefly, the time horizon considered might be determinant for the differences between the price elasticities of different groups of consumers. This can be addressed by future research through the application of dynamic adjustment models in the context of heterogeneity analysis. Dynamic adjustment models have previously often been used in the fields of electricity and car fuel demand (Boogen et al., 2017; Dargay & Vythoulkas, 1999; Filippini, 2011; Santos, 2013; Alberini et al., 2011). In addition, because the choice of energy-consuming appliances and their features, such as their efficiency, are endogenous in the long run, the previous research question should be examined in the discrete-continuous framework suggested by Dubin & McFadden (1984) and discussed in detail in the general introduction to this dissertation.

The use of alternative segmentation criteria presents another possibility to broaden the analysis of Chapters 2 and 3. For instance, in order to examine the vulnerability to fuel price increases across groups of drivers in the UK, Mattioli et al. (2018) combine income level, with the share of driving cost in income to define several consumer groups. Groups of drivers could be defined on the basis of their income level and living

[8] This example concerns car fuel demand. The demand for mileage may, on the other hand, not be affected by the short term/long term differences discussed in this context.
[9] Similar scenarios are conceivable with respect to the heating systems of dwellings. In the long run, households (or facility management firms for rental buildings) could choose to replace their old and inefficient heating with new equipment when the price of heating oil rises.

location (e.g., as combination of binary controls: low-income rural households, low-income urban households, high-income rural households, high-income urban households), or by combining their driving intensity with living location (e.g., by using interaction terms in a quantile regression model). This would allow us to investigate the price elasticities of more specific consumer groups.[10] Similar combinations between segmentation criteria could be applied in the field of residential electricity demand. Unlike car travel demand, this domain is still characterized by a limited number of studies on price heterogeneity (notable exceptions are Chindarkar & Goyal (2019), Frondel et al., (2019), Reiss & White (2005)), therefore future analyses could also focus closely on "plain" socio-economic and socio-demographic segmentation criteria. Further, heterogeneity in both car travel and electricity demand could also be addressed by latent-class regression (i.e., finite-mixture) models, which rely on the definition of *a priori* unknown heterogeneous groups of consumers (Hagenaars & McCutcheon, 2002; McLachlan et al., 2019; Tuma & Decker, 2013; Wedel & DeSarbo, 1994). This econometric method has been previously applied in energy domains such as car travel and electricity consumption (e.g., Yang, 2014; Zahabi et al., 2015), but its use remains uncommon, particularly when applied to panel data (d'Uva, 2005)

Finally, unlike Chapter 1, Chapters 2 and 3 used energy prices to investigate the possible effects of policy measures. In those chapters, we argued that our price measures are not biased by endogeneity, although it is possible that in the long run consumers self-select their individual electricity tariff or gasoline prices. In Chapter 2, we used a variable, capturing the mean electricity price of households in a similar consumption category, and electricity tariffs for different season and time-of-day were also averaged. For this reason, individual electricity consumers were considered as price-takers of the average electricity price paid by *all* households. We also argued that it is probable that over short periods of time few households are unlikely to change their electricity tariffs, due to inertia (see Hortaçsu et al., 2017). The disadvantage of using aggregate price data is that it "averages out" important variation, which leads to an estimation bias, as

[10] This fine-tuning could be essential in practice. For instance, the movement of the so-called "yellow vests" in France originated as a protest against higher diesel prices, and was led mainly by groups of drivers with modest incomes, high mileage and living in the countryside. For anecdotal evidence, see *The Economist* (2018).

outlined by Kirman (1992) and Oum et al. (1992). In the long run, endogeneity could be a problem both with average and individual price data. To address this issue, Frondel et al. (2019) use the regulated components of electricity prices in Germany (grid fees, taxes, and levies) to instrument individual electricity prices. In Switzerland, electricity prices contain two regulated elements: a constant feed-in tariff per kWh of electricity and a variable cost levied at the communal level. Consumers also do not have a choice over the grid-access costs specified by electricity providers: this component of electricity tariffs reflects grid construction and maintenance costs, which are dependent on the particularities of the physical landscape (Volland & Tilov, 2018), and not on individual characteristics. Before addressing the technical aspects of an IV estimation, it is however necessary to seek a better insight into the question of price endogeneity, namely, whether it an issue going beyond theoretical assumptions. For this purpose, the design of energy consumption surveys such as the SHEDS could integrate additional price-related questions, such as *"Since the last wave of the questionnaire, did you choose a new electricity tariff?"*; *"When was the last time you changed your electricity tariff?"*; *"Why did you change your electricity tariff?"; "How do you get informed about a change in electricity prices?"*.[11]

It should be noted that the previously described endogeneity issue may also exist at the level of individual gasoline prices if drivers choose to fill the tank at cheaper gas stations. While this could be an issue with cross-section data, as well as with long panels (i.e., in the long run), we do not believe it exists in the short run, where the choice of a gasoline station is likely to be determined by routines and convenience preferences (BCG, 2014; GasBuddy, 2021; Kitamura & Sperling, 1987). In contrast to electricity tariffs, car fuel prices are close to impossible to instrument. Perhaps partly due to this fact, and partly due to the difficulty of accessing datasets with individual car fuel prices, the vast majority of studies in this field use average state-, municipality- or city-level price data (e.g., Baranzini & Weber, 2013; Gillingham, 2014). Levin et al. (2017) shows that this strategy is likely to lead to an important downward bias in the estimated

[11] The formulation of these questions, their sequence and the answers possibilities presented to respondents should be carefully designed. The intention behind the questions presented here is to serve as an example.

price elasticities of car fuel demand, to an extent that price elasticities could *"...differ by magnitudes large enough to substantially impact subsequent policy evaluation or market analysis."* (Levin et al., 2017, p. 344). Therefore, before using aggregate car fuel prices as an instrument (or proxy) for individual prices, additional questions about pump behavior in Switzerland should be included in the SHEDS survey in order to better assess the risk of endogeneity. More precisely, survey participants could be asked to report their pump habits (attention to fuel prices; reasons to fill the tank at a given gasoline station: price, convenience, loyalty program; readiness to drive to a gasoline station further away to fill the tank, etc.). For this, the questionnaire used by the travel and navigation application GasBuddy (GasBuddy, 2021) about about behaviour relating to the choice of a gasoline stations could be used as an example.

The topics discussed above provide a brief glimpse of some possible directions for future research. It is however important to stress that the questions and improvement possibilities addressed here should not be considered as a set of recommendations, but rather as ideas or suggestions that could be used to extend the analyses presented in this dissertation. Nor do they present an exhaustive list of research possibilities. Their specific place in the existing literature, in addition to their theoretical and technical relevance, must be further critically assessed before carrying out in-depth investigations.

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