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Electricity prices and preferences for climate and energy policy*†

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Abstract

We analyse the impact of high electricity prices on individual preferences and attitudes toward climate and energy policy in Sweden. Our identification strategy leverages key features of the data and study design. First, consumers are distributed across four electricity price areas, each characterized by varying and often divergent electricity prices. Second, surveys were conducted in four distinct waves. Notably, between the second and third waves, electricity prices were nearly identical across price areas, whereas after the third wave, significant price differences emerged. Using multiple estimators that exploit these features, we find that higher electricity prices: (1) reduce acceptance of a carbon tax, (2) increase support for nuclear power,(3) diminish concerns about climate change, and (4) have no significant impact on other political attitudes or food consumption preferences.

Keywords: Electricity prices, environmental policy, individual preferences, inflation expectation
JEL Classification: D12, O33, Q53, Q58

1 Introduction

Historically, electricity has been treated as an essential service, implying that scholars and policy makers have placed significant emphasis on consumer prefer-

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ences when evaluating electricity prices. The literature consistently shows that consumers, including industrial and commercial customers, have strong preferences for low price levels (e.g., Bonev et al., 2024; Kaenzig et al., 2013; Park and Woo, 2023; Labandeira et al., 2017).[1] Furthermore, both residential and industrial customers prefer low price volatility, indicating that high price levels, even if temporary, is associated with a cost (e.g. Biggar and Söderberg, 2018; Cardella et al., 2017). These preferences have driven the development of electricity systems with substantial shares of baseload generation.

Recently, there has been a shift in policy priorities, leading to an increase in intermittent generation across many systems. Consequently, electricity consumers are expected to play a more active role and should prepare for higher price levels and greater price volatility (e.g., Abdelmotteleb et al., 2022; Lee, 2023; Mallapragada et al., 2023; Steriotis et al., 2018; Tsitsiklis and Xu, 2015). Although this transition supports the decarbonization of the electricity system, it poses challenges to consumers' preference for low and stable prices.

Preferences against high and volatile electricity prices may influence consumers' support for climate and energy policies. Several studies suggest that worsening economic conditions generally reduce support for such policies. For instance, Aklin (2021) and Bergquist et al. (2020) report that support for energy policies declines when their associated costs, such as higher energy expenditures, are explicitly presented to respondents. Similar findings are documented by Carattini et al. (2018), Douenne and Fabre (2020), and Gevrek and Uyduranoglu (2015). Additionally, Duijndam and Beukering (2021) demonstrate in a cross-country analysis that citizens' climate concern diminishes as GDP per capita decreases, while within-country analyses show a similar decline when unemployment rates decrease. Comparable results are also observed by Shum (2012).[2]

Yet, establishing a clear causal relationship between changes in (expected) electricity prices and consumers' attitudes and preferences remains a challenging empirical task. As discussed in detail in Section 2, most related studies rely on hypothetical scenarios or inflation predictions. For instance, Douenne and Fabre (2022) and Ewald et al. (2022) examine hypothetical policy scenarios, while Fuster et al. (2021) and Roth and Wohlfart (2020) focus on inflation predictions.

[1] More generally, Stantcheva (2024) show that consumers believe that inflation reduces purchasing power, provokes stress, and creates a sense of inequity, and that they often blame the government for high inflation. Other studies on inflation aversion include Aklin (2021), Aklin et al. (2022), and Hofstetter and Rosas (2021), as well as the seminal work by Shiller (1997).

[2] Furthermore, Brännlund and Peterson (2024) and Brännlund et al. (2024) use survey data from Sweden, and show that electricity price shocks in 2021 and 2022 affected the 2022 Swedish election outcomes, suggesting that voters hold governments accountable for poor economic performance. Similar results have been found in other countries. For example, Kim and Yang (2022) show that voters tend to hold the incumbent government accountable for high gasoline prices in the U.S..

Although these studies provide valuable insights, consumers may respond differently when exposed to actual inflation, a critique analogous to the common limitation of lab experiments (Bowles and Polania-Reyes, 2012). Moreover, actual inflation or electricity price volatility typically affects the entire population, making it difficult to construct a valid counterfactual.

In this paper, we examine whether electricity price increases reduce Swedish citizens' support for climate, energy, and welfare policies. This analysis is particularly relevant, as electricity prices and price volatility have been higher in recent years compared to levels observed during the post-deregulatory period, beginning in 1990s. Furthermore, the challenges posed by high and volatile electricity prices are expected to intensify, with electricity prices projected to rise over the coming decade (see, e.g., Table 7b in Gabrielli et al., 2022). To the best of our knowledge, this paper is the first to analyze the relationship between electricity price increases and attitudes towards energy and climate policy.

We employ an innovative empirical design that specifically addresses the aforementioned empirical challenges. The preferences of Swedish households are surveyed across a broad set of policies, enabling a comparison of these preferences under different, yet actual, electricity prices and price trends among otherwise similar consumers. In particular, we leverage a unique feature of Sweden's electricity market: the country is divided into four electricity areas, with prices set independently in each. While prices in these areas are generally similar, there are periods of substantial divergence in both magnitude and trend. Notably, the locations of the area borders were determined nearly 15 years ago based on electricity flow bottlenecks, making them unrelated to institutional or socio-economic factors. In some instances, these borders pass through municipalities and even urban areas, meaning that two houses only meters apart can fall into different price areas.

The survey design exploits this feature in two ways. First, we survey individuals who live close to the price borders. Thus, we ensure that on average, individuals surveyed on different sides of the border are similar with respect to demographics, income, and other socio-economic characteristics, and are exposed to similar institutions and economic conditions. Second, we set up the survey so that it is sent out in several waves, with one month in between each wave. While the electricity prices and trends are almost identical in and across the first, second and third waves, they diverge both in magnitude and trend (increasing vs. decreasing) between the third and fourth waves. This allows us to compare preferences of individuals on both sides of a border who have experienced a recent and unexpected divergence of electricity prices.

This empirical design provides two different sources of identifying variation. First, it allows us to exploit the discontinuity of prices at the price border under the identifying assumption that all other characteristics relevant for the policy preferences are continuous. Second, the availability of several waves with equal prices and price trends provides valuable pre-treatment information. To exploit both sources of identifying variation, we employ several estimators, including regression discontinuity (e.g., Hahn et al., 2001), difference-in-differences, and difference-in-discontinuity (e.g., Butts, 2023; Grembi et al., 2016). Importantly, we also survey demographic and socio-eceonomic variables, which allow us to condition on these variables in a third source of identifying variation (selection on observables, integrated into the other approaches), and which, on the other hand, allows us to examine effect heterogeneity. We provide comprehensive evidence in support of our identifying assumptions, both for the discontinuity and the time-related assumptions. As an example, the availability of pre-treatment outcome information allows us to test for differences in pre-treatment preferences, both in trends and in absolute levels. The access to information on socio-economic indicators, on the other hand, allows us to assess the assumption on continuity at the border, which is central for the regression discontinuity design.

In addition to the novel empirical design, the paper stands out due to its broader scope compared to previous studies. The analysis is not limited to a single aspect of consumer behavior (as in, for example, Douenne and Fabre, 2022; Ewald et al., 2022). Instead, we examine how energy price increases influence consumer preferences across several broad categories. These include preferences for durable goods, such as investments in energy-efficient appliances and home improvements, and consumption of non-durable goods, such as food. Including these goods allows us to assess how consumers adjust their consumption behavior of goods not directly related to electricity. It also allows testing recent mechanisms on adjustment of durable and non-durable good spending suggested in the inflation expectation literature (Burke and Ozdagli, 2023). We also assess how energy price increases impact economic preferences, including spending aimed at supporting industry competitiveness and economic growth. Furthermore, we explore attitudes towards social welfare initiatives, particularly those aimed at combating energy poverty and supporting vulnerable populations. Lastly, we analyze how fluctuations in energy prices influence perceptions of risk and support for climate change mitigation efforts, and expansion of nuclear power.

By examining these diverse categories, the study provides a comprehensive understanding of how electricity price increases affect consumer behavior and policy preferences. This broader scope allows us to capture the multifaceted impacts electricity has on society, offering valuable insights for policymakers and stakeholders.

Our main results are as follows. First, higher electricity prices decrease the willingness to pay for CO2 emission reductions, suggesting that carbon taxes are more difficult to implement when electricity prices are high. Second, higher electricity prices positively influence attitudes toward nuclear power, a result consistent with recent findings in the literature (Bonev et al., 2024). Third, we find that high electricity prices decrease concerns about climate change, aligning with much of the literature on climate change attitudes (Duijndam and Beukering, 2021). Together, these three findings support the explanation that energy prices alter consumers subjective intertemporal rate of substitution and lead to a greater emphasis on near-term economic well-being. Interestingly, these effects do not extend to preferences regarding environmentally friendly food production. One possible interpretation of this finding is that it provides indirect evidence of mental accounting. Alternatively, a more traditional explanation is that spending on durable and non-durable goods adjusts differently in response to expected inflation (Burke and Ozdagli, 2023). Fourth, we observe that higher electricity prices decrease the relative importance of households suffering from energy poverty, and increase the relative importance of industrial competitiveness. Overall, these findings suggest that during periods of economic hardship, there is greater opposition to both climate and welfare policies, which aligns with recent shifts in voter preferences observed in Europe.

The rest of the paper is structured as follows. In Section 2, we describe the research design and data, including a brief description of the institutional background in Section 2.1, a detailed description of our survey in Section 2.2 and descriptive statistics in Section 2.3. Next, we describe the empirical approach in Section 3. Results are presented in Section 4 including support for the identifying assumptions in Section 4.3 and interpretation of the results in Section 4.5. Section 5 concludes.

2 Setup and data

2.1 Institutional background

Because of geographic transmission constraints, the Swedish electricity market is divided into four independent wholesale electricity price areas: Luleå (SE1), Sundsvall (SE2), Stockholm (SE3), and Malmö (SE4). The four markets are represented in Figure A.1 in the Appendix. Within each area, the electricity

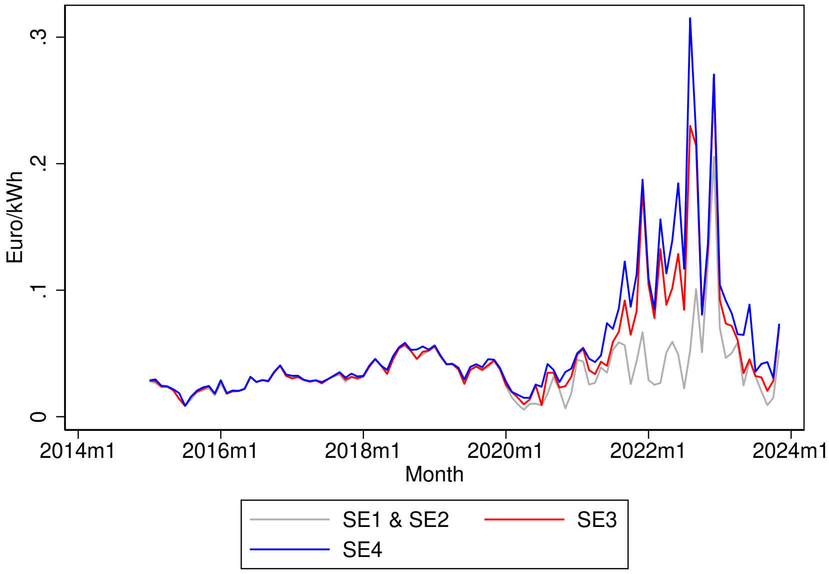

Figure 1: Monthly wholesale price per price area, 2015 to 2023

price is determined by the demand and supply of electricity and the available transmission capacity. Importantly for our identification strategy, the division into price areas was implemented for political reasons and not related to, for example, socio-economic characteristics, see Appendix A for details. In many cases, the borders run through municipalities, implying that households located directly at the border of the electricity areas, but on different sides, share common infrastructure, labor market conditions, and other important factors that influence consumption and preferences.

Figure 1 illustrates the monthly average of the wholesale price per price area. Up until 2021, prices were relatively similar in each of the four areas, but since then, prices have diverged substantially. The major reasons for these differences are capacity constraints in transmission, the generation mix, and the location of energy production; Appendix A has further details.

The retail market is deregulated and households are free to choose between retailers and different type of retail price contracts. In 2023, approximately 65% of all households had a retail contract with prices varying by month; 10% had a contract with prices varying by the hour, and the remaining households had a contract with prices fixed for a year or longer. Consumers can learn about the electricity price through their invoices (most households receive a monthly invoice), through the retailer's website and through media. The latter may have become an important channel through which electricity prices were communicated to consumers, with the number of newspaper articles including the word "electricity price" per month increasing from approximately 50 in 2020 to more than 8000 at the end of 2022.[3]

In addition to the retail price (charged as kWh per kWh), the consumer price of electricity includes an energy tax (approx. 0.05 Euro/kWh), an electricity certificate fee (0.002 Euro/kWh on average for 2022), Value Added Tax (25%), and a transmission fee consisting of a variable part, which is about 0.01 Euro/kWh, and a fixed part, which varies between 150 Euro and 1500 Euro per year, depending on the size of the household's fuse amp. None of these price components changed during our sample period, and except for the distribution price, they are identical across price areas.

2.2 Survey

The survey was conducted online at four different points in time (calendar weeks 9, 13, 17, and 20 in 2023) in a repeated cross-section design, i.e., each participant was surveyed only once. In total, 3008 individuals were surveyed (almost equal number in each wave). Participants were chosen at random from a pre-recruited pool of participants by the market research firm responsible for conducting the survey. The pre-recruited sample is representative for Sweden in terms of observed demographics and socio-economic characteristics. As we elaborate in detail in the empirical strategy section below, for the purposes of this study, we restricted the sampling location of individuals to the municipalities at the borders of the electricity price areas. These municipalities are displayed in Figure B.1 in Appendix B. Municipalities in SE1 and SE2 are colored grey, those in SE3 are red, and those in SE4 are blue. Municipalities that belong to more than one electricity area are colored yellow. All respondents live in owner-occupied detached dwellings. The survey was performed through a standardized online mask and participants were not informed about its purpose. A detailed description of the survey process can be found in Appendix B.

Our survey was designed as a structured questionnaire. The questionnaire contained 19 questions with pre-determined response options. We asked four different categories of questions. The first contains electricity-related questions such as the size of respondents' indoor space, type of space heating, energy efficiency investments made in the dwelling, and the type of retail electricity price contract, see questions Q1 - Q7 in Appendix C. The second category includes questions about energy and climate policy (questions Q8, Q9, Q10, Q12, and Q13). The third category includes questions about food and its relation to prices, health, and

[3]Source: Media database Retriever, https://www.retrievergroup.com/product-research

Number	Question	Response/coding
Q8	Are you willing to pay 10% more for your electricity if it means a large reduction of carbon dioxide emissions?	Yes = 1/no = 0
Q9	If Sweden had a general referendum about whether to build new nuclear reactors today, how would you vote?	Yes = 1/no = 0
Q11	To what extent do you agree that Sweden should use tax money to reduce energy poverty	Likert scale
Q12	How worried are you about the consequences of climate change?	From "Not worried" to "Very worried"
Q13	Do you think Swedish politicians do enough to address climate change?	Yes = 1/no = 0
Q14	When buying food, how important to you is the price?	From 1 "Not at all important" to 5 "Very important"
Q15	Do you frequently buy organic food?	Yes = 1/no = 0
Q16	Would you support a ban of pesticides usage in the agriculture sector if that raised fruits and vegetable prices by 30%?	Yes = 1/no = 0

Table 1: Survey questions 8, 9 and 11 to 16

environment (Q14 - Q16). The fourth category includes questions about electricity in the context of social welfare (Q10 and Q11). Finally, we also asked basic demographic and economic questions such as number of individuals and children in the household (Q17-Q19). Throughout, we refer to the questions as Q1, Q2 and so on. The exact phrasing of the questions in Swedish are presented in Table C.2 in the Appendix.

In our causal evaluation section, we interpret category 1 (Q1 - Q7), category 4 (Q17 - Q19), as well as the pre-survey information known by the survey company as control variables, while Q8 - Q16 are interpreted as outcome variables. Q8, Q9 and Q11 - Q16 are presented in Table 1, and Q10 is presented in Table 2. Q1 - Q7 and Q17 - Q19 are presented in Table C.1 in Appendix C.

2.3 Descriptive statistics

First, we illustrate the distance (in km) to the nearest price area border in Figure 2. The median distance is approximately 30 km, and approximately 25% of the respondents live 0 - 15 km from a border. In Section 3, we discuss how the scattered locations around the borders influence our results.

If you had a fixed budget to spend on the five objectives below, how would you spend it (in %)?
The electricity price for residential customers at a level that is low enough to prevent households from experiencing financial hardship and that they do not have to compromise on basic comfort (e.g. to lower the indoor temperature).
The electricity price for industry customers at a level that guarantees economic growth and a level of competitiveness that is at the same level as it has been during the past decades.
All electricity consumed in Sweden is produced by fossil free production technologies.
Use electricity productions that have as little impact as possible on the biological diversity.
As much as possible of the electricity consumed in other countries is produced by fossil free production technologies.

Table 2: Question 10

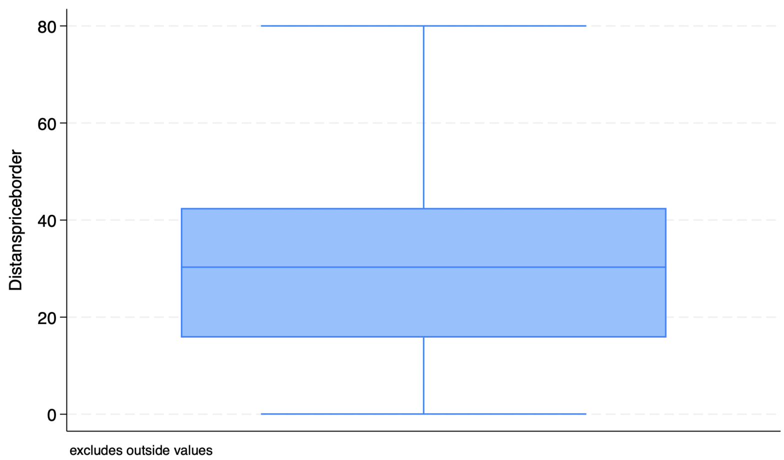

Figure 2: Distance to the nearest price area border

Next, we turn to descriptive statistics of our variables, beginning with the control variable in Table 3. We illustrate how the variables differ across price areas, and focus our discussion on comparing SE2, SE3 and SE4 since SE1 is under-sampled. The areas are very similar in terms of demographic characteristics. The average age is almost identical, and the same holds for the number of individuals and children per household. The share of male respondents is slightly higher in SE4. Next, consider energy characteristics of the households. SE4 has the largest average indoor space. Figure D.4 in the Appendix reveals that the entire distribution of indoor space in SE4 is shifted to the right relative to the corresponding densities of SE2 and SE3. Nevertheless, this difference is rather small. Furthermore, SE4 has the smallest share of households with ground heating, and the largest share with heat pumps.[4] The three regions are very similar with respect to other characteristics, such as the share of households with pellets burner, wood stoves, and oil heating.

Furthermore, Figure D.2 in the Appendix contains four barplots, each displaying the absolute frequencies of education levels in each of the four regions. Each number between 1 and 7 corresponds to a given completed educational level, with increasing number corresponding to increasing number of completed years, see Appendix C for a detailed explanation of the coding. In all areas except for the under-sampled SE1, the relative frequencies of the different categories are very similar across areas, with completed secondary school (category 4) and university masters degree (category 7) being the most common. Figure D.3 in the Appendix displays barplots of the income distribution for the 4 areas. The income distribution is divided into 13 categories, with category 1 corresponding to an annual income up to 100,000 SEK (about 10,000 €) and category 11 corresponding to an annual income above 1 million SEK.[5] The distribution of income in regions 3 and 4 appear to be very similar, and a chi-square test of equality of distributions yields a p-value of 0.32. In contrast, the income distribution in area 2 has a more pronounced mode around category 7 and is less flat than the distributions in areas 3 and 4, suggesting a more concentrated "middle class".

Finally, Figure D.5 in the Appendix shows boxplots of distributions of the type of electricity contract in each region (Q7 in the survey). The options vary from "hourly plan" (categories 2 and 3) to long term plans such a fixed 3-month plan (category 5) and longer (category 6). The shares of the hourly plans are roughly

[4]We also note that SE4 has the largest share of households who have implemented energy efficiency measures since 2022. The major difference in this last category stems from the share of households who replaced their windows. However, this variable is potentially an outcome of higher prices, and is thus treated as such.

[5]Category 12 corresponds to "Don't know" and 13 to "Don't want to disclose".

Table 3: Means/shares of selected variables

	SE1	SE2	SE3	SE4
Panel A: means/shares of control variables				
Age	53.12	51.03	51.91	52.80
Share of male respondents	0.31	0.45	0.46	0.50
Indoor space	119.93	133.79	142.82	144.78
Number of individuals per household	2.56	2.76	2.73	2.75
Number of children of age below 7	0.55	0.32	0.34	0.34
Distance to price border	22.70	39.58	27.06	37.39
Share households with ground heating	0.31	0.28	0.32	0.23
Heat pump	0.25	0.24	0.32	0.39
Share households with pellets burner	0.00	0.03	0.03	0.04
Share households with wood stove	0.19	0.24	0.24	0.22
Share households with direct electric heating	0.56	0.24	0.20	0.20
Share households with district heating	0.06	0.28	0.19	0.20
Share households with oil heating	0.00	0.00	0.00	0.00
Share households with solar panels	0.00	0.00	0.00	0.00
Share households invested in efficiency since 2022	0.40	0.27	0.29	0.36
Such as insulated roof	0.00	0.06	0.03	0.05
Such as changed windows	0.00	0.11	0.06	0.12
Such as changed doors	0.20	0.06	0.05	0.05
Such as new wood stove	0.00	0.00	0.00	0.00
Such as adjustments in the heat pump	0.00	0.00	0.00	0.00
Others	0.00	0.05	0.05	0.05
Panel B: means of questions 8 and 9				
Paying more?	0.31	0.26	0.28	0.26
New nuclear power?	0.73	0.70	0.78	0.77
Panel C: shares of budget for different causes (question 10)				
Electricity poverty	34.38	28.63	30.35	30.01
Industrial competitiveness	14.44	18.66	19.93	20.53
Swedish electricity is CO_2-free	16.44	19.56	19.22	19.52
Biodiversity-friendly elecricity	19.75	19.09	17.56	17.12
Global consumption of CO_2-free electricity	15.00	14.06	12.95	12.82
Panel D: means of further output variables				
Tax money to reduce energy poverty? (Q11)	0.26	0.24	0.26	0.26
Worried about climate change? (Q12)	0.34	0.47	0.46	0.45
Politicians do enough to stop climate change? (Q13)	0.35	0.48	0.42	0.42
Food price important? (Q14)	0.48	0.61	0.60	0.62
Frequent buyer of organic food? (Q15)	0.17	0.35	0.34	0.32
Pay 30% more for food to ban pesticides? (Q16)	0.22	0.25	0.26	0.24

15% and 5% in all three areas. Customers with these plans are particularly affected by short-term fluctuations in the electricity prices. The shares of customers with monthly contracts (category 4), as well as those with long-term contracts (category 6) are pronounced in all three areas, even though there are differences in shares across areas.

Turning to the outcome variables, in Q8 of the survey, we ask whether respondents would pay 10% more for their electricity if it would mean a large reduction in carbon dioxide emissions. The shares of "Yes" in each of the price areas are presented in Panel B of Table 3 and also depicted in Figure D.6 in the Appendix. The relative order of areas according to that share varies substantially from period to period with no clear dominance. Figure D.7 in the Appendix plots the share of "Yes" responses to Q9 "If Sweden had a general referendum on whether to build new nuclear reactors, how would you vote?". In SE3 (red line) and SE4 (blue line), there is a decrease in this share in the first three waves and an increase in wave 4. SE2 (grey line) shows a changing pattern.

Next, panel C in Table 3 shows the average share of a fixed budget that an individual in each of the 4 price areas would spend on 5 different objectives: (i) reducing electricity price to reduce electricity poverty, (ii) maintaining industrial competitiveness by lowering industry electricity price, (iii) producing CO2-free electricity in Sweden, (iv) using biodiversity-friendly electricity, and (v) global consumption of CO2-free electricity. The highest average share of this fictional budget for all four regions is devoted to reducing energy poverty. Second, third, and fourth, with almost identical averages, are Swedish CO_2-free electricity, biodiversity-friendly electricity, and industrial competitiveness.

Panel D in Table 3 summarizes further outcome variables. Nearly every fourth respondent agrees, or strongly agrees, that tax money should be used to reduce energy poverty. Almost half of all respondents in each region are worried or very worried about climate change, but 40% or more do not think politicians do enough in any, or most, policy fields to mitigate it. Finally, around 60% consider food prices to be important or very important, a little more than 30% buy organic food, and only every fourth respondent would support a ban of pesticides if that means a 30% increase in food prices.

3 Empirical Framework

3.1 Notation and treatment effects of interest

To construct a treatment variable, we analyze the electricity price dynamics in early 2023, focusing specifically on the divergence in wholesale spot prices after week 18. Since other price components, such as the distribution price, are either fixed for long periods (typically one year) or are of minimal magnitude, the wholesale price primarily drives the overall electricity price volatility during the observation period.

Figure 3 provides a detailed view of 2023, showing the weekly average wholesale spot prices for each of the four regions. Note that prices in SE1 and SE2 are identical and represented by a single gray line. The x-axis indicates the week, while the y-axis shows the average spot price. The four vertical dashed lines correspond to the weeks when the survey was conducted.

Between weeks 10 and 18, average prices in all four regions follow parallel trends and are similar in magnitude. However, from week 19 onwards, discrepancies emerge between SE4 and SE1, SE2, and SE3, both in trend and magnitude. Specifically, the price in SE4 (blue line) shows a stable rising trend, while prices in SE1, SE2, and SE3 drop significantly until week 21, after which they slightly increase.

Several factors contribute to this divergence. First, the price levels in SE1, SE2, and SE3 decreased due to a relatively windy May (with significant wind power located in northern Sweden, mainly in SE2), substantial snowmelt that filled reservoirs in northern Sweden (where most hydro production is in SE1 and SE2), and warmer temperatures in May which reduced demand. Conversely, prices in SE4 increased due to limited transmission capacity, preventing the surplus of hydro and wind power from being transmitted south. Additionally, maintenance work on nuclear power plants in SE4 further decreased supply and raised prices.[6]

To quantify the price divergence before survey waves 3 and 4, at its peak, the increase in electricity prices in SE4 implies a rise in the household budget share from approximately 8% to 13% relative to SE3. This approximation is based on an average household consuming 20,000 kWh per year and experiencing an increase in the wholesale price from 0.3 to 1 SEK. This increase is then related to the annual average income in Sweden, which was approximately 32,000 euros in 2022, according to Statistics Sweden. Thus, this increase is economically significant.

[6]Source: the Swedish Energy Agency, see https://www.energimyndigheten.se/49c773/globalassets/om-oss/lagesrapporter/elmarknaden/2023/nulaget-pa-elmarknaden-maj-2023.pdf.

With $t = 1, 2, 3, 4$ indicating the survey wave, we define a binary treatment variable D_{it} that is equal to 1 whenever an individual from SE4 is exposed to the electricity prices after survey wave 3 and just prior to wave 4:

$$D_{it} = \begin{cases} 1 & \text{if} \quad t = 4 \,\&\, Region_i = 4 \\ 0 & \text{otherwise.} \end{cases}$$

With this definition of a treatment variable, we define the main effect of interest as

$$\Delta = \mathbb{E}[Y_{i4}(1) - Y_{i4}(0) | D_{i4} = 1],$$

where $Y_{it}(d)$ represents the potential outcome of individual i had she been exposed to treatment $d = 0, 1$. Intuitively, this effect represents the average effect of being exposed to high and increasing electricity prices *relative to low and decreasing prices* for those exposed to the high prices (average treatment effect on the treated (ATT)). As outcome variables, we use the responses of the individuals to questions 8 to 16 as described in the previous section.

3.2 Empirical strategy

To construct unbiased estimates for Δ, we exploit two key features of our setup. First, and as described in more detail in the Appendix, the price borders were set in a political process and the borders' location were not related to landscape or infrastructure, which is common when geographical borders are determined. As a result, localities that are divided by the price borders are very similar in terms of key socio-economic and geographical characteristics. In some cases, the price border also split municipalities to create two different electricity prices within the same municipality.

Consequently, we adopt the identifying assumption of regression discontinuity design that all other determinants of the outcome variable (excluding the price of electricity) change continuously at the border (see, e.g., Butts, 2023; Keele and Titiunik, 2015). This assumption is the main motivation of our sampling choice, namely targeting individuals living in municipalities directly at (or in some cases, "on") the price borders. We back the continuity assumption with empirical evidence in Section 4.3. For example, we show that pre-treatment covariates does not change discretely at the borders.[7]

[7] We also note that census data from Statistics Sweden (`www.scb.se/en/`) shows that relatively few people move per year, e.g., between municipalities (which, in many cases, is required in order to move to a different price area. Importantly, there is also a negative trend in the number of people moving

The second feature we exploit is the availability of repeated cross-sections. The survey waves, together with weekly average wholesale prices, are presented in Figure 3. Evidently, in waves 2 and 3 (roughly between weeks 10 and 18), electricity prices and their trends are very similar across regions. From week 19 on, there is discrepancy between SE4 (blue line) and SE1, SE2 (grey line) and SE3 (red line) - both in trend and in magnitude.[8] In particular, the price in SE4 is characterized by a stable rising trend, while prices in SE1, SE2 and SE3 drop significantly at least until week 21 before they again slightly increase.[9]

We use four different estimators to exploit these two features. First, we use a "naive" Regression Discontinuity Design (RDD) estimator that represents a simple difference in means between the post-treatment outcomes in wave 4 for areas 3 and 4 for those observations at the mutual border (we also apply the estimator to the other waves, and discuss any differences in estimates).[10] Second, we use the standard nonparametric RDD estimator with a forcing variable defined as the distance from the households to the border between SE3 and SE4. However, since there is only limited variation in the distance from households to the border (with many households having practically the same difference to the border), this approach is less practical, and we use it only as supportive evidence. To choose a bandwidth, we use the Imbens-Kalyanaraman optimal bandwidth calculation and the Silverman's rule-of-thumb approach (see Imbens and Lemieux, 2008). Since both generate very similar results, we only show the latter.

Both these RDD estimators exploits the first feature of our setup, namely the discontinuity in prices at the border. That is, these estimators measure the differences in outcomes between individuals living in price area 4 to those living in SE3. It is important to note that the differences in outcomes that we measure may depend on both recent price differentials during the sample period and on

per year, as illustrated by Figure D.1 in the Appendix. However, these aggregate quantities should be interpreted with caution.

[8] To give a sense of magnitude, the increase of prices electricity in region 4 implies an increase in the household budget share from approximately 8% to 13% relative to region 3. We calculate this approximation for an average household consuming 20,000 kWh per year and facing an increase in the wholesale price from 0.3 to 1 SEK. This increase is then related to the annual average income in Sweden which, according to Statistics Sweden (see www.statistikdatabasen.scb.se), was approximately 32,000 euros in 2022. Thus, this increase is economically significant.

[9] There are several reasons for this divergence. First, the price level in SE1, SE2 and SE3 decreased because the month of May was windy and a lot of wind power is located in northern Sweden, mainly in SE2. Second, there was a lot of snow melting, which filled up reservoirs in northern Sweden (similar to wind, most hydro production is in the north in SE1 and SE2). Third, May was warmer than April, meaning that demand decreased. On the contrary, prices in SE4 increased because of limited transmission capacity to SE4, meaning that the surplus of hydro and wind could not be transmitted to the south. In addition, in May there were some large maintenance works on nuclear power plants located in SE4, which decreased supply and raised prices. See https://www.energimyndigheten.se/49c773/globalassets/om-oss/lagesrapporter/elmarknaden/2023/nulaget-pa-elmarknaden-maj-2023.pdf

[10] See, Cattaneo et al. (2019) and Hahn et al. (2001) for a detailed discussion on RDD estimators.

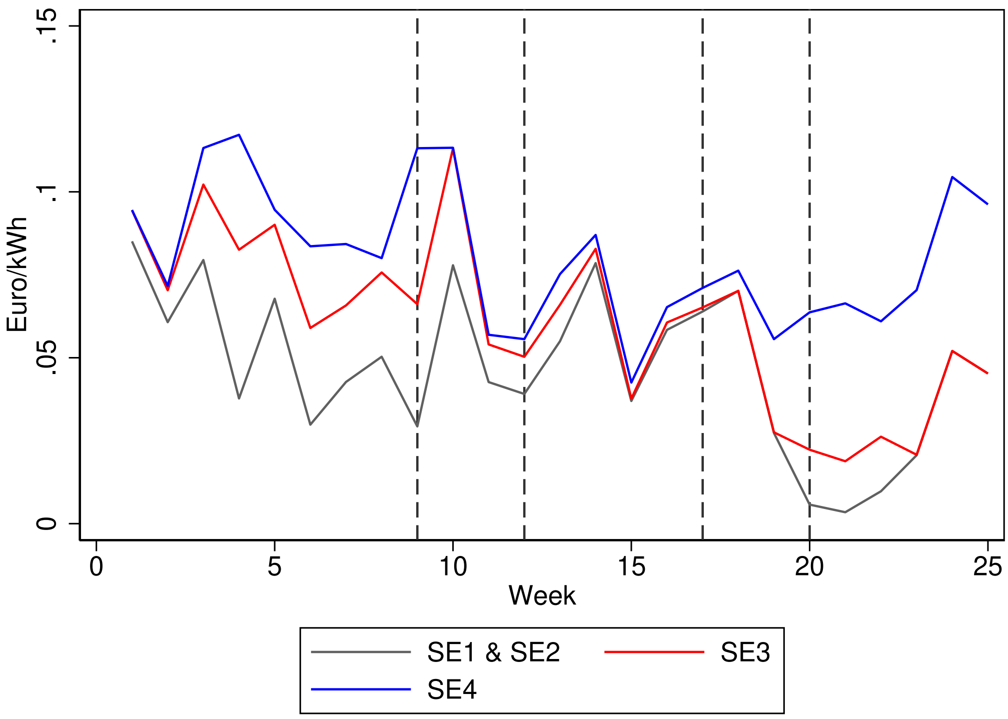

Figure 3: Average weekly spot price and timing of survey waves

a potentially long history of prices (from 2021, when area specific prices started to diverge). The effect of the discontinuity in prices is measured at the border, and we are agnostic about to what extent any differences in outcome depend on recent or more distant price differentials.[11] However, we note that applying the naive RDD to the first wave produces similar results as in the fourth wave. We also note that it is not straight-forward to pool observations across waves, since the treatment intensity (and possibly other variables; e.g., outdoor temperature) may have changed across waves.

Third, we use a standard linear difference-in-differences (DiD) estimator of the type

$$Y_{ijt} = Area_j + Wave_t + \beta \mathbf{1}\{j = 4, t = 4\} + X_{ijt}\beta_X + \varepsilon_{ijt} \tag{1}$$

where Y_{ijt} is the measured outcome for individual i living in price area j in period t, where $Area_j$ and $Wave_t$ are area and survey wave dummies, $\mathbf{1}$ is an

[11] If we had had data on outcomes since 2021, a more sophisticated structural model could include discounting of past prices on contemporaneous outcome. For example, Lanot and Vesterberg (2019) use a Bayesian learning model to show that households discount past prices when they choose electricity retail contracts. However, given our data, this is outside the scope of the current paper but an interesting suggestion for further research.

indicator variable that is equal to one when its condition is satisfied, X is the vector of observed pre-treatment individual characteristics such as age, income, indoor space, type of electricity contract, and so on, and ε_{ijt} is an idiosyncratic term. The coefficient of interest is β. The identifying assumption is that trends in outcome variables between wave 3 and 4 would have been parallel had the prices and their trends been identical. The availability of two pre-treatment waves with equal prices allow for testing of parallel pre-treatment trends. We perform these tests in Section 4.3. Note that contrary to the previous two estimators, the linear DiD estimator uses SE1, SE2 and SE3 as control groups and uses all covariates for the estimation. The price for using this additional information is that the linear form is prone to misspecification bias.

Finally, we use a difference-in-differences estimator (Diff. in Disc.), but using only observations at the border of SE3 and SE4. This is a difference-in-discontinuity type of estimator (see, e.g., Butts, 2023; Grembi et al., 2016) since it combines the naive RDD estimator with a difference-in-differences estimator. Its formal definition is provided in Section E in the Appendix. To obtain standard errors, we use the block bootstrap approach. We refer to the naive RDD and the difference-in-discontinuity estimators as our baseline estimators.

4 Results

4.1 Average effects

The estimation results are presented question by question for Q8-Q12, comparing estimates from the different estimators outlined in the previous section. For Q13-Q16, results are presented in Figures F.1 to F.4 in the Appendix (in general, the estimates for these questions are unfortunately too noisy to be interpreted). Evidence supporting the main assumptions in our empirical strategy is provided in Section 4.3.

Starting with Q8, which addresses whether consumers are willing to pay more for electricity to reduce CO2 emissions, Figure 4 shows the results from the naive RDD, the Diff. in Disc., and the DiD. The results from the non-parametric RDD estimation are presented separately in Figure 5.

The graphs show that higher electricity prices reduce the willingness to pay 10% more for electricity in exchange for a significant reduction in CO2 emissions. According to the Naive RDD approach and the DiD, this effect amounts to an approximate 4 percentage point reduction, while the Difference-in-Discontinuity approach predicts a roughly 6 percentage point reduction. The non-parametric

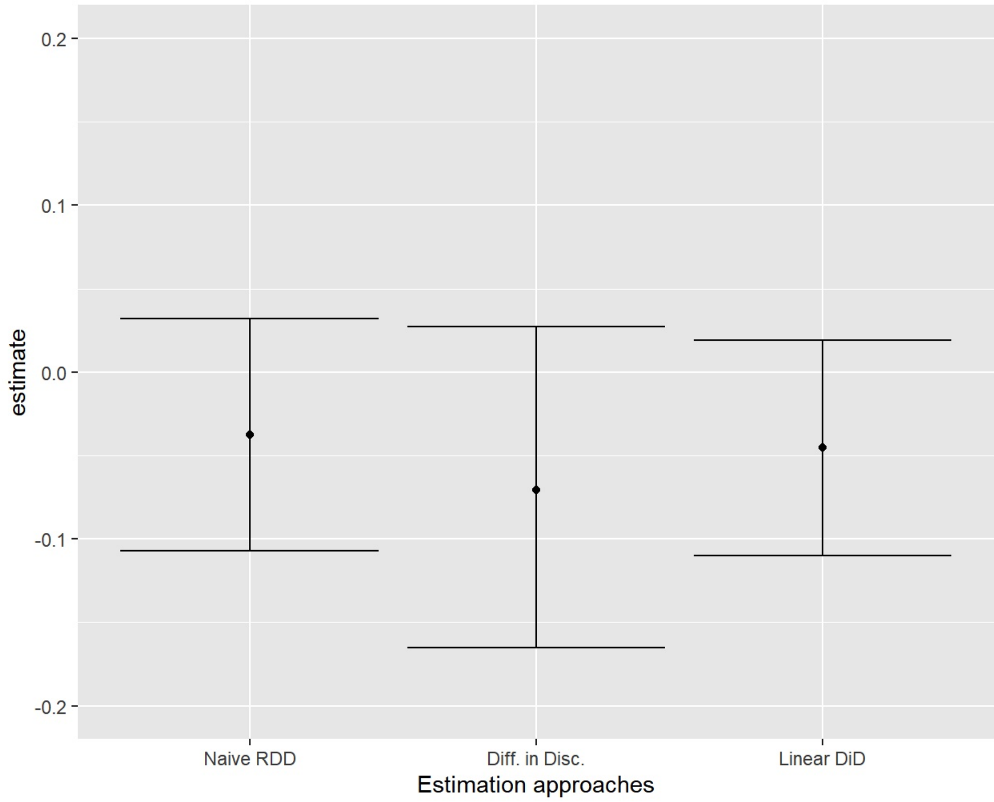

Figure 4: Estimation results, Q8: "Are you willing to pay 10% more your electricity if it means a large reduction of carbon dioxide emissions?"

RDD estimate (Figure 5) is somewhat smaller and noisier than the naive RDD estimates but is similar in direction. To put these numbers into perspective, the above estimates correspond to a economically substantial decrease of 22% to 32% of the average willingness to pay 10% more for cleaner electricity.

Next, Figures 6 and 7 show the results for Q9. The estimates suggest that higher electricity prices increase the share of individuals who would vote "Yes" to new nuclear power plants in a hypothetical referendum. For example, the less noisy Naive RDD estimate is roughly equal to 6.5 p. p., while the noisier Diff. in Disc. estimate is about 4 percentage points. The DiD produces an estimate of similiar magnitude as the Diff. in Disc., but with better precision. With an average acceptance rate of 64.4% across all periods and regions, these estimates translate to an increase of 6 to 10 percentage points. Similar to the results for Q8, the non-parametric RDD (in Figure 7) produces a somewhat noisier estimate, but it is similar in magnitude to the other estimates.

Next, we examine the effect on the relative importance of objectives measured by the fictive budget distribution in question Q10. The causal estimates are dis-

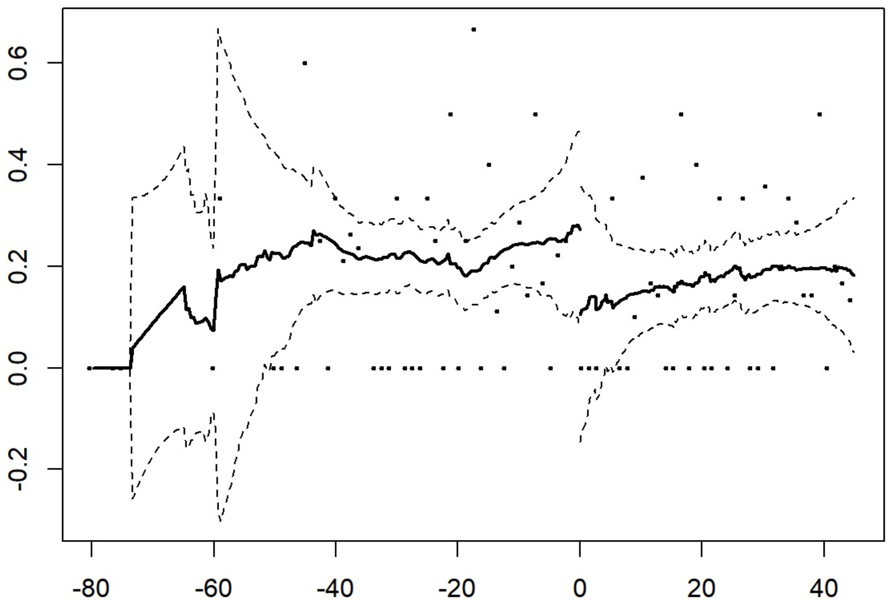

Figure 5: Non-parametric RDD with distance to border as forcing variable, results for Q8: : "Are you willing to pay 10% more your electricity if it means a large reduction of carbon dioxide emissions?"

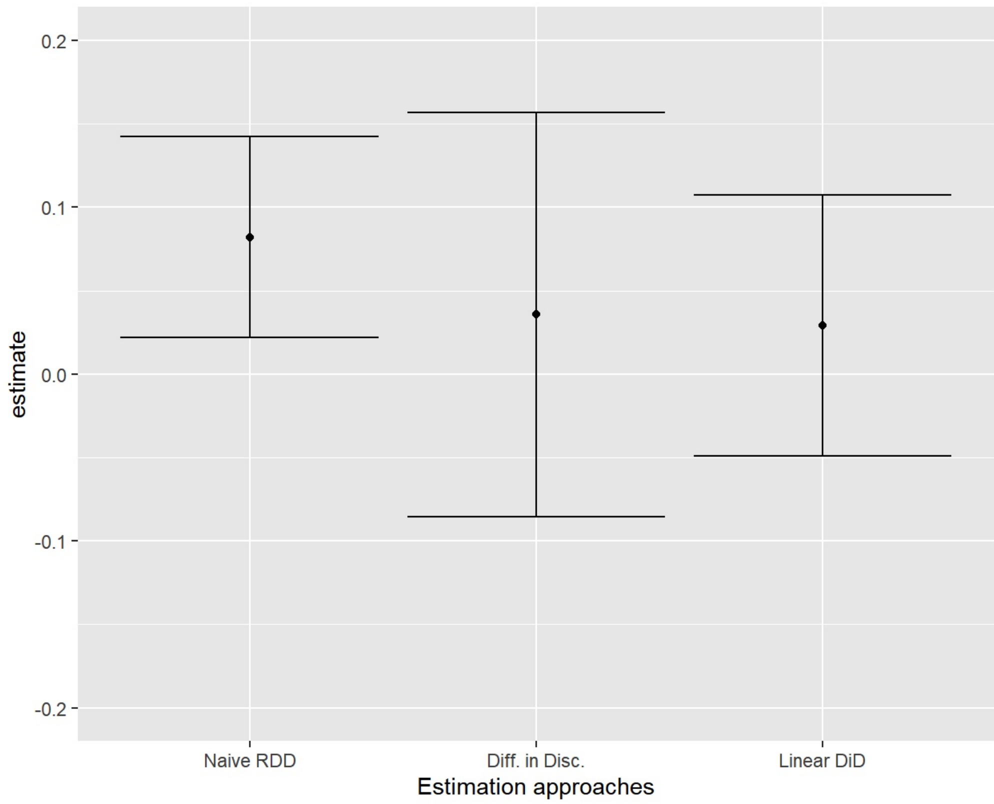

Figure 6: Estimation results, Q9: "If Sweden had a general referendum about whether to build new nuclear reactors today, how would you vote?"

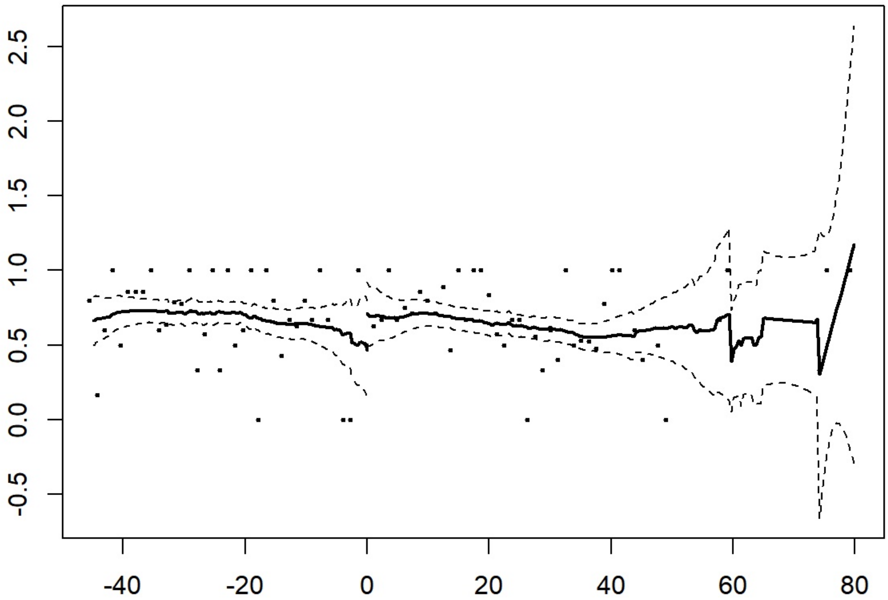

Figure 7: Non-parametric RDD with distance to border as forcing variable, results for Q9: "If Sweden had a general referendum about whether to build new nuclear reactors today, how would you vote?"

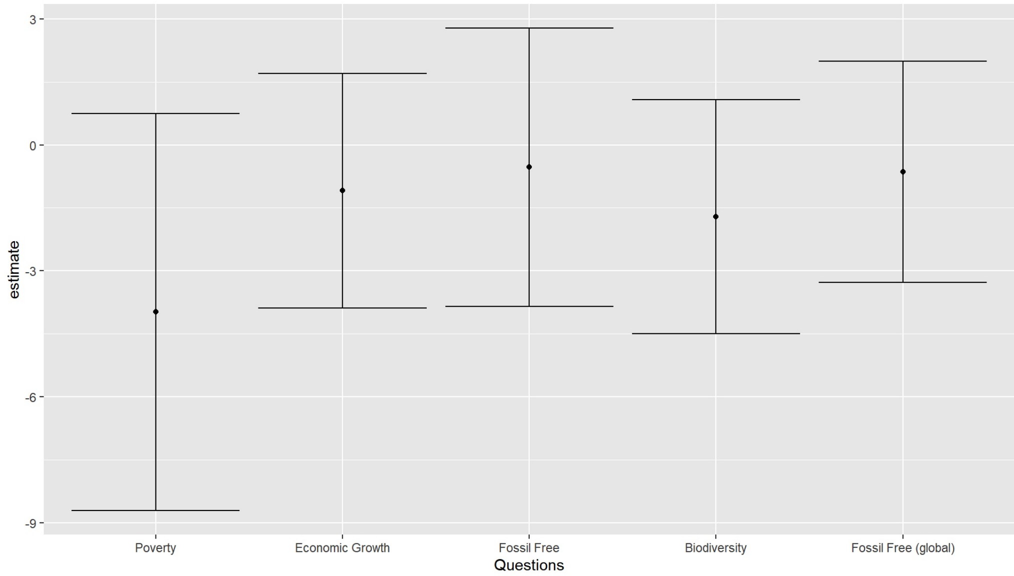

Figure 8: Naive RDD results, Q10: "If you had a fixed budget to spend on the five objectives below, how would you spend it (in %)?"

played in Figures 8 and 9 for the Naive RDD and Diff. in Disc. approaches, respectively. Each estimate reflects the change in the average percentage of the fictive budget resulting from high energy prices. Both approaches predict a negative change in the budget allocated to energy poverty, which involves subsidizing electricity prices to prevent households from experiencing financial hardship due to high electricity prices. The corresponding changes are -4 percentage points and -6 percentage points, which represent roughly 13% and 20% of the average budget for energy poverty.

According to the Diff. in Disc. approach, this reduction appears to be offset by an increase in the share of the budget allocated to industrial competitiveness, which aims to ensure economic growth. The Naive RDD estimate is noisier and does not predict such an offset. The estimates for budget changes in other categories are smaller and very noisy, making them difficult to interpret.

Q11 addresses the extent to which consumers agree that Sweden should use tax money to reduce energy poverty. The estimation results are presented in Figure 10. All three approaches produce very noisy estimates regarding the propensity to agree to use tax money for alleviating energy poverty. The estimates are small and positive, but the confidence bounds, especially in the Diff. in Disc. approach, are large. We therefore abstain from interpreting these results.[12]

In Q12, we ask respondents whether they are worried about climate change,

[12] A nonparametric RDD also leads to noninformative bounds and we omit it here.

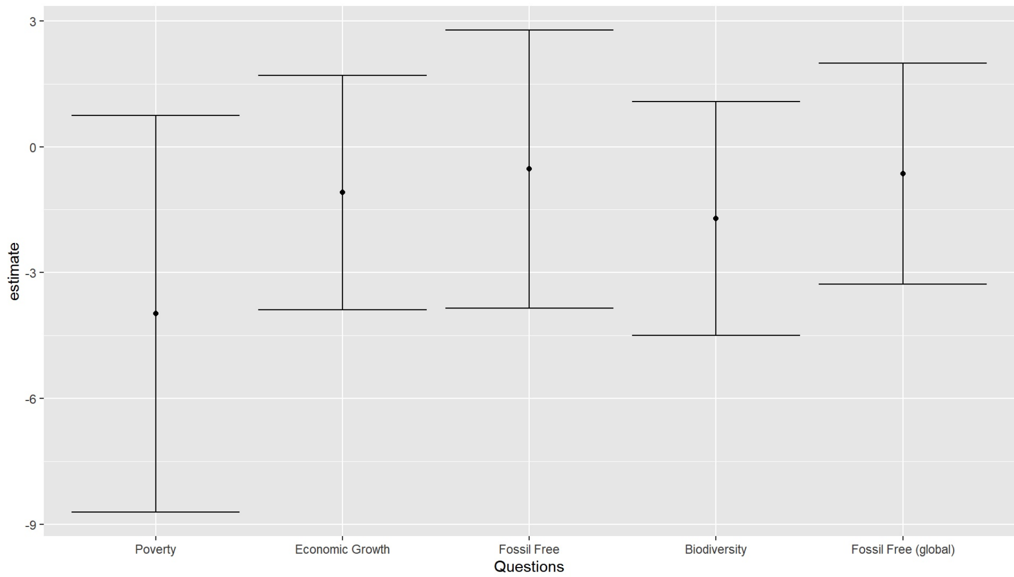

Figure 9: Difference-in-discontinuity results, Q10: "If you had a fixed budget to spend on the five objectives below, how would you spend it (in %)?"

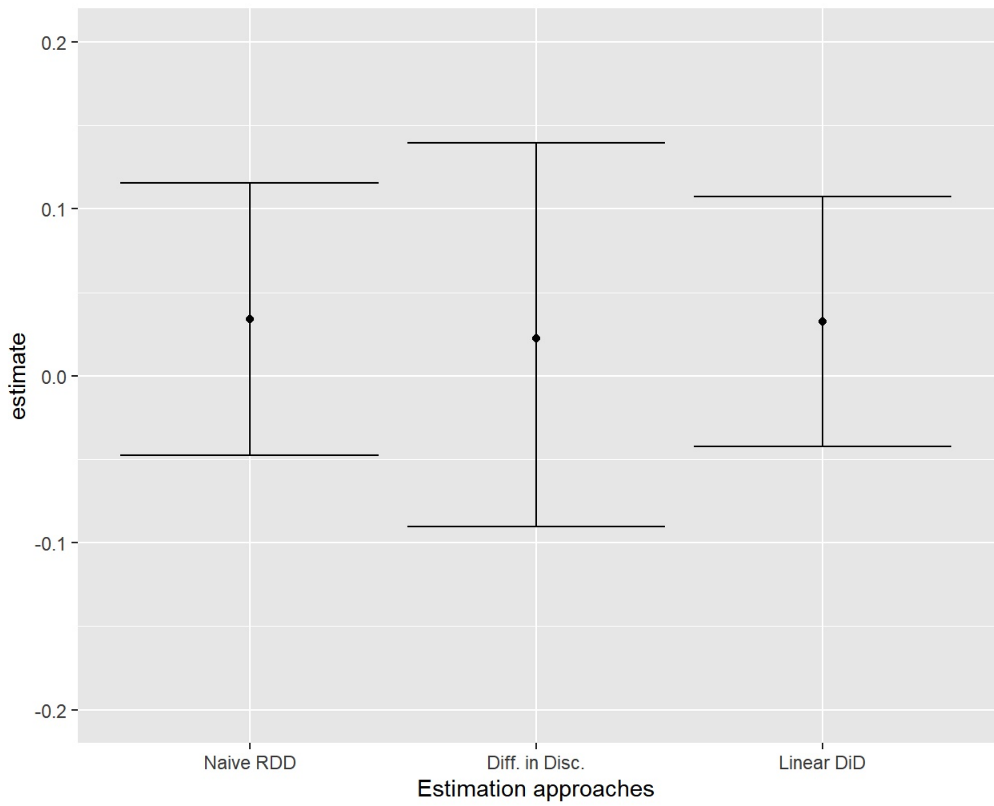

Figure 10: Estimation results, Q11: "To what extent do you agree that Sweden should use tax money to reduce energy poverty?"

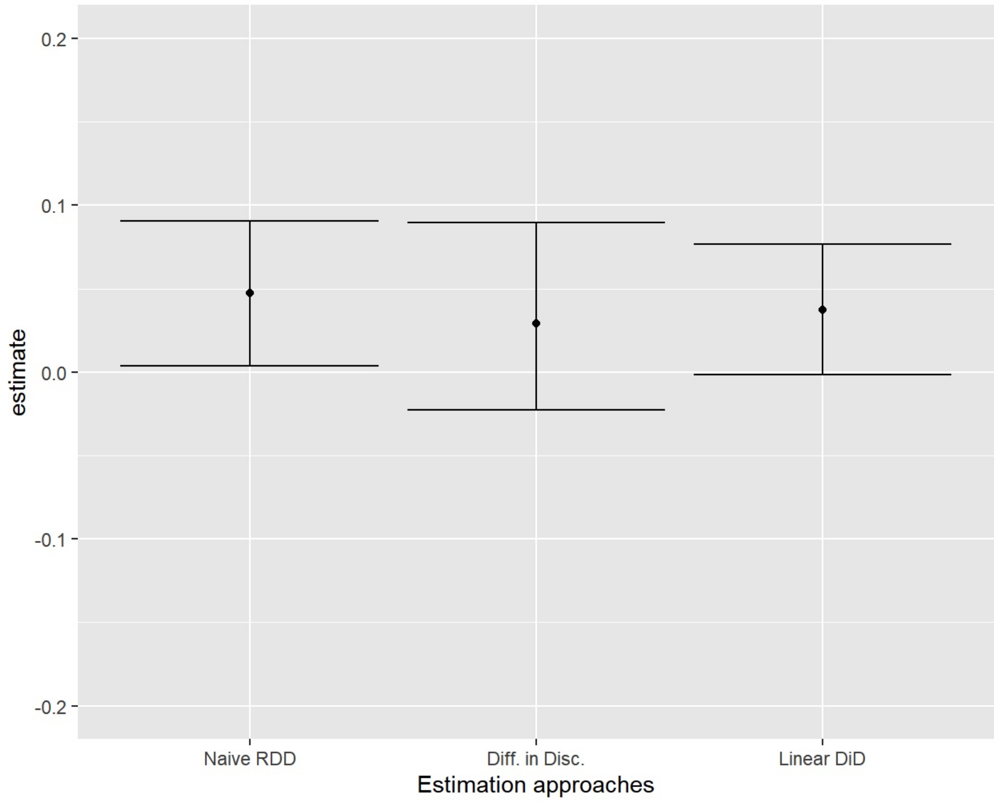

Figure 11: Estimation results, Q12: "How worried are you about the consequences of climate change?". A positive outcome means that the respondent is "Not worried".

with a positive outcome indicating that consumers are not worried. The estimation results are presented in Figures 11 and 12. These results show that high electricity prices significantly increase the propensity to not be worried about climate change, with the Naive RDD predicting a 5 percentage point change and the Diff. in Disc. and DiD approachs predicting a 4.5 percentage point change. Compared to an average of 6.1%, these estimates imply almost a doubling in the average propensity. The estimated treatment effect is very similar across the different estimators.

To summarize, the results indicate that higher electricity prices decrease consumers' concerns about climate change (Q12) and their willingness for environmental policies (Q8), and that there is a shift towards preferences for more nuclear power (Q9) and higher industrial competitiveness (Q10). An interpretation of these results from the point of view of economic theory is provided in section 4.5, after we have studied effect heterogeneity.

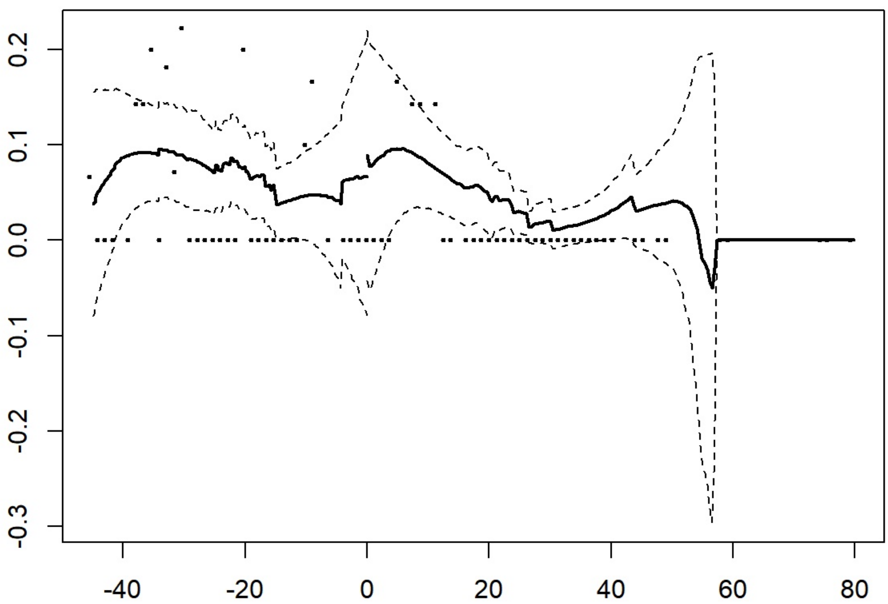

Figure 12: RDD with distance to border as forcing variable, results for Q12: "How worried are you about the consequences of climate change?". A positive outcome means that the respondent is "Not worried".

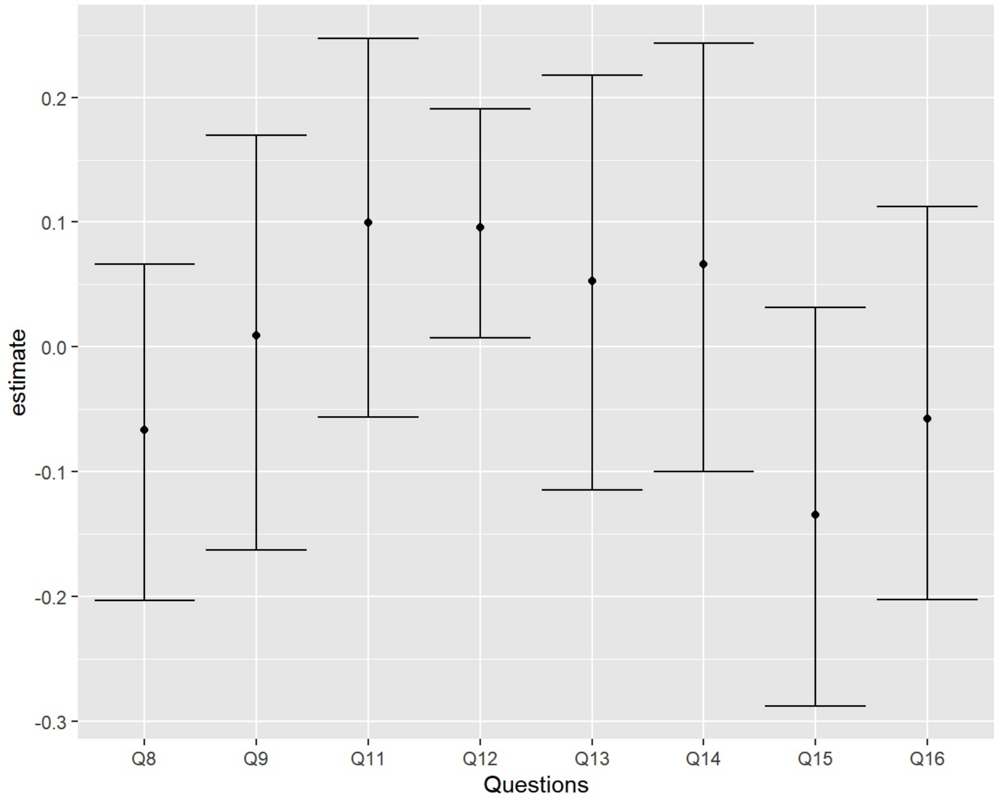

Figure 13: Heterogeneous effects, naive RDD results, Q8, Q9 and Q11-Q16

4.2 Heterogeneous treatment effects

To study the heterogeneity of the treatment effect, we split the main sample according to values of observed pre-treatment characteristics. As an example, we evaluate the treatment effect on the subsample of all individuals with only high school or below. The resulting estimates represent so-called Group Average Treatment Effects (GATEs). In our context, one could study several GATEs for several pre-treatment characteristics: type of electricity plan, income, and education. The type of electricity plan (how often adjustments in the electricity price paid by the customer occur) and income reflect how vulnerable a customer is to a change in the price. In addition, economic theory predicts different patterns of adjustment to inflation expectation along the income distribution. Education has been shown to be correlated with inflation expectation and adaptation of purchasing behavior in the empirical literature on inflation expectation Burke and Ozdagli, 2023.

Figures 13 and 14 show the results according to the type of electricity contract. GATE estimates for the group with frequently adjusted prices (frequency of adjustment: monthly or more frequently) are displayed in Figure 13. Due to the

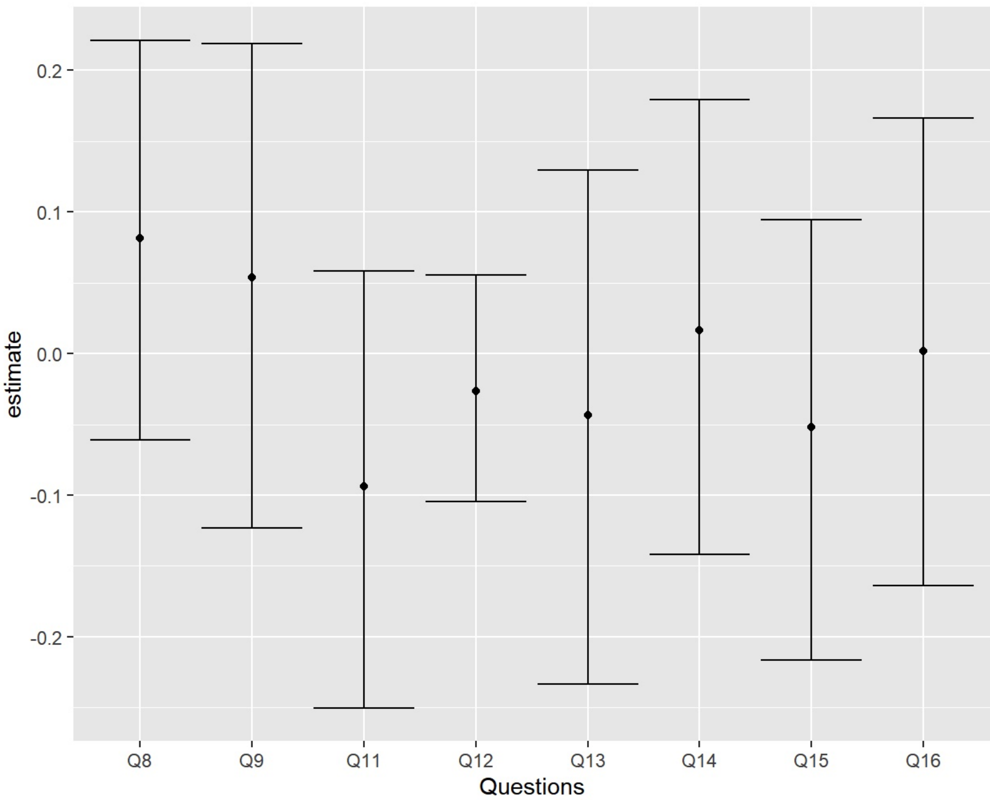

Figure 14: Heterogeneous effects, difference-in-discontinuity results, Q8, Q9 and Q11-Q16

Table 4: Placebo effect of living in region 4 on pre-treatment covariates: a nonparametric RDD approach

Pseudo outcome	Estimate	S.E.	P-val.
Education	0.29	0.80	0.71
Household income	0.9528	2.00	0.63
Indoor space	23.05	31.77	0.46
Number of individuals per household	0.41	0.39	0.31
Share households with ground heating	0.12	0.18	0.48
Heat pump	-0.72	0.18	0.0009
Share households with pellets burner	0.18	0.30	0.54
Share households with wood stove	-0.25	0.18	0.16
Share households with solar panels	0.33	0.36	0.356
Electricity plan	0.17	0.83	0.82

smaller sample, most estimates (those for questions Q8, Q9, Q11, Q13, Q14 and Q16) are associated with large uncertainty and we abstain from interpreting them, even though in tendency they are in line with the main results. The estimate for question Q12 is in line with the unconditional estimate. The estimate for question Q15, on the contrary, reveals a large (over 13% points) decrease in the share of individuals who frequently buy organic food products. A much noisier estimate for question Q16 supports the former, indicating a drop in the share of individuals who would support a ban in pesticides if this were to raise food prices by 30%. Similarly, a noisy estimate for question Q14 is also in line with the previous two estimates, indicating higher sensitivity to food prices as a result to higher energy prices. Estimates for the group of individuals with a contract adjusted every three months or less frequently are not informative due to high uncertainty, reflected in their confidence bounds (Figure 14). The same holds for all other GATEs for different subgroups according to education and income (see Figures F.5 to F.8).

4.3 Evidence supporting the identifying assumptions

To provide support of the identifying assumptions, we first present evidence that pre-treatment covariates do not jump at the border between price areas. Specifically, using only data from wave 4, we estimate the (pseudo) effect of being in area 4 (relative to being at the border in area 3) on pre-treatment characteristics using the nonparametric RDD approach. Again, we use distance to the border as a forcing variable. The estimated effects is shown in Table 4 together with two different measures of uncertainty. The large p-values indicate that we are not able to reject a null hypothesis of no effect.

Second, for the two estimators where the different survey waves are used (the

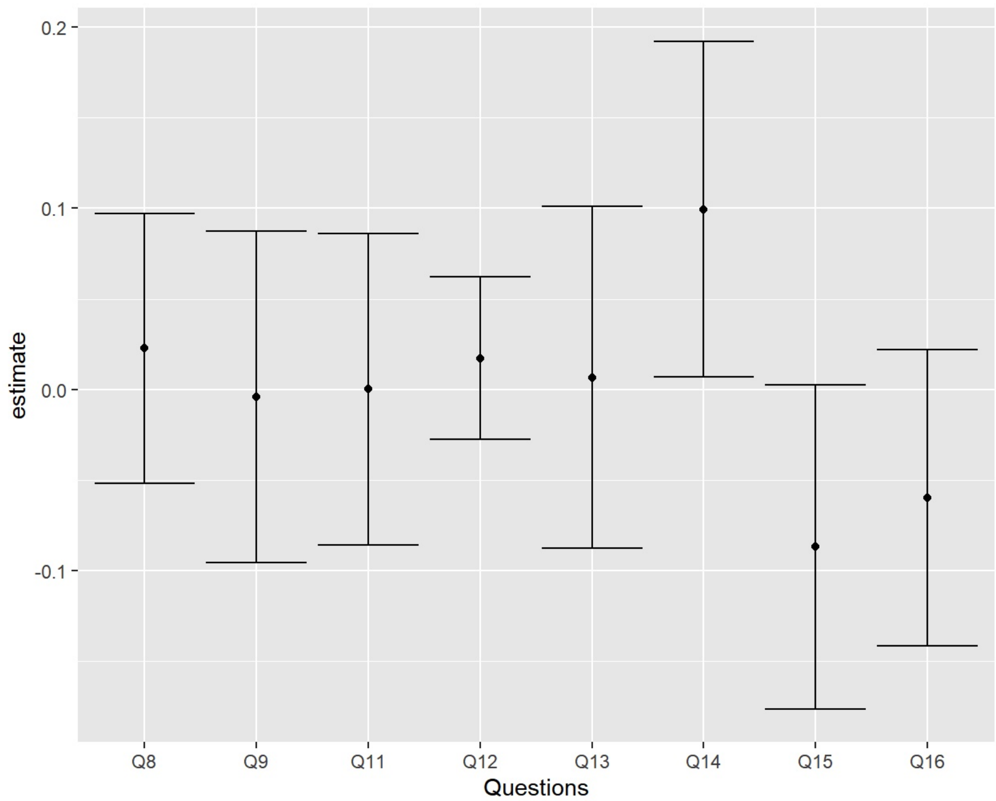

Figure 15: Placebo results, unconditional difference-in-difference, Q8, Q9 and Q11-Q16

DiD and Diff. in Disc. estimators), we estimate "placebo" treatment effects for a fictive treatment between wave 2 and 3, using the same approaches as in Section 3. The intuition of this approach is that, since collecting the survey responses of waves 2 and 3, electricity prices were nearly identical in all regions, we should not be able to detect a treatment effect during these periods if our identifying assumptions are correct. This approach uses data from two periods and hence, due to the price difference in wave 1, a placebo DiD and Diff. in Disc. estimation is only meaningful for period 3.

First, we present placebo estimates for the DiD model. The estimates for the unconditional model are presented in Figure 15 and the estimates for the model with covariates in Figure 16. The placebo estimates for questions Q8 - Q13 are very close in magnitude to zero, while the estimates for questions Q14 - Q16 not. This indicates that the parallel trends for the former is plausible, while for the latter we find no such support. Accordingly, the estimates produced for the latter questions should be interpreted with caution.

Next, Figure 17 present the placebo tests for the Diff. in Disc. estimator. Almost all estimates are of small magnitude and the corresponding confidence

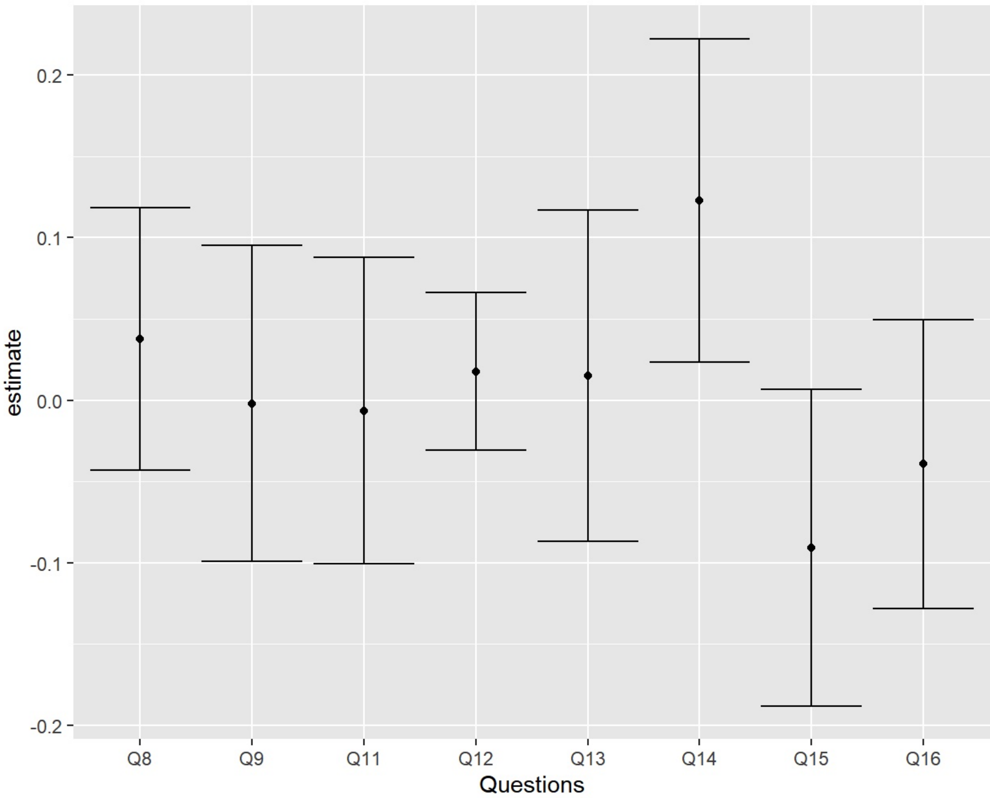

Figure 16: Placebo results, conditional difference-in-difference, Q8, Q9 and Q11-Q16

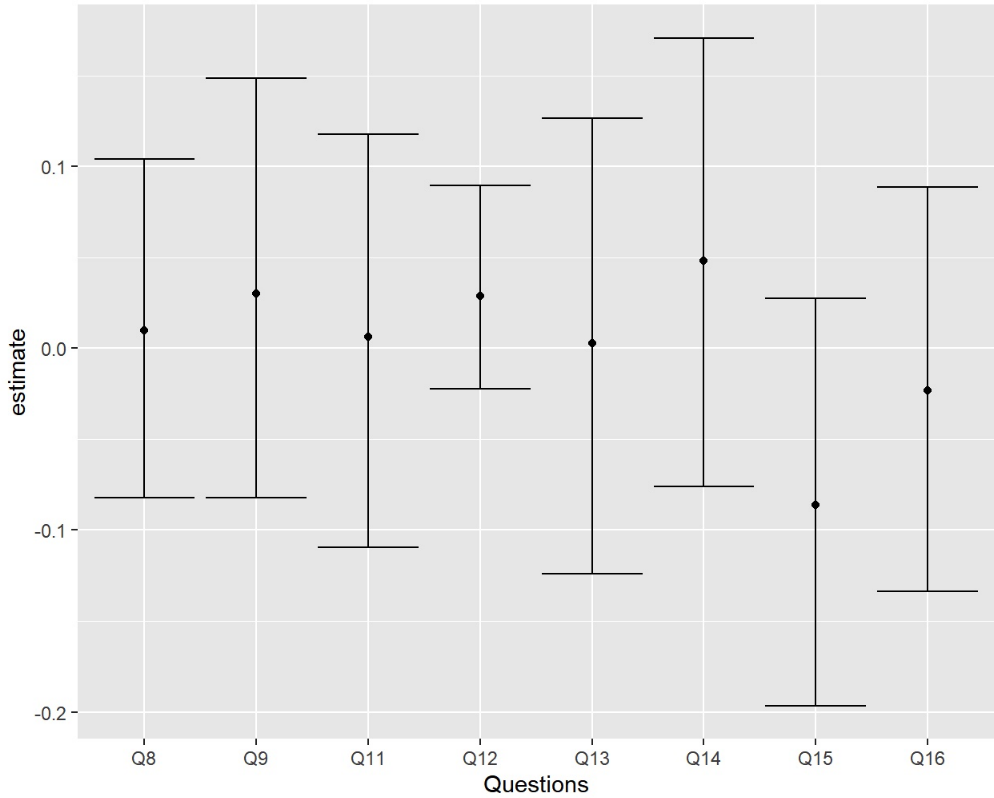

Figure 17: Placebo results, difference-in-discontinuity, Q8, Q9 and Q11-Q16

intervals encompass 0 and are close to symmetric around 0. The only exception is the estimate corresponding to Q15.

Finally, we discuss the plausibility of the parallel trends assumption in the context of dynamic choice models. A recent paper by Marx et al., 2024 studies conditions, under which dynamic utility maximization and parallel trends are compatible. Our evidence on parallel pre-treatment trends, equality of characteristics at the border, as well as the equality for long periods before the last wave, imply that both information sets and pretreatment potential outcomes may be considered equal at the price border. Translated into the dynamic utility maximization problem in Marx et al., 2024, this empirical evidence directly implies parallel trends (see for example their result in example 2). Thus, our empirical results support the parallel trends assumption both by means of extrapolation, as well as compatibility with theoretical results.

4.4 Statistical analysis of uncertainty

In this subsection, we conduct an analysis of uncertainty. The objective is to assess the credibility of the estimates for questions 8, 9, 12, which depend on modest sample sizes and, in some cases, are associated with confidence intervals that contain the 0. To this end, we use a simple Monte Carlo simulation that is inspired by the Monte Carlo design in Huber et al. (2013). The design of the distributions mirror the actual empirical distributions of all variables. We proceed as follows. For each question, a range of possible effect sizes including zero, are considered. For a grid of effects from this range, we simulate a model with a known effect. Specifically, for each value of the effect in this grid, we bootstrap $N = 100$ samples from the joint distribution of all covariates (including the treatment variable) and generate an outcome variable that follows a known (linear) specification. This model mirrors the linear DiD model that is estimated in the results section above. Each covariate (except the treatment) impacts the outcome through a coefficient that we estimated in the DiD model. The error term is drawn from a distribution that matches the distribution of the residuals. Importantly, we correct for serial correlation using the procedure described by Bertrand et al. (2004). Generating such a model for different effect sizes allows us to assess the confidence bounds in an actual, real-world, situation, assuming that the joint distribution of the covariates follows the one in the real sample.

The results are presented in Figures 18 to 20 for questions 8, 9, and 12, respectively. Consider Figure 18 first. The x-axis depicts four different true effect sizes that were simulated. The y-axis depicts the estimates from the Monte Carlo simulation and the 0.95-level confidence bounds, i.e. the 0.025 and 0.975 quantiles from the simulated distribution. The first simulated effect is -0.05, which is very close to what we find in the different specifications. The confidence bounds closely match the confidence bounds from the different specification, with the bulk of the possible values on the negative side but some of the estimates on the positive side. As the effect decreases, the confidence bounds become more and more symmetric around zero (we keep the standard error of the error term). Thus, these simulated results provide a picture that is overall very close to what is presented as the estimation results. This provides confidence that the findings do not represent only noise. The analysis of questions 9 and 12 give equivalent conclusions.

4.5 Interpretation of results

In the following section, the empirical results above are related to economic theory and existing empirical findings. First, Q8 allows us to study the relationship between electricity prices and the acceptance of a carbon electricity tax. Our results indicate that higher electricity prices reduce acceptance. This is in line with economic theory that ceteris paribus, an increase in the price of a good decreases its demand. The result is also in line with studies that find a clear and

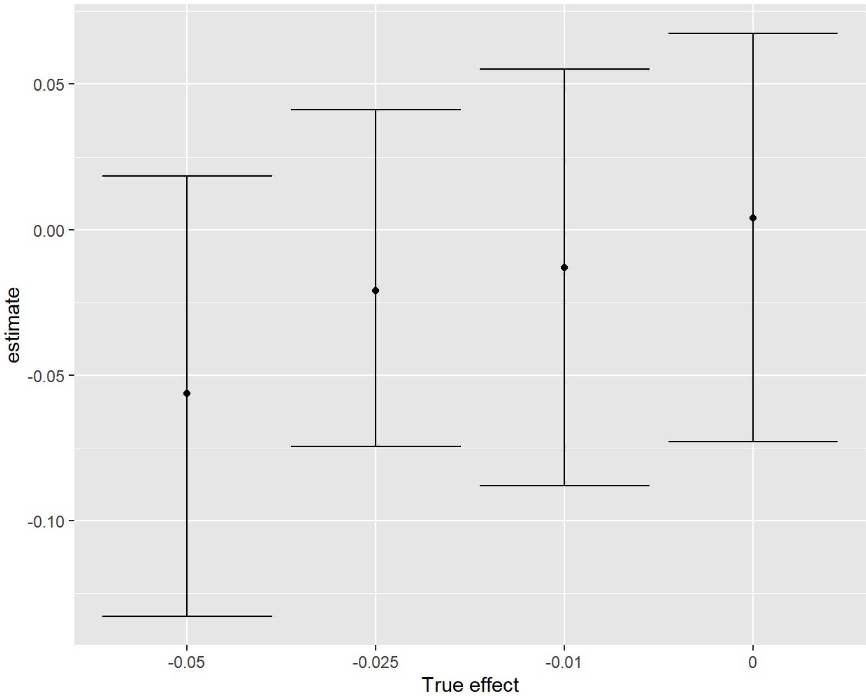

Figure 18: Analysis of uncertainty for Q8.

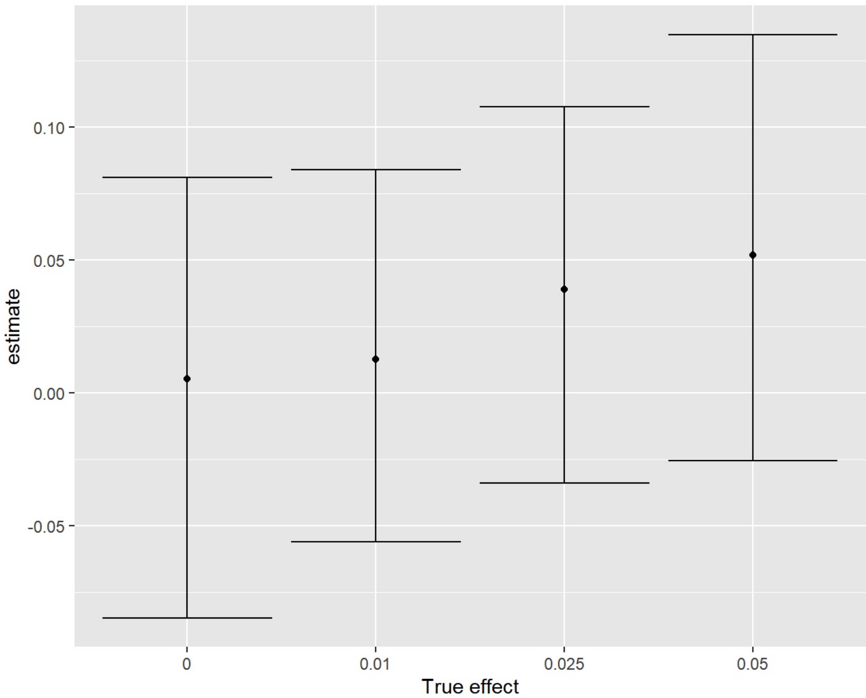

Figure 19: Analysis of uncertainty for Q9.

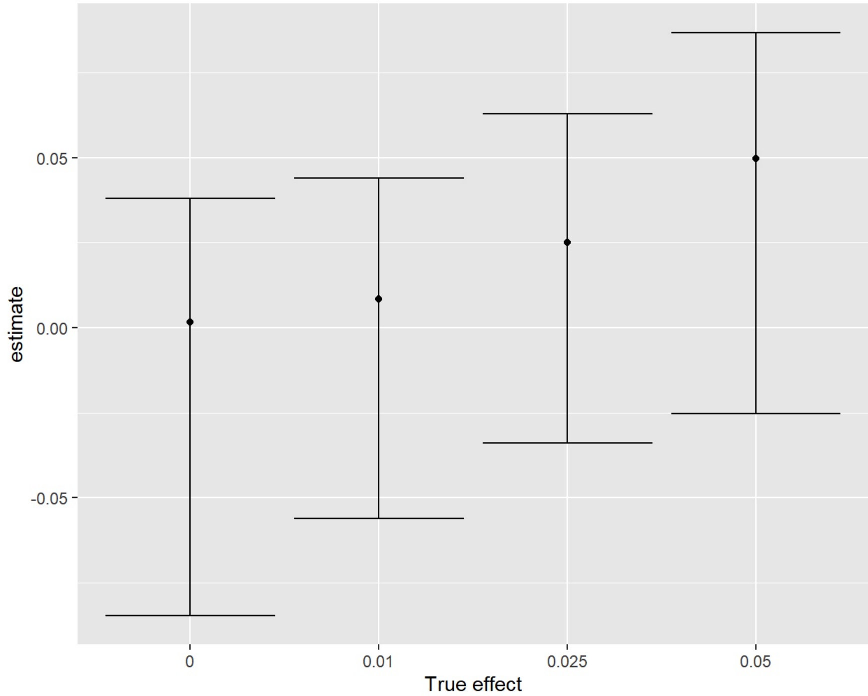

Figure 20: Analysis of uncertainty for Q12.

negative relationship between acceptance and concerns for that a carbon tax will increase the cost pressure (Jagers and Hammar, 2009).

The result that higher electricity prices increase support for new nuclear power plants is intriguing and also confirms recent findings. One possible explanation is that, during the survey waves, the share of nuclear power in the Swedish energy mix was below 30%, while the share of electricity from renewable sources exceeded 65%.[13] Moreover, an increase in the electricity price may impact energy inflation expectations, causing individuals to expect higher prices in the future. Thus, an increase in electricity prices may be perceived as an increase in the relative future price of electricity from renewable sources compared to nuclear power. In such a case, individuals may demand more of the relatively cheaper good.

The next finding is essential, namely that higher electricity prices reduce the concerns for climate change. This adds to an ongoing academic debate of whether, and how, the economic situation of agents is related to their climate concerns. While some studies find no, or only a weak, relationship between these two factors (e.g., Kachi et al., 2015), others find a strong, negative relationship Duijndam and Beukering, 2021; Shum, 2012. Duijndam and Beukering (2021) suggest that the potential explanation for this negative impact is a "finite pool of worry" -

[13] Source: www.statista.com.

i.e., limited resources that can be devoted to "concern". An alternative and more traditional explanation is offered by Shum (2012), who interprets this relationship as a trade-off between short-run and long-run benefits. This explanation is intimately related to the economic literature on the subjective rate of intertemporal substitution, see Crump et al. (2022) for a recent investigation.

Together, our first and third finding are related to the recent debate on why individuals oppose carbon taxes. Specifically, recent contributions by Bergquist et al. (2020), Douenne and Fabre (2022), Ewald et al. (2022), and Mildenberger et al. (2022) highlight the importance of political ideology and distrust in institutions for predicting acceptance of carbon taxes. Ewald et al. (2022) find that in the Swedish context, citizens are concerned about climate change but they mistrust the institutions and ultimately how carbon taxes will be used. Douenne and Fabre (2022) explain opposition to carbon taxes with poor economic assessment that is partially driven by a bias that arises from partisan political preferences. Schwarz et al. (2024) provide further empirical support for these studies, showing that tailored information may increase acceptance to a small extent. On the contrary, our findings display a clear link between economic interests, climate concern and opposition to carbon taxes. This link is easy to explain within a standard rational choice model with intertermporal consumption and does not involve cognitive biases and mistrust in institutions.

The interpretation of intertemporal substitution is further supported by our findings that the increasing energy prices changed the relative importance of poverty and industrial competitiveness as measured by question Q10 (while, however, they had no effect on the absolute importance of social welfare as measured by question Q11). Specifically, it can be argued that if equality is interpreted as a good that enters the utility function of individuals, increasing energy prices has a negative impact on its relative price. This result is in line with the findings in Ewald et al. (2022), who show that equity and fairness is an important determinant for preferences for carbon taxes.

Next, our heterogeneity results suggest that the effects are particularly pronounced for those who have higher exposure to the risk resulting from electricity price inflation. This finding is consistent with empirical evidence on expectation formation in the context of macroeconomic risk; see, e.g., Roth and Wohlfart (2020), and also with macroeconomic models with imperfect information.

Interestingly, we find no effect of participants' opinions about whether politicians are doing a good job to tackle climate change. This suggests that a shift in consumption preferences and in the intertemporal substitution rate may not be accompanied by a shift in political preferences. This result goes against findings in the previous literature that respondents tend to blame policy makers for bad economic outcomes (e.g., Douenne and Fabre (2022), Ewald et al. (2022), and Stantcheva (2024)

We find no effects on stated preferences in the context of food purchasing behavior. These results seemingly contradicts the intuition that preferences should change when either the budget constraint and/or the relative prices of food change. However, if increasing energy prices impact inflation expectations, both economic theory and empirical evidence predict that non-durables purchasing behavior may not be adjusted (Burke and Ozdagli, 2023). An alternative explanation from bounded rationality theories is that individuals subject their purchasing behavior to mental accounting; see, e.g., Akerlof (2007). Our setup does not allow for distinguishing between these two effects.

Finally, the fact that we for some questions (e.g., Q9 and to some extent Q12) find a larger effect (in absolute values) when using the Naive RDD approach, than the Diff. in Disc. approach, suggests that it is a potentially long time-series of price differentials that determines preferences for energy and climate policy. This finding is in line with the literature on sticky information, where previous studies have shown that people update their information infrequently (Maćkowiak and Wiederholt, 2009; Mankiw and Reis, 2002). The literature has shown that this is the case for general inflation expectations (D'Acunto et al., 2023), and our results suggest that it is also the case for electricity prices.

5 Conclusions

In this paper, we evaluate the effect of high electricity prices on a variety of individual preferences and attitudes relating to climate and energy policy.

For the purposes of our study, we surveyed consumer opinions in Sweden. Our identification strategy draws on two features of our data and setup. First, we surveyed consumers from four different electricity regions, in which electricity prices differ substantially. Second, our survey consists of four consecutive survey waves (repeated cross sections). During the second and third of them (and in between them), electricity prices were identical, while after the third wave, prices in the different regions differed substantially.

We use four different estimators that exploit these two features of our setup. Especially the Diff. in Disc. estimator is interesting, given that it allow us to account for differences in outcomes in the beginning of our sample period and compare these to differences in outcome in the end of our sample. This feature distinguish our paper from the recent papers exploiting spatial discontinuities in electricity prices to measure determinants of preferences.

Our results reveal that high electricity prices (1) decreased acceptance of carbon tax, (2) increased acceptance of nuclear power, (3) decreased concerns about climate change, (4) had no effect on other political attitudes and (5) had no effect on food consumption preferences. Furthermore, our results suggest that it is the accumulated body of information over time that determines preferences, and that more recent but smaller price differentials matter less to the formation of preferences.

These findings have a number of important policy implications: Most importantly, our findings highlight the catch 22 of climate policy, in the sense that climate policy (e.g., carbon taxes, electrification of industries) most likely will increase electricity prices, but that high electricity prices reduce the support for climate policy. Thus, for a sustainable climate policy, policy makers need to ensure that prices do not hike too much even in the face of large increases in demand. This talks in favor of a large expansion of renewable electricity generation to offset the consequences of demand expansion. On the other hand, this is easier said than done, given the lumpy nature of supply expansions, that takes time to build. Short-term policies are therefore likely needed in the mean time.

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Appendix A Institutional background

The deregulation of the hitherto highly regulated Swedish electricity market in 1996, following the example of other European countries, introduced competition between electricity-supplying companies, with distribution a state monopoly. This period also marked the market integration with the other Nordic countries (Finland, Norway, Denmark) and the Baltic states via a common spot market, the "Nord Pool Spot". Following this deregulation, the market price today is determined by demand and supply on the Nord Pool power exchange, located in Oslo, Norway. The day-ahead market, Elspot, is the main venue for trading electricity in region, with 90% of total electric supply in the Nordic countries traded here. Contracts are concluded between approximately 300 sellers and buyers for delivery of power the following day, and the price is determined based upon the supply and demand of electricity on that day (see https://www.nordpoolgroup.com/en/the-power-market/Day-ahead-market/).

The bulk of electricity produced in Sweden is from hydro and nuclear sources, constituting approximately 41 and 29 percent of total production, respectively (figures for 2021, from the Swedish Energy Agency). The remaining production is from windpower (19%) and thermal (co-generation) plants (9%), together with so-called sources of peak capacity. This peak capacity consists of gas turbines and oil-fired condensing power plants. Sweden has a very high — among the ten highest — electricity intensity per capita, at roughly 15,000 kWh per year. This is explained both by the cold and long winters and an energy intensive industry.

Because of the geographic transmission constraints and bottlenecks, Sweden is, since the end of 2011, divided into four electricity price areas: Luleå (SE1), Sundsvall (SE2), Stockholm (SE3), and Malmö (SE4). The four price areas are illustrated in Figure A.1. The background to the division into price areas was that the Danish Energy Association filed a complaint against the Swedish transmission system operator (TSO) Svenska Kraftnät (SVK) to the European commission, arguing that SVK broke the EU competition laws when restricting transmission to Denmark (in order to prioritize Swedish customers before Danish customers). In response to this, the Swedish government asked SVK to investigate a division of Sweden into price areas (Energimarknadsinspektionen, 2012). Initially, the plan was for three price areas (Energimarknadsinspektionen, 2007), with the motivation that few and large price areas would ensure liquidity on each market. Eventually, this turned into four price areas, which was then realized in 2011. The bidding areas are intended to enable better control of electricity transmission between different regions and to encourage the construction of new power plants and transmission capacity in and to regions with an electricity shortage and bottlenecks.

In more detail, the Swedish main grid is an alternating current grid with transmission in the north-south direction. The grid is built to transfer energy produced in the north to consumers in the southern parts of the country. The need for transfer varies with demand and the hydrological situation. A bottleneck is a section in the transmission network that is often at risk of being congested. Congestion risks occurring when the market demand to transmit electricity through a section is greater than what is physically possible. The demarcation of the four Swedish electricity areas follows three of the most common sections found in the electricity grid. There are four sections where bottlenecks occur frequently. Three of these cuts through the country in an east-west direction, and risk being congested

Figure A.1: Electricity price areas in Sweden when the electricity transmission goes in a north-south direction. The maximum transmission capacity across each section is not constant, but can vary from hour to hour and day to day, depending on the configuration of the grid (for example, if the grid is intact or if lines are disconnected for maintenance), production and consumption, and imports and exports. For more details, see, e.g., Energimarknadsinspektionen (2012).

Within each area, the electricity price is determined by the demand and supply of electricity and the available transmission capacity. Up intil 2021, prices were relatively similar in each of the bidding areas, but since then, prices have been varying quite substantially across the four areas. There are several explanations to this: First, there are capacity constraints in transmission, especially between SE2 and SE3, and between SE3 and SE4. Second, the electricity generation mix is quite different across the bidding areas, where, for example, nuclear power dominates local generation capacity in the middle part of Sweden (SE3), while in the northern part of Sweden (SE1 and SE2), hydropower is dominating. Importantly, Sweden has shut down a number of nuclear reactors the last few years, and these were located in the south. Third, most electricity production (especially hydro power) is located in the north of Sweden while most demand is in the southern part. Fourth, there have also been price differentials during periods typically associated with low demand, which have been attributed to production or transmission malfunction and hence are not associated with high electricity usage. All in all, this results in prices typically higher in the two southern price areas, compared to the north.

Appendix B Survey

The survey was performed by the private company Norstat, a private company specialized in collecting consumer data from online access panels (https://norstat.co/sv). Norstat disposes of a pool of pre-recruited respondents (3 million people in 15 countries according to their website). For each recruited participant in that pool, the information on address, type of house (detached, apartment), age, gender, income, and education level is known. When a particular survey is designed, it is sent online to the target subgroup of pre-recruited participants that satisfies the pre-determined criteria of the study. In our case, for example, we requested respondents to live in owner-occupied, detached dwellings and in particular municipalities (those close to electricity price boarders). Once strata are determined (based on the characteristics of the target group), sampling of individuals is random within stratas. The municipalities we sampled from are illustrated in Figure B.1

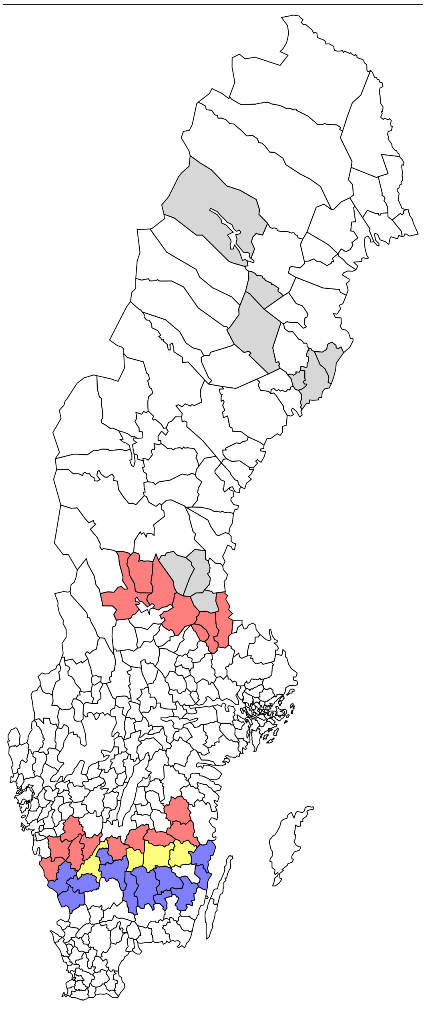

Figure B.1: Sampled municipalities, where a blue color indicates that the municipality is located in SE4, a red color is SE3 and a gray color is SE1 and SE2. For some municipalities, the price area border between SE3 and SE4 crosses through the municipality, and these are indicated by the yellow color.

If a recruited participant does not respond to the participation request, a reminder is sent three days after the first invitation is sent. If the person does not answer after 3+3 days, they are replaced with another person of the same gender and age group. Answers are collected until the targeted number of answers is collected. In our case, the target number of individuals was 3000 split into 4 waves (750 observations per wave). Households and individuals do not appear in more than one wave.

Part of the panel of Norstat is randomly recruited via population sampling. Since many firms are particularly interested in the younger population, an extra recruitment is conducted that targets this sub-group of the population. That recruitment is not random and takes place on social media. The panel is regularly reviewed and compared to the population as a whole in terms of gender, age groups and NUTS2 areas. Moreover, every year additional checks are made on other variables as well (e.g. education, family relationships, employment, etc.), the distribution of which is then compared with Statistics Sweden's published data on the general population.

Individuals were not aware of the purpose of our study. A standard invitation by Nostat was sent out. This invitation is neutral and only informs the potential respondents how long the survey is estimated to take and what reward they will receive if they answer all mandatory questions. The compensation consists of receiving Norstat coins (1 Norstat coin = 1 SEK) deposited into the respondent's account. These coins can then be exchanged for gift cards, lottery tickets, tree planting, charity, etc. For this survey, each participant received 7 coins.

Appendix C Survey questions

Appendix D Data

Appendix E Empirical Framework

Our Difference-in-Discontinuity estimator is defined as

$$\hat{\Delta}_{baseline} = \Big(\frac{\sum_{i=1}^{n} Y_{i,4} 1\{Region_{i,4} = 4 \& Neighbor_{i,4} = 3\}}{\sum_{i=1}^{n} 1\{Region_{i,4} = 4 \& Neighbor_{i,4} = 3\}} - \frac{\sum_{i=1}^{n} Y_{i,3} 1\{Region_{i,3} = 4 \& Neighbor}{\sum_{i=1}^{n} 1\{Region_{i,3} = 4 \& Neighbor_{i,3}}$$
$$-\Big(\frac{\sum_{i=1}^{n} Y_{i,4} 1\{Region_{i,4} = 3 \& Neighbor_{i,4} = 4\}}{\sum_{i=1}^{n} 1\{Region_{i,4} = 3 \& Neighbor_{i,4} = 4\}} - \frac{\sum_{i=1}^{n} Y_{i,3} 1\{Region_{i,3} = 3 \& Neighbor_{i,3} = 4\}}{\sum_{i=1}^{n} 1\{Region_{i,3} = 3 \& Neighbor_{i,3} = 4\}}\Big)$$

Appendix F Additional results

Number	Question	Response
Q1	What is your indoor space area?	m^2
Q2	What heating system(s) do you currently have installed	Most common heating systems
Q3	Have you installed solar panels and/or electricity storage batteries since 1 January 2022?	Yes/No/No, but we plan to
Q4	When did you install (at least some part of) your current heating system?	2023/2022/2021/Pre 2021
Q5	Have you invested in any energy efficiency measures in your dwelling since 1 January 2022?	Yes/No
Q6	Do you plan to invest in any new heating system and/or energy efficiency measures in your dwelling during the coming 6 months?	Yes/No + list if yes
Q7	What type of electricity plan do you have?	Most common plans
Q17	Have you purchased a car, or started a new leasing contract for a car, after the 1 January 2022?	Yes, new/Yes, second-hand/No
Q18	How many persons in total (incl yourself) lives in the same dwelling as you?	Number of persons
Q19	How many of them are below age seven?	Number of kids

Table C.1: Survey questions 1 to 7 and 17 to 19

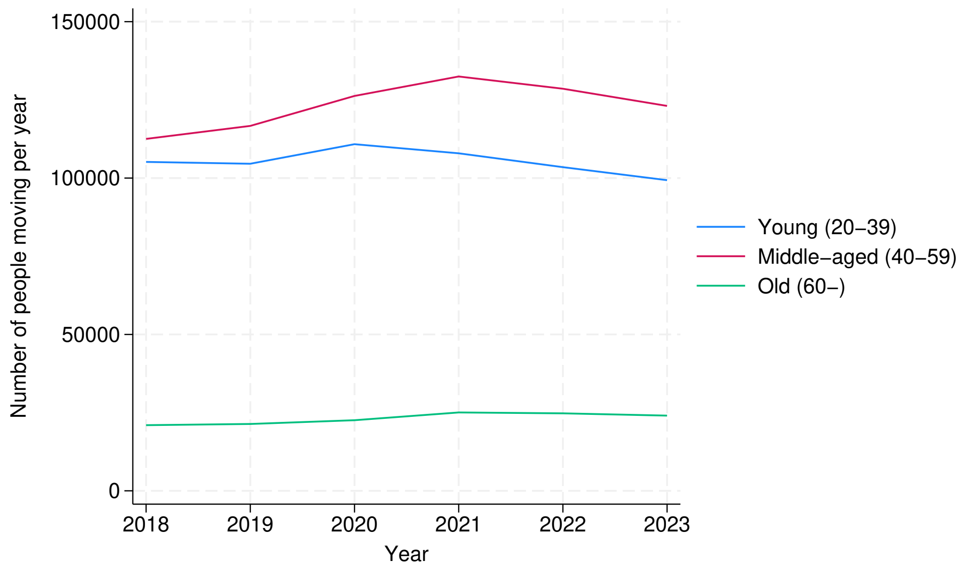

Figure D.1: Number of people moving per year. Source: https://www.scb.se/

Number	Question
Q1	Hur stor är boytan i den bostad där du bor?
Q2	Vilket uppvärmningssystem har du i din bostad?
Q3	Har du installerat solpaneler och/eller batteri(er) för lagring av el i din bostad sedan den 1 januari 2022?
Q4	När installerades senast någon del av ditt uppvärmningssystem?
Q5	Har du gjort någon investering i din bostad sedan 1 januari 2022 för att minska din energiförbrukning?
Q6	Planerar du att investera i ett nytt uppvärmningssystem och/eller något som minskar din bostads energiförbrukning under de kommande 6 månaderna?
Q7	Vilket elavtal har du?
Q8	Är du villig att betala 10% mer för din el om det innebär en stor reduktion av koldioxidutsläppen?
Q9	Om Sverige folkomröstade om att bygga nya kärnkraftreaktorer idag, hur hade du då röstat?
Q10	Om du hade en fast budget att spendera för att (helt eller delvis) uppnå de fem målen nedan, hur hade du då fördelat den budgeten?
Q11	I vilken utsträckning håller du med om att Sverige ska använda skatteintäkter för att minska energifattigdom (dvs. för att stödja elanvändare som inte har råd att betala för en rimlig förbrukning av el)?
Q12	Hur orolig är du för konsekvenserna av klimatförändringarna?
Q13	Tycker du att svenska politiker gör tillräckligt för att adressera problem relaterade till klimatförändringarna?
Q14	När du handlar mat, i vilken utsträckning bry du dig då om priset?
Q15	Köper du ofta ekologisk mat?
Q16	Skulle du stödja ett förbud mot bekämpningsmedel i jordbrukssektorn om det innebar att priset på frukt och grönsaker ökade med 30%?
Q17	Har du köpt ny bil, eller ingått avtal om att leasa bil, efter den 1 januari 2022?
Q18	Hur många personer totalt bor i samma bostad som du (inklusive dig själv)?
Q19	Hur många personer som bor i samma bostad som du är yngre än 7 år?

Table C.2: Survey questions in Swedish

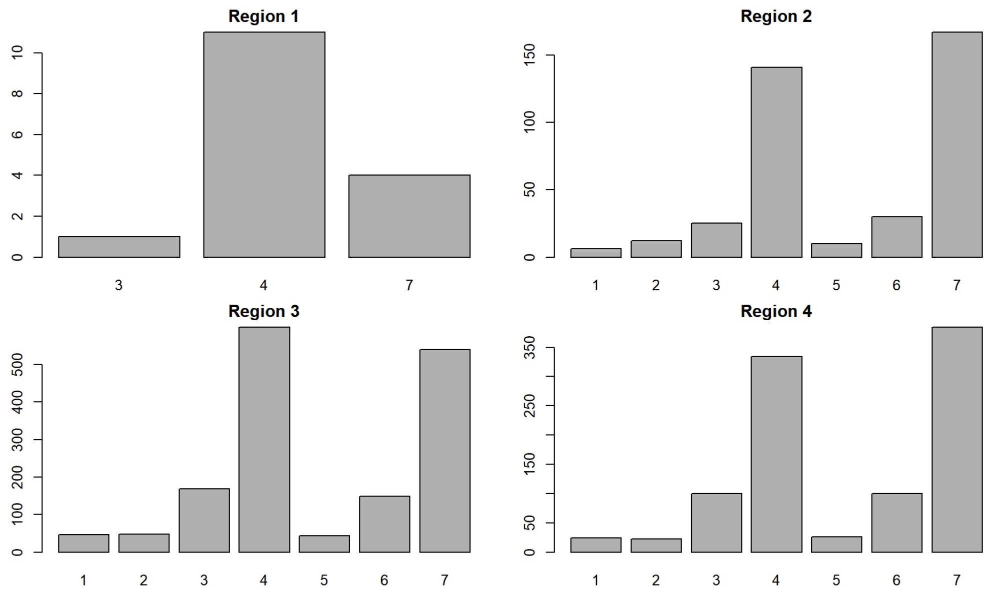

Figure D.2: Bar plots of education

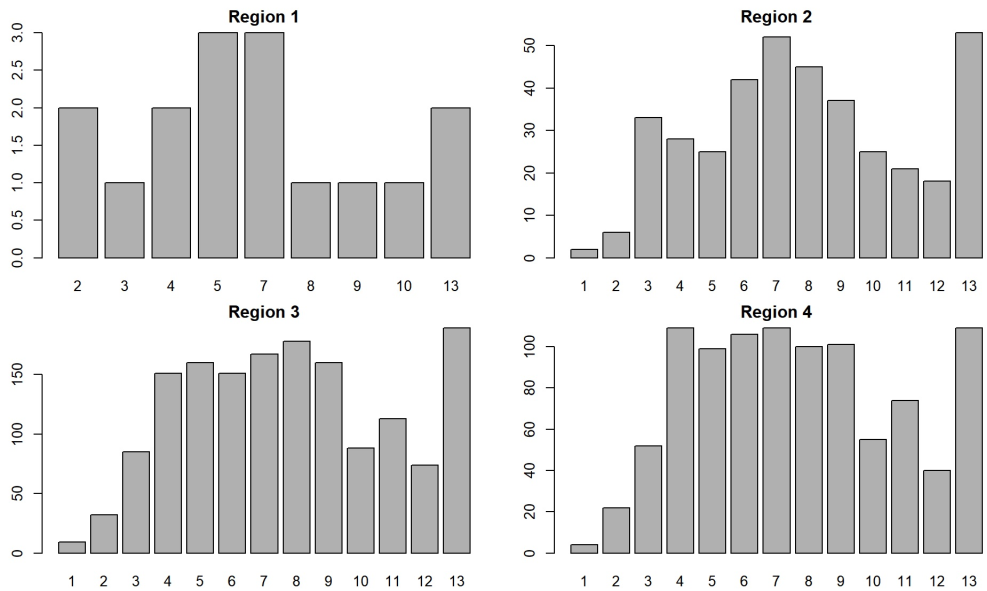

Figure D.3: Bar plots of income

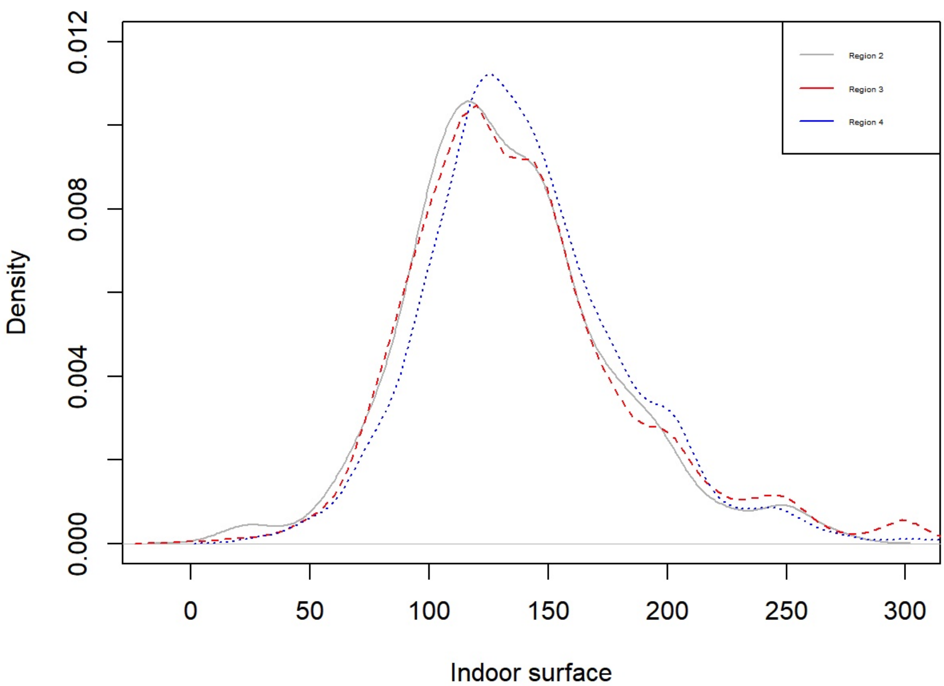

Figure D.4: Kernel estimates of densities of indoor space. SE1 and SE2: grey line. SE3: red line. SE4: blue line.

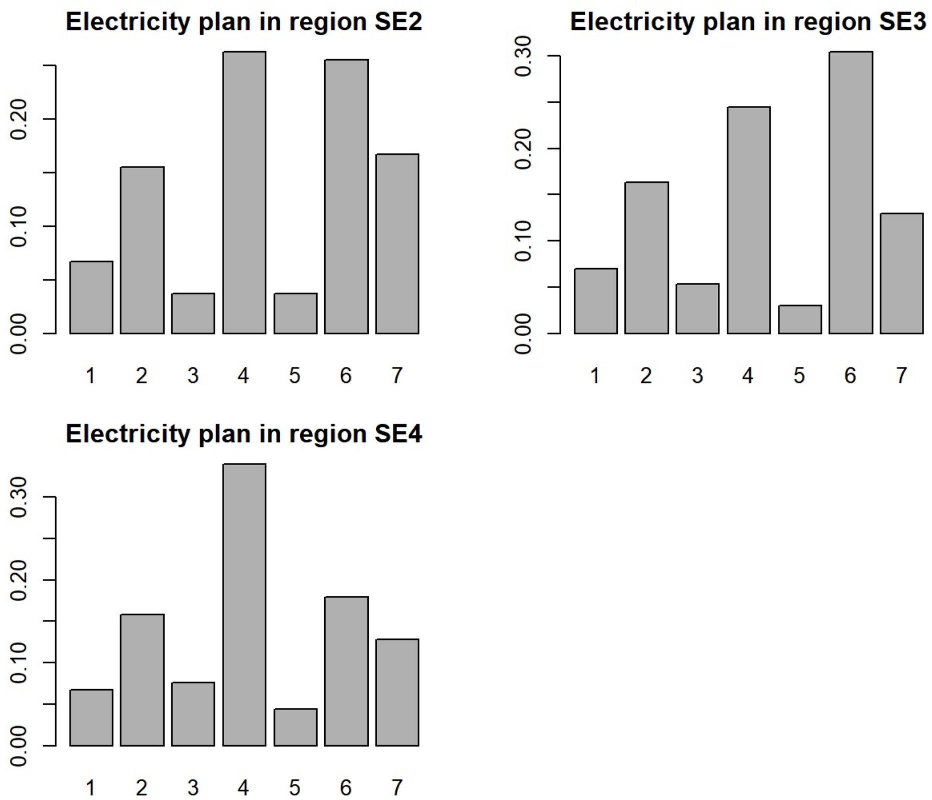

Figure D.5: Barplots of the distributions of the type of contract. Regions SE2, SE3, and SE4

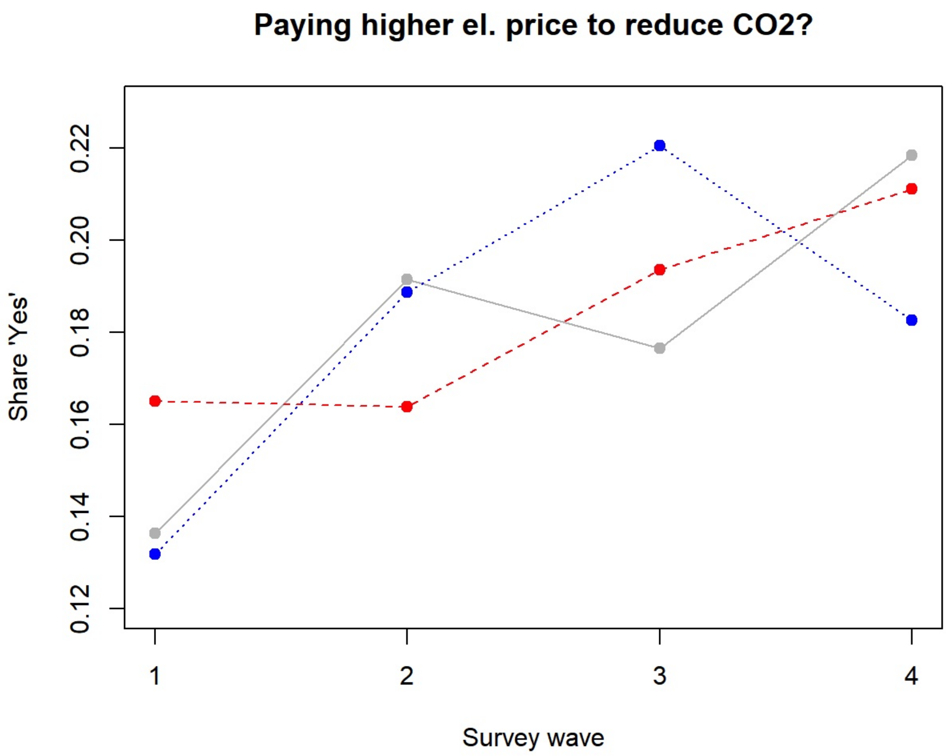

Figure D.6: Q8. Shares of “Yes” in each wave, for price area 2 (grey line), price area 3 (red line) and price area 4 (blue line).

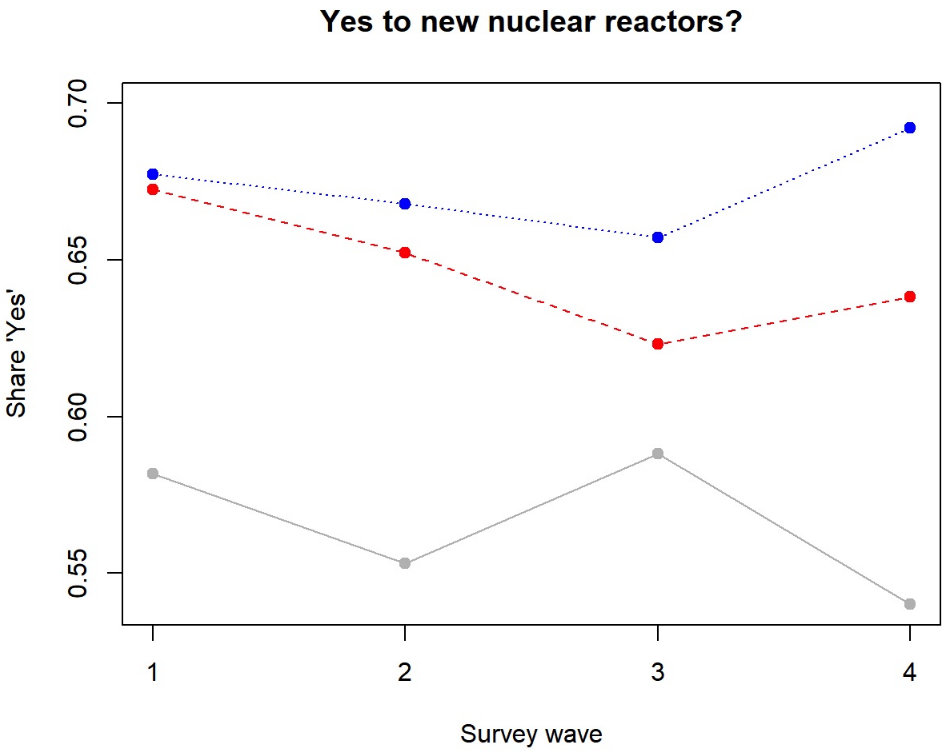

Figure D.7: Q9. Shares of "Yes" in each wave, for price area 2 (grey line), price area 3 (red line) and price area 4 (blue line).

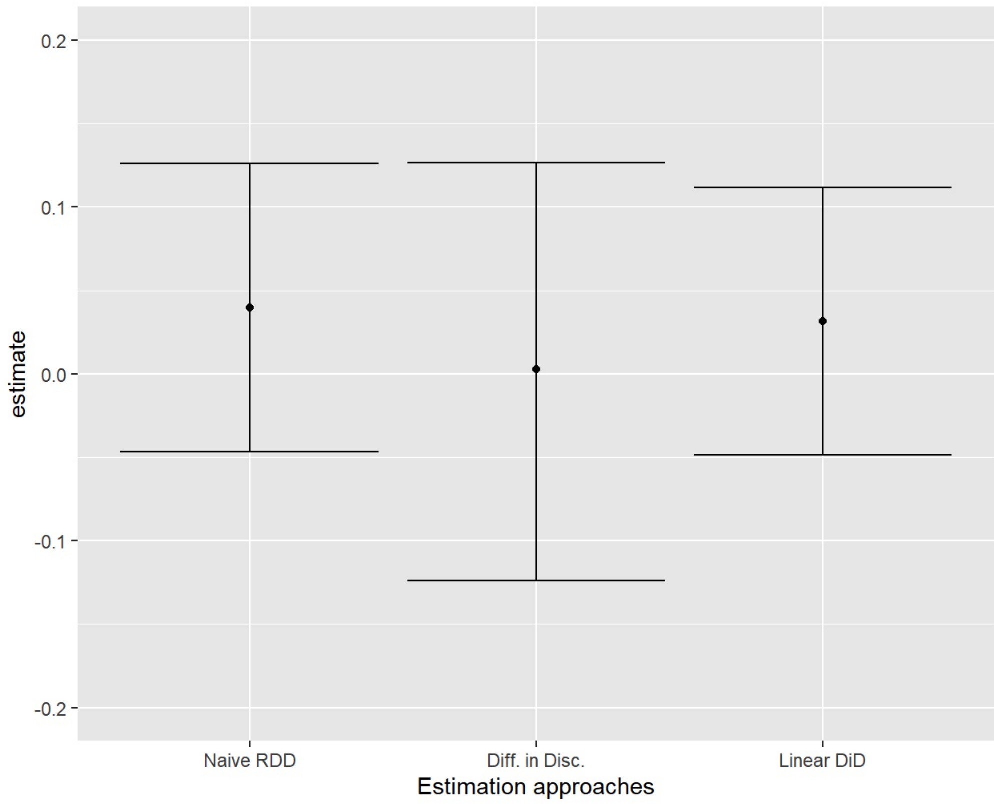

Figure F.1: Estimation results, Q13: "Do you think Swedish politicians do enough to address climate change?"

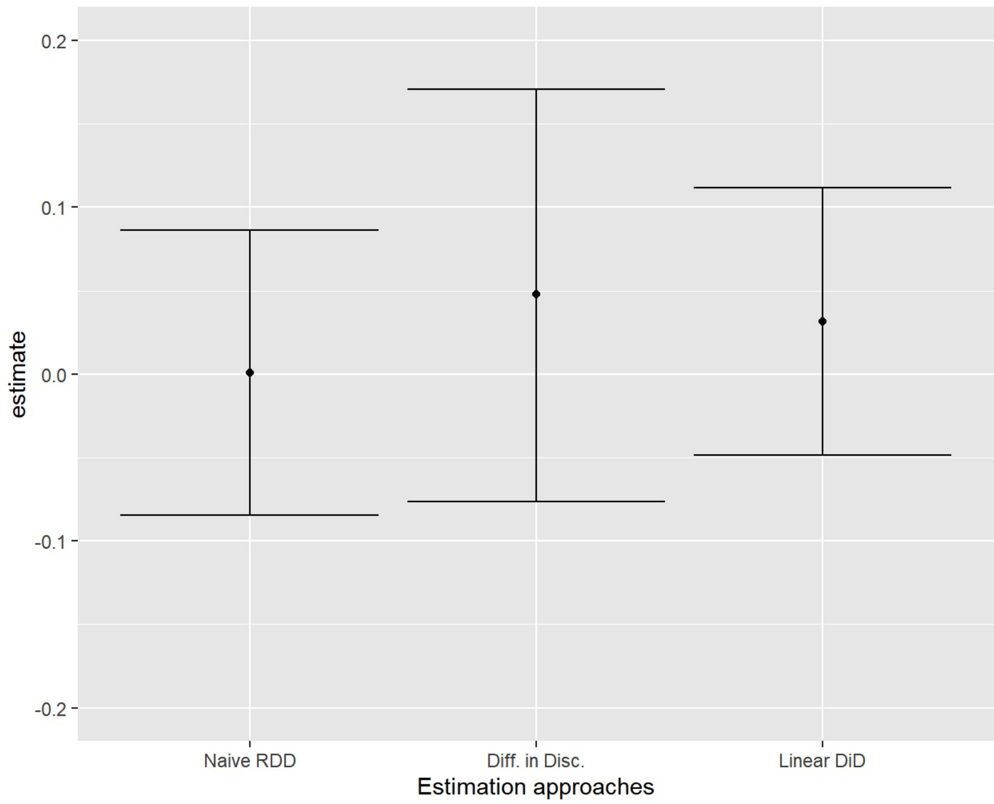

Figure F.2: Estimation results, Q14: "When buying food, how important to you is the price?"

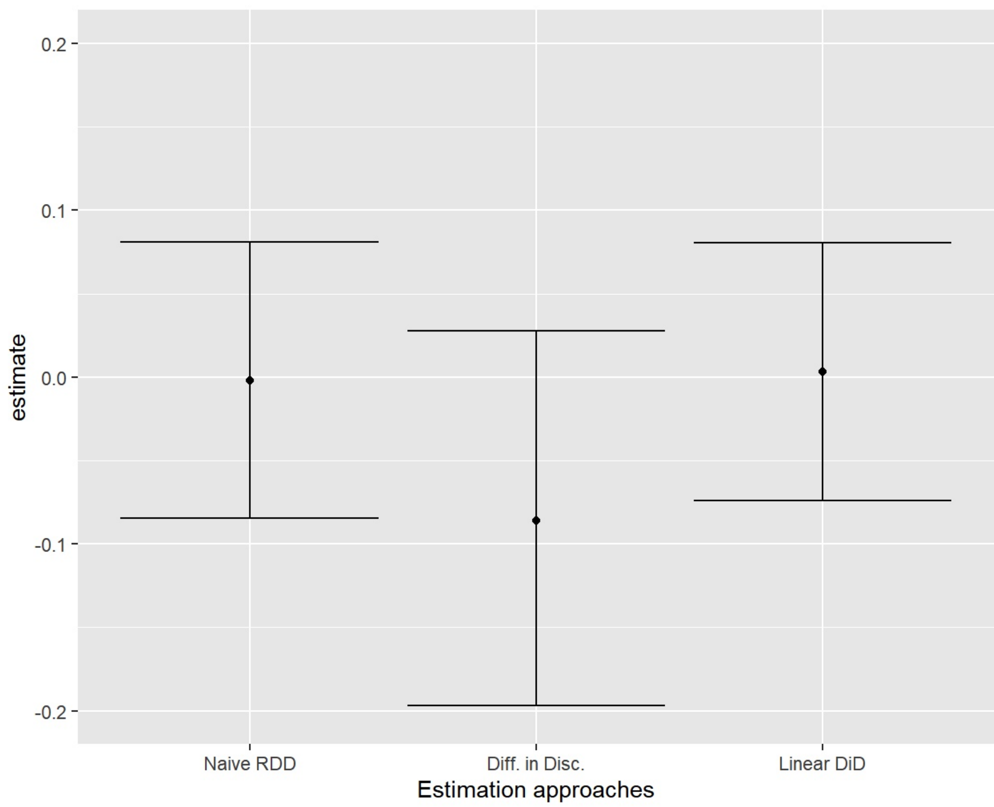

Figure F.3: Estimation results, Q15: "Do you freqently buy organic food?"

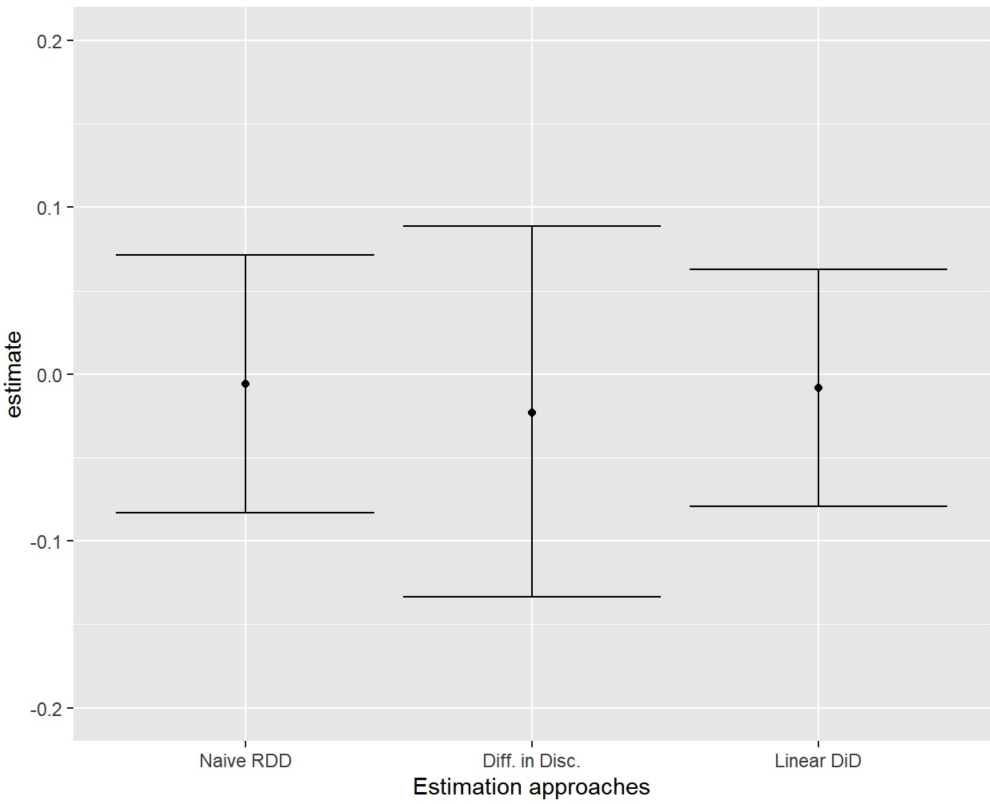

Figure F.4: Estimation results, Q16: "Would you support a ban on pesticides usage in the agriculture sector if that raised fruits and vegetables price by 30%?"

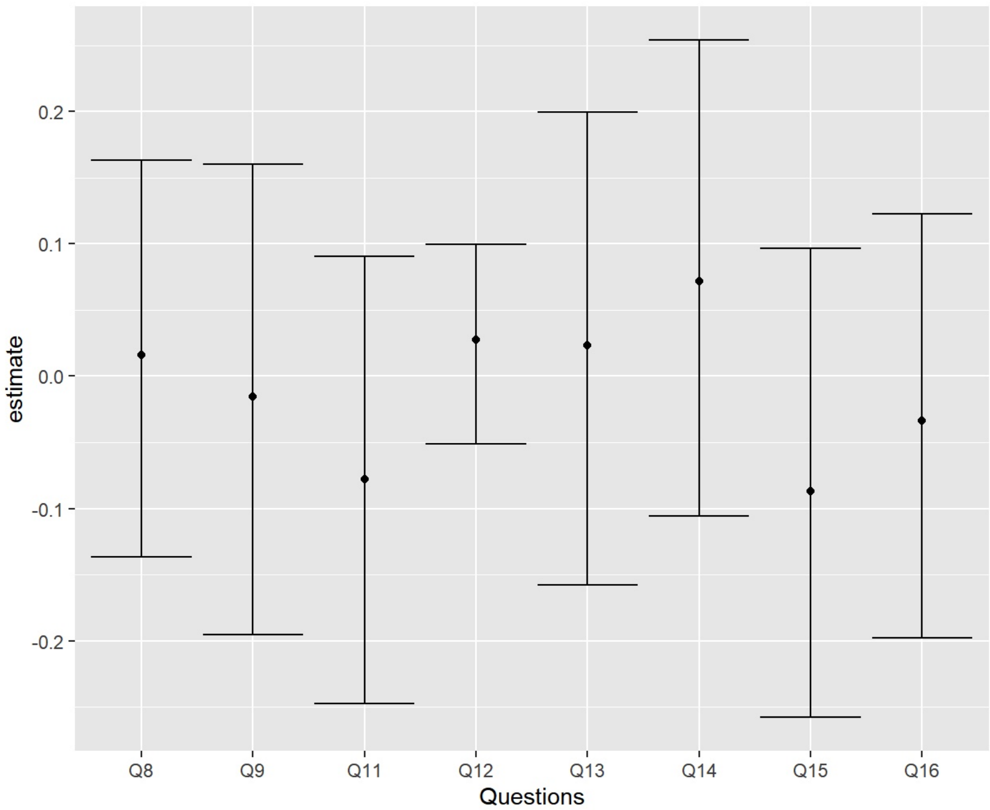

Figure F.5: Heterogeneous effects, difference-in-discontinuity results, Q8, Q9 and Q11-Q16, consumers with high education

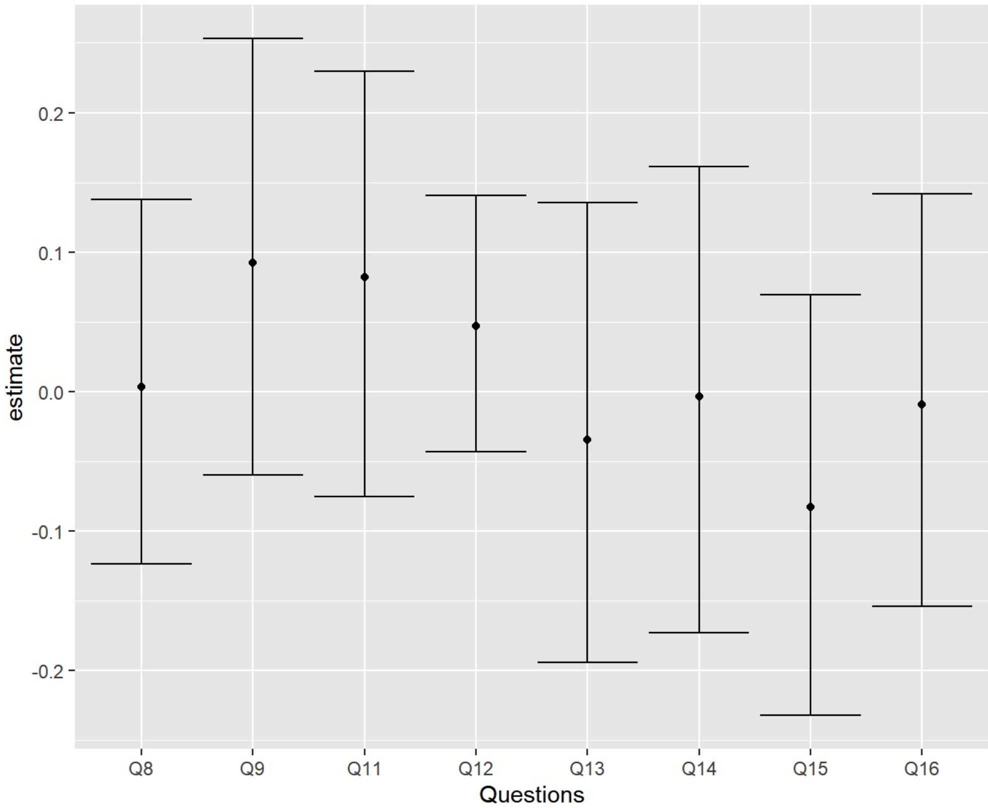

Figure F.6: Heterogeneous effects, difference-in-discontinuity results, Q8, Q9 and Q11-Q16, consumers with low education

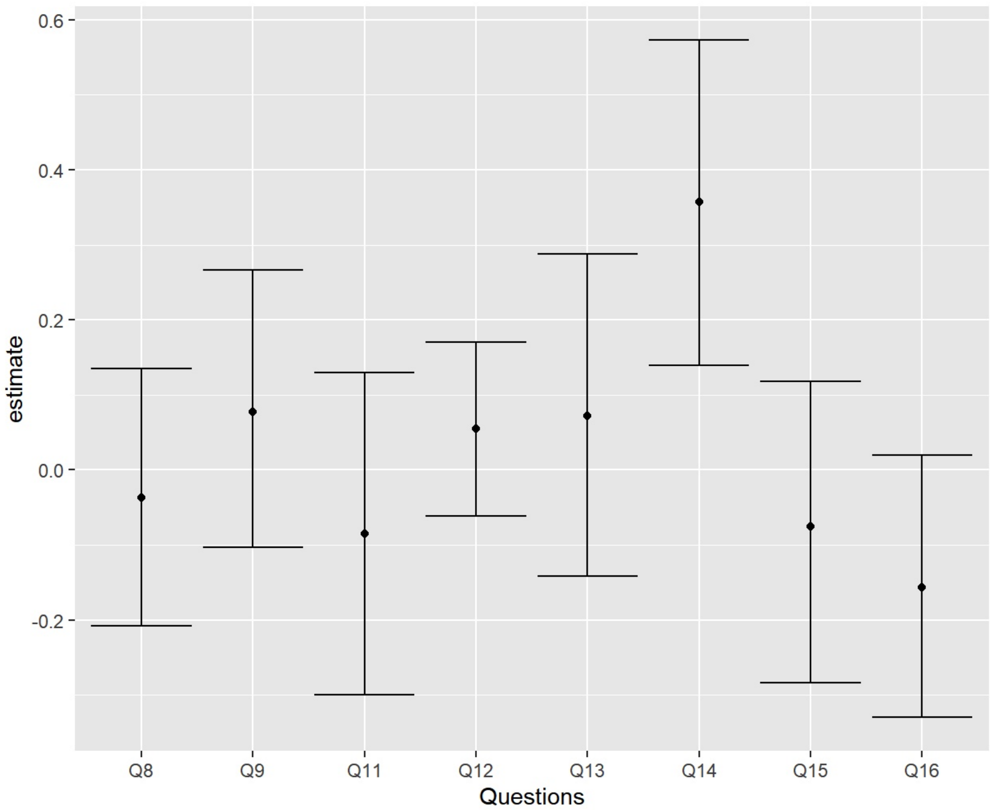

Figure F.7: Heterogeneous effects, difference-in-discontinuity results, Q8, Q9 and Q11-Q16, consumers with high income

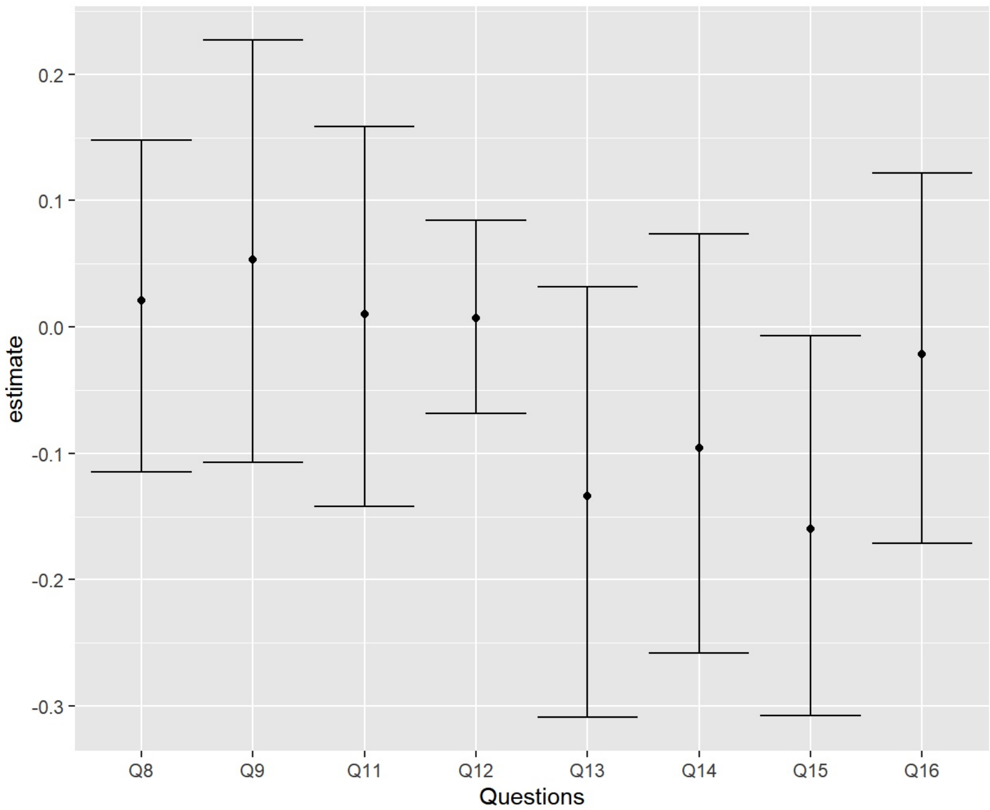

Figure F.8: Heterogeneous effects, difference-in-discontinuity results, Q8, Q9 and Q11-Q16, consumers with low income