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Essays on Behavioral Environmental Economics Applied to Energy and Production Efficiency

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Esės apie elgsenos aplinkos ekonomiką, taikomą energijos ir gamybos efektyvumui

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1. INTRODUCTION

It is a well-known fact that climate change is a global threat. Unless concerted measures are taken in every sector to tackle this catastrophe, the effect of climate change on human beings and all other life forms on earth will be much more devastating and irreversible (IPCC, 2022). This dissertation aims to achieve two broad goals: first, to evaluate the impact of different behavioral interventions aiming to mitigate climate change in the residential energy sector, and second, to investigate how climate change adaptation strategies impact production efficiency in smallholder farming agriculture. To this end, I conducted four interrelated case studies.

Climate change mitigation is one of today's primary policy concerns. The major goal of climate change mitigation strategies is to reduce greenhouse gas (GHG) emissions at a global scale. Various policies and international agreements emphasize the implementation of a wide range of actions to mitigate climate change, such as reducing carbon emissions by stopping rampant deforestation, increasing the share of renewables in the overall global electricity generation, and all-inclusive efforts to reduce GHG emissions from the burning of fossil fuels. However, climate change mitigation actions adopted so far remain insufficient to achieve the global target of limiting average temperature increase to 2 °C.

The improvement of energy efficiency (i.e., conservation) plays a central role in mitigating climate change. Because a rapid increase in energy consumption has contributed significantly to GHG emissions, effective energy conservation would be essential to protect the climate. For instance, in 2021, the energy sector alone emitted 36.3 Gt of CO_2—a 6% increase over the sector's 2020 emissions level (IEA, 2022). According to International Energy Agency (IEA) estimates, more than one third of the total reductions of GHG emissions necessary to stabilize climate change could be attained through energy efficiency improvements (IEA, 2018). The European Union's (EU) climate target envisages net-zero GHG emissions by 2050; it also aims to reduce emissions by at least 55%, relative to the 1990 levels, in 2030 (EC, 2020c). In the EU, households accounted for 27.4% of final energy consumption in 2020; electricity is the second-greatest contributor to this final energy consumption (24.8%) after natural gas (31.7%) (Eurostat, 2020a). In this regard, the residential sector can be considered one of the areas where there exists potential for energy conservation and energy efficiency improvements. This raises a critical question: what instruments and policy options should be used to achieve energy efficiency in the residential sector?

Depending on the contexts and desired policy targets, various approaches have been used to promote energy efficiency and conservation in the residential sector. One way to encourage energy conservation is to use *non-price instruments*. Traditionally, market mechanisms such as (Pigouvian) taxes and subsidies have served as common policy tools to conserve energy. However, market mechanisms are not always effective in achieving socially optimal objectives due to market failures (i.e., imperfect information) and behavioral anomalies such as bounded rationality and lack of attention. This is because if there is imperfect information, or if prices fail to signal true resource scarcity, or if individuals act irrationally, consumers will fail to make a socially optimal decision.

Recently, the application of non-price instruments to improve energy conservation has received considerable attention in the behavioral economics literature (see the reviews by Andor & Fels, 2018; Buckley, 2020). When market mechanisms fail to attain socially optimal targets, non-price measures could serve as an effective measure to achieve energy conservation. Non-price (i.e., behavioral) interventions, such as information feedback about one's own energy consumption and social comparison, enable households to conserve energy by reducing cognitive and information biases that hinder their optimal decision-making capacity. For instance, social comparison allows individuals to correct biased beliefs about their conservation behavior relative to that of others. The problem of information bias (i.e., imperfect information) is highly prevalent in the residential sector because households typically receive utility bills based on the total monthly amount of electricity usage. This lack of more granular information about households' electricity use can lead households to make imperfect decisions due to insufficient information.

Several studies report that information feedback effectively reduces households' energy consumption, at least in the short run (see, e.g., Abrahamse et al., 2005; Buckley, 2020; Darby, 2006; Ehrhardt-Martinez et al., 2010; Faruqui et al., 2010; Fischer, 2008). However, previous studies evaluating the effect of information feedback on energy conservation have tended to concentrate on the U.S. or other wealthy OECD countries, where individuals tend to be more concerned about the environmental footprint of their decisions. Furthermore, these studies focus on the effect of information feedback, combining it with other normative types of interventions such as energy-saving tips or goal-setting.

Social comparison is one of the most widely studied types of behavioral interventions that has been shown to alter consumer behavior in energy use (Allcott, 2011; Allcott & Rogers, 2014; Kažukauskas et al., 2021). However, it remains unclear whether the effect of social comparison information provision in one resource domain spills over into the other domain. If the social comparison information effect extends to other resource domains (spillover), it will change the cost effectiveness and welfare implications of the intervention (see, e.g., Jessoe et al., 2021). So far, these cross-domain or "spillover" effects remain poorly understood and have received very little attention in academic literature, presumably due to the lack of possibilities for analyzing and measuring them in a rigorous way.

The other way to increase energy efficiency (and energy conservation) in the residential sector is to retrofit energy-inefficient multiapartment buildings. Because buildings contribute about 36% of GHG emissions and constitute 40% of energy consumption at the EU level, achieving energy efficiency in the residential sector is pivotal to achieve climate policy targets. Indeed, retrofit investment has been identified by the EU as one of the priority intervention areas that countries could leverage to improve energy efficiency (EC, 2020a).

In Lithuania, energy-inefficient Soviet-era multiapartment buildings account for 55% of the country's total multiapartment buildings as of 2019. Even if these buildings constitute more than 75% of the primary energy of the building stocks, retrofit investment is quite limited; less than 10% of old multiapartment buildings (3,158 buildings out of 35,000 total) were retrofitted between 2005 and 2019 (NAOL, 2020). If this slow pace of retrofitting continues, it will take about a century to fully retrofit all energy-inefficient residential apartment buildings in Lithuania. While different studies provide various explanations for the low level of retrofit investment decisions (Filippini & Kumar, 2022; Schleich, 2019), a new strand of research argues that individuals usually make mistakes in computing the life-cycle costs and benefits of retrofit investments due to a low level of cognitive and computational ability, hereinafter called "energy-related financial literacy" (ERFL). This means that to make a wise investment decision, households must have the capacity to calculate the cost and benefits of the investment over the lifetime of the durable, as well as energy-related knowledge. It has been shown that a substantial share of individuals lack the capacity and knowledge to process energy-related financial investments, which represents an important bottleneck for large-scale multiapartment building retrofit (Blasch et al., 2017b). However, no study has brought this agenda under empirical scrutiny in the case of Lithuania.

Climate change adaptation is the other established strategy to address climate change impacts. Particularly in the agriculture sector, which is highly vulnerable to climate-related risks, adaptation to climate change is paramount in improving agricultural productivity and hedging against climate-related risks. According to the Intergovernmental Panel on Climate Change (IPCC), climate change adaptation can be defined as *"the process of adjustment to actual or expected climate and its effects in order to moderate harm or take advantage of beneficial opportunities" (2022).*

Numerous studies have suggested using robust climate change adaptation strategies to improve production efficiency and thereby lessen the impact of climate change and to build a climate-resilient ecosystem (Bradshaw et al., 2004; Di Falco et al., 2011; Huang & Sim, 2021; Lin, 2011; Teklewold et al., 2013). In the context of agriculture, climate change adaptation may increase production efficiency by improving farmers' resilience capacity against various climate-related risks. Furthermore, implementing adaptation strategies introduces new or improved agricultural practices, which subsequently increase productivity and assist farmers in using farm inputs in an efficient manner. To what extent the implemented adaptation strategies affect the productive efficiency of subsistence farmers is not clearly known. In addition, what factors facilitate or hinder the adoption behavior of farmers in the face of climate change is another important question that calls for appropriate empirical scrutiny. Addressing this issue is more critical in countries like Ethiopia, where reconciling food production and environmental sustainability is particularly vexing, due in part to the country's alarming population growth and low rates of agricultural technology adoption, coupled with the prevalence of highly inefficient traditional agricultural practices.

Against the above-discussed background, the overarching goal of this dissertation is to evaluate the impact of various behavioral interventions aiming to abate/adapt to climate change, focusing on the residential energy and agricultural sectors.

1.1 Objectives and tasks

This dissertation has two broad objectives. The first is to evaluate the impact of different behavioral interventions aiming to mitigate climate change in the residential energy sector. Under this broad objective, the thesis aims to address two specific objectives:

- ❖ Measure the direct impact of information provision and the indirect (spillover) impact of social comparison on energy conservation.
- ❖ Explore the role of ERFL in explaining energy-efficiency retrofit investment decisions.

The second broad objective is to measure how climate change adaptation impacts production efficiency in the agriculture sector. Specifically, it seeks to evaluate the impact of selected climate change adaptation strategies on technical efficiency (TE) of subsistence farmers in Ethiopia.

To achieve these objectives and thereby contribute to the growing literature in behavioral environmental economics, the following main tasks were undertaken:

- Review of international literature about the application of non-price instruments in energy conservation as well as the role of climate change adaptation in production efficiency
- Development of the conceptual frameworks (1) to define the components of ERFL, and (2) to understand the linkages between climate-related risks, climate change adaptation decision, and production efficiency
- Collection and management of data required to answer the research questions of the dissertation
- Measurement of the direct and indirect (spillover) impacts of behavioral interventions on residential energy use by using panel data experimental impact evaluation methods, such as the difference-in-differences (DID) fixed effect model
- Assessment of the relationship between ERFL and multiapartment retrofit investment decisions based on a cross-sectional survey data from Lithuania
- Quantification of the effect of climate change adaptation on technical efficiency of subsistence farmers in Ethiopia by employing quasi-experimental impact evaluation tools, such as propensity score matching (PSM) and stochastic frontier analysis (SFA)

1.2 Methodology

The studies conducted in this dissertation rely on experimental and quasi-experimental impact evaluation methods.

For the second and the third chapters, I conducted randomized experiments in Lithuania and Sweden, respectively. The experiment in Lithuania involved 419 households in the treatment group, and 632 households in the control group. I observed both groups for two years (March 2015–February 2017), one year before the treatment period started and one year after I applied the treatment. Delivered via a web portal, the treatment intervention consisted of providing pure information feedback about each household's electricity consumption for each hour of the day. Electricity consumption data was generated from smart meters in collaboration with a research partner, AB ESO. On the other hand, the field experiment in Umeå, a city in northern Sweden, was started in March 2016, and the continuous treatments lasted for one year. The treatments were delivered via preinstalled in-home displays, which were salient and updated in real time. Two separate treatment groups were constructed—one for electricity-use-targeted social comparison and another for water-use-targeted social comparison. To measure the direct and indirect (spillover) impacts of the interventions, I estimated the difference-in-differences fixed effect models. To shed light on the distributional impacts of the interventions, I used (spillover) quantile treatment effects.

In the fourth and fifth chapters, I mainly used quasi-experimental methods based on survey data from Lithuania and Ethiopia, respectively. The fourth chapter is based on an incentivized survey data collected in May–June 2021 in Lithuania by a professional survey company. The company recruited 1,111 respondents who own and live in Soviet-era multi-dwelling buildings from a representative online panel (out of 3,174 requests). The survey accounted for questions to measure the dimensions of ERFL (financial literacy, energy-related financial literacy, energy interest and electricity cost awareness), rate of time preference and risk aversion, the level of trust in different stakeholders related to the retrofit activity, and demographic factors. I estimated a simple binary probit and multivariate probit models (MVP) in the instrumental variable (IV) framework to measure the relationship between ERFL and multiapartment buildings retrofit investment.

Finally, seeking to quantify the impact of climate change adaptation strategies on productive efficiency of subsistence farmers, I exploited plot-level panel data collected from about 6,820 plots during the survey years of 2015, 2016, and 2017 in the Nile basins of Ethiopia. To address selection biases from observed and unobserved heterogeneities—and thus appropriately measure the impact of climate change adaptation on production efficiency—I used PSM and Greene's (2010) selection bias correction method in the SFA framework, respectively.

1.3 Scientific novelty and contributions

The findings of this dissertation are novel and contribute to the behavioral environmental economics literature in at least four dimensions.

First, previous studies evaluated the impact of information provision by combining it with various normative behavioral measures, such as social comparison, goal-setting, and energy-saving tips. As a result, they were not able to disentangle the effect of information from that of social norms or electricity-saving tips. In contrast to those studies, I study the specific impact of individuals' own pure information provision on saving electricity. Except for the study by Gleerup et al. (2010) who showed that pure information provision reduced electricity consumption by about 3% among Danish households, I am not aware of any other study on this issue. Building on this finding, this thesis brings new evidence from a different context, namely Lithuania. In doing so, it contributes to the literature that seeks primarily to reveal the pure effect of information provision. Because acquiring information is costly and difficult, testing whether the provision of such information alters individuals' energy conservation behavior—without mixing it with other behavioral interventions—will have interesting policy implications. Such testing will inform policymakers about the suitability of similar interventions to achieve the broad goals of energy efficiency and net-zero emission targets in the residential sector. Furthermore, general behavioral intervention studies in the form of social comparison (or using other approaches) are more concentrated in the U.S. or other wealthy OECD countries. Hence, it will be of interest to academics and policymakers alike to know whether similar interventions could be used as alternative policy tools to achieve energy-saving objectives in less wealthy countries such as Lithuania, where a large share of the population lives under energy poverty and where individuals are less concerned about their environmental footprint.

Second, although a plethora of researchers have studied the direct impact of social comparison information provision on energy conservation, little is known about whether behavioral interventions in one resource domain spill over into the other resource domain. By exploiting the social psychology theory of behavioral spillovers, this thesis tests the spillover effect of social comparison information targeting electricity and water in the same experimental setting. To my knowledge, there are only three published studies that conduct similar analyses (i.e., Carlsson et al., 2021; Jessoe et al., 2021; Tiefenbeck et al., 2013). However, these studies only consider the effect of social comparison targeting water on electricity—not both. Thus, the current thesis contributes to the behavioral economics literature by experimentally scrutinizing the spillover impact of social comparison interventions aimed at electricity and water conservation on (hot) water use, electricity consumption, and space-heating energy use. To the best of my knowledge, no research has investigated whether behavioral interventions targeting electricity use spill over into the hot water and space-heating domains. The heating of space and water is a central resource domain; for example, in 2019 it accounted for about 80% of the EU's total household final energy consumption and contributed significantly to the EU's carbon footprint (Eurostat, 2020b). This means that even a small reduction in the use of hot water and heating energy induced by behavioral interventions like social comparisons may result in substantial environmental benefits. This is a critical question relevant to both academia and policy, because failure to account for the spillover effects of behavioral interventions will under/overestimate the cost effectiveness of the interventions and welfare implications in general.

Third, the emerging literature about ERFL indicates that the lack of energy-related knowledge and cognitive capacity to conduct energy-related investment computations significantly determines energy-efficiency investment and energy-consumption decisions (Blasch et al., 2021; Brounen et al., 2013; Filippini et al., 2020; Kalmi et al., 2021). Nevertheless, the central focus of these studies is on either smaller investment types, such as appliance replacement, or electricity consumption. Hence, the fourth chapter of this dissertation aims to expand this scant literature by studying the role of ERFL on the decision to invest in large-scale energy-efficiency retrofits. Furthermore, the findings of this chapter are also expected to show policymakers an alternative policy intervention to boost energy-efficient retrofit investments in Lithuania. Even though the Lithuanian government already offers various incentives, including subsidies to cover retrofit costs and technical support to promote multiapartment building retrofits, the retrofit rate remains sluggish.

Finally, this dissertation seeks to contribute to the literature about subsistence farmers' production efficiency. Being dominated by smallholder subsistence farming, agriculture in sub-Sharan African countries like Ethiopia is highly vulnerable to climate-related risks. The agricultural sector is the core of Ethiopia's economy, and is also the sector hardest hit by climate change. Several studies show that climate change adaptation in the agricultural sector improves climate resilience by increasing crop productivity and agricultural income (Arslan et al., 2015; Di Falco & Veronesi, 2013; Suresh et al., 2021; Tambo & Mockshell, 2018; Teklewold et al., 2013). Climate change adaptation strategies are expected to bring new or improved agricultural practices that enable farmers to use farm inputs more efficiently. However, no studies have conducted appropriate measurements on the effect of climate change adaptation strategies on production efficiency using panel data in Ethiopia.

Previous studies that attempted to measure the efficiency effect of climate change adaptation were either based on a limited geographical area using cross-sectional data or failed to appropriately address selection biases stemming from observed and unobserved heterogeneities. Hence, in the fifth chapter, I fill this gap by studying the impact of climate change adaptation strategies on Ethiopian farmers' technical efficiency using plot-level panel data. I address the methodological gaps of previous studies by jointly implementing impact evaluation tools, namely PSM and selection-bias-corrected SFA. I also shed light on the key driving factors behind farmers' decisions to implement climate change adaptation strategies. The Ethiopian government's commitment to abate climate-related risks in the agriculture sector is evident in its Climate-Resilient Green Economy Strategy (CRGE). Hence, the findings of this chapter will provide input that supports the government's goal of transforming the Ethiopian economy to a middle-income level that is resilient to climate-related shocks by 2025.

1.4 Statements presented for defense

1. On average, pure information provision reduces electricity consumption by 0.661 kWh (or 8.6%) per day in Lithuanian households. This is equivalent to an annual energy saving of 241 kWh per household. Furthermore, the intervention induces a greater reduction in electricity consumption for consumption levels above the 75th percentile.
2. Social comparison information targeting electricity has a significant spillover impact on hot water consumption and heating energy use in Umeå, Sweden. On average, households provided with electricity-targeted social comparison information reduced their hot water consumption by around 7 liters per day and indoor temperature by 0.20 °C. The energy savings from the spillover effects are twice as high as the energy savings from the direct effect.
3. ERFL and its dimensions (i.e., financial literacy, energy-related financial literacy, energy interest, and electricity cost awareness) significantly increase the likelihood of investing in multiapartment building retrofit in Lithuania. A unit increase in this all-encompassing index leads to a roughly 15-percentage-point increase in the probability of willingness to retrofit a house.
4. On average, climate change adaptation increases the technical efficiency of subsistence farmers by about 12.37% in the Nile basins of Ethiopia. Failure to account for selection biases from observed and unobserved

heterogeneities underestimates the efficiency impact of climate change adaptation by 4.21%.

1.5 Structure of the dissertation

The dissertation is structured into five chapters. The first chapter provides an overall introduction to the thesis. The remaining four chapters are standalone studies with their own introductions and conclusions. The second chapter is devoted to measuring the impact of information provision on energy conservation; the third chapter evaluates the spillover impact of social comparison information. The fourth chapter explores the relationship between ERFL and multiapartment retrofit investment, and the last chapter delves into the impact of climate change adaptation on subsistence farmers' technical efficiency. Finally, an all-encompassing conclusion that ties together all the standalone chapters is also presented.

2. INFORMATION PROVISION AND ELECTRICITY CONSUMPTION: EXPERIMENTAL EVIDENCE FROM LITHUANIA.

Information tends to be not only imperfect but also costly to access (Caplin & Dean, 2015; Stiglitz, 2000). Studies that sought to ascertain this confirm that filling an information gap affects the individual's decision-making and behavior (Dolls et al., 2018; Duflo & Saez, 2003; Jalan & Somanathan, 2008). The residential energy sector is one of the energy sectors where imperfect information is highly prevalent as households typically receive utility bills based on the total monthly amount of electricity usage. This lack of more granular information about households' electricity use potentially leads to imperfect decisions that households might not make given sufficient information.

Several literature reviews synthesize the earlier studies on the effects of information provision in various forms on residential energy use (see, e.g., Abrahamse et al., 2005; Buckley, 2020; Darby, 2006; Ehrhardt-Martinez et al., 2010; Faruqui et al., 2010; Fischer, 2008). These studies conclude that provision of personalized information can promote households' energy-saving investments and influence consumption behavior, at least in the short run. However, these studies are usually conducted in the U.S. or other rich OECD countries, where households consume more electricity, tend to have stronger environmental concerns, and care more about the environmental footprints of their activities (Hunter, 2000; Krosnick et al., 2020; OECD, 2014). Furthermore, most of these studies analyze interventions in the form of social comparisons combined with energy saving tips and other information. To the best of our knowledge, there are only a few studies that aim to estimate the effect of *purely descriptive* personalized information provision on households' electricity use (Gans et al., 2013; Gleerup et al., 2010; Nilsson et al., 2014). The present analysis aims to expand the existing literature in the field of behavioral and energy economics in the following two unexplored directions. First, our field experiment is based in Lithuania, a recent OECD member country, which is different from other older OECD countries in terms of income and energy intensity. For instance, in 2019, Lithuania's gross domestic product per capita stood at 83 percent of the OECD's average, and Lithuania's overall electricity consumption per capita (4.4 MWh/capita) was only about half as high as the OECD's average (8 MWh/capita). Furthermore, in Lithuania, a high share of households is experiencing energy poverty (Eurostat, 2021).

Second, our experiment aims to estimate the effect of *pure* descriptive information provision on households' electricity use without combining it with other normative types of information, such as social comparisons, energy saving tips or goal setting. Our focus on descriptive information is important from a welfare enhancing perspective. Households facing normative types of information might experience disutility. For instance, Allcott and Kessler (2019) show that a large share of households who were exposed to normative information in the form of injunctive social comparisons preferred not to receive such reports. Broberg and Kažukauskas (2021) show that households prefer more descriptive type of information about their own energy use than information that compares their electricity consumption with others. This might suggest that households would experience less disutility if they received feedback about their electricity use in a more descriptive manner.

Our one-year country-wide field experiment started in July 2016, and was implemented by a national Lithuanian electricity and gas distribution company, AB ESO. The overall objective of this pilot was to test the impact and viability of smart metering technology in Lithuania, and to explore the effect of a descriptive information provision enabled by the installation of smart meters.[1] Specifically, we analyze how an enhanced web portal with additional information on hourly electricity use would influence households' energy use. Compared to dedicated in-home displays, web portals provide a low-cost and simple design solution for making energy feedback available. Given the fast development of smart meters and other information-delivering technologies, our research provides an example of whether the demand-side management of resources through the provision of continuous real-time hourly electricity use information can stimulate resource conservation in poorer OECD economies.

First, we find that, on average, descriptive information provision reduces electricity consumption by 0.661 kWh (or 8.6%) per day in Lithuanian households. This is equivalent to an annual energy saving of 241 kWh per household. Second, we measure the effect of our intervention beyond the mean using quantile treatment effects (QTEs). Our results reveal that a large reduction effect of descriptive information provision is observed at the highest percentiles of electricity consumption. The higher the percentile, the higher the impact. Much higher reduction effects are observed for consumption levels

[1] The EU Member States are required to ensure the implementation of smart metering under EU energy market legislation. This implementation may be subject to cost-benefit analysis (CBA). The state-owned Lithuanian national electricity distribution company AB ESO was asked to implement such CBA. A pilot experiment that is assessed in this study was designed as part of AB ESO's CBA.

above the 75th percentile. The implication of this result is vital for policymakers, as it explicitly suggests which group of consumers policy makers should target to achieve energy conservation objectives.

The remainder of the chapter is organized as follows. In Section 2.1, we review the related literature. We describe our experimental setting and randomization of the treatment and control groups in Section 2.2. The estimation procedure used to generate the ATEs is discussed in section 2.3. The experimental data is presented, and the results are discussed in Section 2.4. Section 2.5 concludes the chapter.

2.1 Related literature review

The effect of personalized information provision on energy conservation has received considerable attention in the behavioral and environmental economics literature. In this section, we review some results of previous studies conducted under the randomized/field experiment framework in the OECD countries that aimed to analyze the effect of non-price information provision on household electricity conservation. Our review only covers those studies that are in line with the scope of our study and are relevant to highlight the contribution of our analysis. Table 2.1 summarizes the studies in terms of their treatment object, type of treatment, mode of treatment provision, duration of the treatment, frequency of measurement, average treatment effect (ATE), geographic location of the experiment, and sample size of the control and treatment groups.

Almost all considered studies find negative ATEs of personalized information provision on households' electricity use (see column 7 in Table 2.1). These effects range from 20 percent (see, e.g., Aydin et al., 2018) to almost none (Delmas & Lessem, 2014). The selected studies evaluate the effect of information provision presented in two different forms: in the form of social comparisons (with or without saving tips) and monetary incentives (Harries et al., 2013; Mizobuchi & Takeuchi, 2013), or in the form of descriptive feedback about their own resource consumption with or without saving tips (Benders et al., 2006).

In the United States, information presented in the form of social comparisons reduces households' electricity consumption by about 2.0-2.9 percent (Allcott, 2011; Allcott & Kessler, 2019; Costa & Kahn, 2013; Henry et al., 2019). Interestingly, Delmas and Lessem (2014) evaluate the effectiveness of detailed private and public information on electricity conservation of students residing in the resident halls at the University of

California. Their results reveal that private feedback in the form of social comparisons alone is ineffective. But a 20 percent average energy saving is attained when private feedback is combined with publicly visible information. The ATEs of social comparisons implemented in other OECD countries range from -0.7 percent (Andor et al., 2020) to about -20 percent (Aydin et al., 2018). However, Andor et al. (2020) note that the cost-effectiveness of letter-based intervention depends not on the size of ATEs, but on the baseline consumption levels and the carbon intensity of electricity generation. Higher average consumption levels translate a given ATE (in terms of percentage reduction of electricity consumption) into the higher absolute electricity saving in terms of kWh. Similarly, higher carbon intensity of electricity generation implies that a given ATE translates into higher reductions in greenhouse gas emissions. In the case of letter-based home energy report interventions that include social comparisons, Andor et al. (2020) use "back-of-the-envelope" calculations to show that, once these dimensions are taken into account, the cost effectiveness of social comparisons is highest for the U.S. and Canada but not so much for other OECD countries.

Table 2.1. Summary of selected field experiment studies on the effects of information provision on household's electricity use

Study[1]	Treatment object	Treatment type	Mode of treatment provision	Duration of treatment	Data frequency in measuring ATE	ATE	Location	Sample size[3]
1	2	3	4	5	6	7	8	9
Our study	**Electricity**	**Descriptive feedback**	**Web portal (continuous)**	**12 months**	**Daily**	**-8.60%**	**Lithuania**	**419 (T), 632 (C)**
Benders et al. (2006)	Electricity	Descriptive feedback with tips	Web portal	5 months	Once in 5 months	-8.50 %	Groningen, the Netherlands	137 (T), 53 (C)
Gleerup et al. (2010)	Electricity	Descriptive feedback	Text messages and email	12 months	Daily	Between 0 and –3.00%	Denmark	92-105 (T), 183-196 (C)
Allcott (2011)	Electricity	Social comparisons with tips[2]	Letters (monthly, bimonthly, quarterly or mixed)	2 years	Daily	-2.03%	U.S. (OPOWER clients in 17 regions)	306,670 (T), 281,776 (C)
Ayres et al. (2013)	Electricity	Social comparisons with tips	Letters (quarterly or monthly)	12 months	Daily	-2.02%	U.S. (OPOWER clients in the Sacramento Municipal Utility District)	34,557 (T), 49,570 (C)
Harries et al. (2013)	Electricity	Descriptive feedback with social comparison	Web portal	16 weeks	Daily	-3.00 %	Residential areas of Bristol, UK	214 (T), 102 (C)
Mizobuchi and Takeuchi (2013)	Electricity	Monetary Incentive	-	8 weeks	Monthly	-5.90%	Matsuyama, Western Japan	103 (T), 52 (C)
		Monetary incentive with social comparison	Web portal			-8.20%		53 (T), 52 (C)
Costa and Kahn (2013)	Electricity	Social comparisons with tips	Letters (quarterly or monthly)	8-10 months	Daily	-2.10%	U.S. (OPOWER clients in California)	33,664(T), 48,058 (C)

Houde et al. (2013)	Electricity	Descriptive feedback with tips	Web portal	9 months	Hourly	-5.70%	U.S., California	752 (T), 313 (C)
Schleich et al. (2013)	Electricity	Descriptive feedback with tips	Web portal and letter	11 months	Yearly data	-4.50%	Linz, Austria	601 (T), 469 (C)
Allcott and Rogers (2014)	Electricity	Social comparisons with tips	Letters (monthly, bimonthly, quarterly or mixed)	4-5 years	Daily, monthly	-2.50%	U.S. (OPOWER clients in 3 sites in upper Midwest and on the West coast)	26,262 (Continued T), 12,368 (Dropped T), 33524 (C)
Delmas and Lessem (2014)	Electricity	Social comparisons (private)	Web portal and email (weekly)	5 weeks	Daily	No effect	U.S.	43 (T), 23 (C)
		Social comparisons (public)	Email and public poster (weekly)	7 weeks		-20.00%		
Aydin et al. (2018)	Electricity	Social comparison with tips and goal setting	In home display (every 15 minutes)	8 months	Monthly	Between – 20.00% & - 23.00%	Texel, Netherlands,	104 (T), 54 (C)
Burkhardt et al. (2019)	Electricity	Social comparison	Web portal	19 months	Minute level	No effect	Austin, U.S.	44 (T), 57 (C)
Henry et al. (2019)	Electricity	Social comparisons with tips	Email (monthly, quarterly, semi-annually, once a year or mixed)	12 months	Monthly	(-2.88%)	U.S.	7,667 (T), 1,275 (C)
Andor et al. (2020)	Electricity	Social comparisons with tips	Letters (quarterly)	12 months	Yearly	-0.70%	Kassel, Germany	5,808 (T), 5,812 (C)
Kažukauskas et al. (2021)	Electricity	Social comparisons	In home display (continuous)	12 months	Daily	-6.70%	Umeå, Sweden	100 (T), 315 (C)

Notes:

1. The studies are listed in chronological order.
2. By tips, we mean that the treatment also includes general or customized advice on how to conserve electricity.
3. (T) refers to the number of households (subjects) in the treatment group. (C) stands for the number of households (subjects) in the control group.

The other studies considered in our literature review measure the effect of descriptive personalized information provisions on households' electricity use. This type of intervention does not allude to social norms, since households are only exposed to their private information and they are not compared to other similar households as in the case of home energy reports (see, e.g., Allcott, 2011). In other words, we might think that households who are exposed to descriptive information might have less unpleasant pressure to conserve energy than those households who receive social comparisons. Furthermore, the latter households might experience higher disutility. For instance, Allcott and Kessler (2019) show that 43 percent of customers who received home energy reports with social comparisons preferred not to receive such reports. This might suggest that households would experience less disutility if they received feedback about their electricity use in a descriptive manner (Broberg & Kažukauskas, 2021).

Results of the selected studies show that the descriptive personalized feedback could be as effective as social comparisons. For instance, Houde et al. (2013) and Schleich et al. (2013) find that the provision of descriptive information reduced households' electricity use by about 5.7 percent and 4.5 percent, respectively. However, these studies (as well as those with social comparisons) combined descriptive feedback with advice on how to conserve electricity, and thus they were not able to disentangle the effect of information from that of electricity-saving tips. In this respect, the study of Gleerup et al. (2010) is different as it tested the effect of *pure* descriptive information provision. They find that such feedback resulted in an electricity saving of about 3 percent among Danish households.

Thus, unlike the previous studies summarized above, the present analysis aims to expand the existing literature in the field of behavioral and energy economics in the following two unexplored directions. First, our field experiment is based in Lithuania, where a relatively high share of households is experiencing energy poverty (Eurostat, 2021). On the one hand, it could mean that these households might be already consuming low electricity levels and might have no room to reduce electricity use any further. On the other hand, households subject to energy poverty might be relatively more responsive to relevant information provision. So far, most experiments directed towards electricity conservation have been implemented in the U.S. and other wealthy OECD countries, where people on average consume more electricity and tend to be more concerned about environmental footprint of their electricity consumption (see, Section 2.1). Second, our experiment aims to estimate the effect of *pure* descriptive information provision through a web portal on households' electricity use without combining it with other normative types of information, such as energy saving tips or goal setting. To the best of our knowledge, not many field experiments have tested this type of intervention.

2.2 Design of the experiment

2.2.1 General Context

Lithuania is a small open economy, a member of the European Union (EU)'s and a new OECD's member state. Since 2010, after the complete closure of the Soviet-era Ignalina Nuclear Power Plant, which had made Lithuania a net electricity exporter, it has been relying on electricity imports from its neighboring countries. For instance, the amount of imported electricity accounted for about 70 percent of Lithuania's total electricity demand in 2019. Lithuania has implemented several national and EU-wide policies aiming to reduce reliance on energy imports, energy-related pollution, and improve energy efficiency in the residential sector and in the economy as a whole. For instance, in June 2018, the Lithuanian Parliament approved the National Energy Independence Strategy, which reflects the key focus areas for Lithuanian energy policy – namely to achieve energy independence, energy security and deep decarbonization at an affordable cost (LME, 2018). Regarding energy efficiency, Lithuania has committed to contribute to the EU's 2030 energy efficiency target by ensuring that primary and final energy intensity is 1.5 times below the 2017 level by 2030 (NECP, 2019).

The timely achievement of those targets would be difficult without the completion of the energy sector's liberalization, and a nation-wide rollout of smart electricity meters. From January 2021, household's retail electricity price deregulation was started, and the mass installation of smart meters will commence in the first quarter of 2022. It should be also added that Lithuania is one of the most affected EU member states by energy poverty. According to the EU Survey on Income and Living Conditions (Eurostat, 2021), in 2019, 26.7 percent of its people could not afford to keep their houses adequately warm, that is the second highest percentage among the EU countries after Bulgaria. This context might suggest that the provision of personalized information about electricity use might not encourage households experiencing energy poverty to reduce their electricity consumption as these households might use electricity below the subsistence consumption level.

2.2.2 Formation of the treatment and control groups

The experiment was implemented and financed by a national electricity and gas distribution company, AB ESO, which is based in Lithuania. The formation of the treatment and control groups was done in the following steps. First, the sample of households living in apartments or detached houses and urban or rural areas in Lithuania was selected. Second, by using a simple randomization, from each block, a group of households was selected to receive the treatment in the form of personalized hourly electricity consumption data on their personal ESO web portals. The provision of hourly electricity consumption information for the treatment group was enabled by replacing old household electricity meters with new smart meters.[2]

In total, 2,927 households were selected to form a treatment group. Prior to the start of experiment, as in general population, the randomly selected households were already equipped with mainly two types of electricity meters: electromechanical and analogue electricity meters. Some of electromechanical electricity meters had an internal memory for storing hourly electricity consumption data. However, most of the selected households had electricity meters that did not have internal memory for storing historical hourly electricity consumption. After dropping households without available historical electricity consumption data or with inaccurate and missing data due to faulty old meters, we were left with 419 households in the treatment group. Hourly electricity consumption data from old electricity meters were retrieved by AB ESO after these meters were replaced by new smart meters. A control group of 702 households equipped with electromechanical electricity meters with internal data storage capacity was randomly selected from the same blocks as the treatment group (households living in apartments/detached houses and urban/rural areas). Again, after dropping households without any available historical electricity consumption data for the pre-treatment period or with inaccurate and missing data due to faulty old meters, 632 households formed our control group. Hourly electricity consumption data from these meters were retrieved after the treatment ended.

[2] The explicit consent for replacing old meters with the new ones from participating households was not needed as AB ESO owns these meters. However, households had an option to opt-out from this experiment if they wanted (just few cases of opt-outs were reported).

2.2.3 The treatment

Hourly electricity consumption of participating households was observed for 24 months – 12 months before (1 June 2015 – 31 May 2016) and 12 months after the start of the treatment (1 July 2016 – 30 June 2017). The length of the experiment was decided to be based on the objective to study the persistence of the treatment effect, and the need to control for the seasonal variation in electricity consumption. Most of the smart meters for households in the treatment group were installed in one month (June, 2016). We do not take this month in our analysis, as it caused many missing or inaccurate observations.

The main difference between the treatment group and the control group is that households in the treatment group have received additional information available on their personal ESO web portals (see Figure 2.1). This additional information includes information about a particular household's hourly electricity consumption patterns, highlights electricity use in the morning, day, evening and night hours, and shows the expected electricity consumption for the current month. About a half of households in both groups logged into their personal ESO accounts. Unfortunately, we were not provided with data on who from experiment participants checked their personalized electricity consumption information.[3]

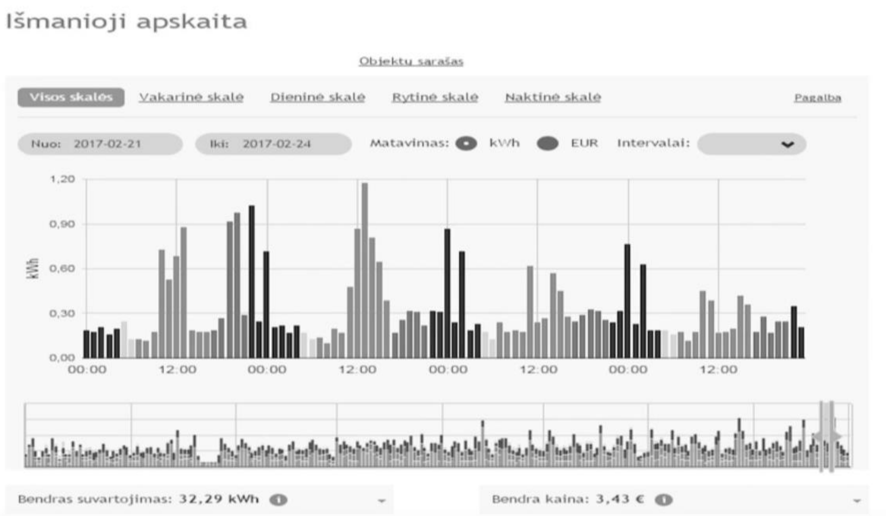

Figure 2.1 Additional information on the personal web portal available for the household in the treatment group

[3] We asked AB ESO to provide us with such information, but the company refused to do it on the grounds of personal data protection laws and due to lack of resources to retrieve such data.

2.3 Estimation of ATEs

Our key objective of household randomization to the treatment and control groups is to identify the causal effect of the descriptive information provided by the personal web portals on the average consumption of electricity. Ideally, we would have liked to have as "clean" as possible a randomized controlled trial (RCT) setting. However, due to technical difficulties to retrieve historical electricity consumption from the old meters for the control group in the beginning of experiment we were left with uneven daily observations across time for the treatment and control groups. The unbalanced number of observations across the pre- and post-treatment periods does not allow to claim that we analyze an ideal RCT.[4] However, our experiment arguably resembles RCT, which is why we consider it to be more a "natural field experiment," in line with the taxonomy provided by (Harrison & List, 2004). In the absence of a completely "clean" RCT, we must turn to natural experimental methods that try to mimic the randomized allocation setting under reasonable conditions. A major concern is that the control and treatment groups might be different in observable and unobservable variables, and these differences may be correlated with the outcome variable (electricity). A common method of controlling for observable and time-invariant unobserved heterogeneity is to use difference-in-differences (DID) models. The main advantage of DID method is that it is an intuitive and flexible way to measure the impact of an intervention, which has been widely used in studies based on natural field experiments. Moreover, it also relaxes the assumption of selection only on observables and provides a tracible way to account for biases from time invariant unobserved factors (Abadie & Cattaneo, 2018; Angrist & Pischke, 2009; Imbens & Wooldridge, 2009).

To estimate the ATEs, we run the following difference-in-differences regression model:

$$y_{it} = \beta_1 TREAT_i + \beta_2 POST_{it} + \beta_3 TREAT_i * POST_{it} + \boldsymbol{\mu} X_t' + \alpha_i + \varepsilon_{it}, \qquad (2.1)$$

where y_{it} is the daily electricity use (in kWh) in household i at time t, $TREAT_i$ is a dummy variable indicating whether household i is in the treatment group or the control group, $POST_{it}$ is a dummy variable indicating

[4] See Figure A2.1 in the Appendix for the number of observations available for each month for both the treatment and control groups before and after the treatment.

the pre- and post-treatment periods, X_t' is a set of the time-varying covariates[5] (year-monthly fixed effects, daily temperature, and cloudiness), α_i are household fixed effects, and ε_{it} is an idiosyncratic error term (unobserved household-specific shocks). This model is estimated in OLS by using the standard fixed-effects estimator with Huber-White standard errors, which are clustered at the household level to account for serial correlation (Bertrand et al., 2004). The estimated coefficient β_3 measures the ATE of provision of personalized information about hourly electricity use.

2.4 Results and discussion

2.4.1 Variable description and summary statistics

Table 2.2 presents the average daily electricity consumption for households in the treatment and control groups along with the other control variables one year before and one year after the delivery of the treatment. In our main analysis, we exclude all observations with zero values of electricity consumption. We have strong reasons to believe that most of these observations are mistakes; hence, we think it is unreasonable to consider them as truthful observations.[6]

Panel A of Table 2.2 shows that the average daily electricity use in the treatment group increased by 0.095 kWh (from 7.575 kWh to 7.670 kWh), while in the control group it decreased by 0.359 kWh. We can observe that our sample is imbalanced in terms of the temperature variable across the treatment and control groups before the start of the treatment.[7] This could be

[5] At the time of experiment, retail electricity market was not yet liberalized and all households were subject to the same regulated electricity prices. Unfortunately, we do not observe household characteristics such as income.

[6] We identified 15-25 percent of total monthly observations with zero electricity consumption values for the treatment group one month before and two months after the major installations of smart meters in June 2016. In other months, we observe only 1-2 percent of observations with zero values for both the treatment and control groups (see Figure A2.1 in the Appendix). It seems that the replacement of old meters temporarily disrupted the collection of electricity consumption data for some households. Furthermore, zero value observations suggest that all appliances, including the fridge and freezer, must have been switched off for the entire day. Smart meters themselves consume a small amount of electricity, which should be visible in our data.

[7] We have conducted the parametric t-test, a non-parametric test based on K-sample test on the equality of medians, and the Mann-Whitney two-sample test to test the equality of sample characteristics between the treated and control groups before

explained by the fact that in the control group we have more observations in the cold-season months (see Figure A2.2 in the Appendix). The DID approach will help us to control for the seasonal variation, and changes in weather conditions. In panel B of Table 2.2, we present the average daily electricity consumption across the housing types (houses *vs.* apartments) and geographical locations (urban *vs.* rural). We observe that households living in the rural parts of the country, and those who are living in detached houses consume twice as much electricity than households living in apartments and urban areas.

Table 2.2: Descriptive statistics before and after the treatment

	Panel A: Definition and summary statistics of variables							
	Pre treatment				Post treatment			
	Treated		Control		Treated		Control	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Daily electricity (kWh)	7.575	6.364	7.687	8.91	7.670	7.033	7.328	8.473
House type (1= Detached house)	0.266	0.442	0.254	0.435	0.291	0.454	0.214	0.410
Daily temp. (C^o)	6.808	8.402	5.825	8.290	7.010	8.222	7.164	8.235
Daily cloudiness (%)	67.07	30.62	68.14	30.37	73.87	26.89	73.75	26.70
Location (1=Rural)	0.204	0.403	0.164	0.370	0.224	0.417	0.136	0.343
No. of non-zero daily obs.	103,547		185,613		150,709		230,249	

	Panel B: Average daily electricity consumption by location and housing type, kWh		
	Mean	S.D.	No. of daily obs.
Rural	12.530	14.300	113,495
Urban	6.495	5.360	541,408
Detached house	12.170	12.850	162,723
Apartment	6.012	4.655	492,180

the treatment period started. All test results suggest that we cannot reject the hypothesis of no differences between the treatment and control groups in terms of electricity use. However, we find significant differences in terms of house type, location and weather variables.

Figure 2.2 plots the dynamics of the monthly daily average electricity consumption before and after the treatment for the treatment and control groups. It is evident that the residential consumption of electricity is seasonal – the electricity tends to be used less in summer months than in winter months. Both the treatment and control groups have very similar pre-treatment and post-treatment trends. However, in May-August 2016, the average daily electricity consumption of the treatment group is below that of the control group. A possible explanation of this discrepancy is the disruption caused by the installation of new smart meters for households in the treatment group. In addition, during this time period, the number of valid observations for the control group is much higher than for the treatment group (see Figure A2.2 in the Appendix). Overall, we can conclude that, from the visual inspection of the raw average electricity consumption data across the treatment and control groups, it is not clear whether the treatment had any effect at all.

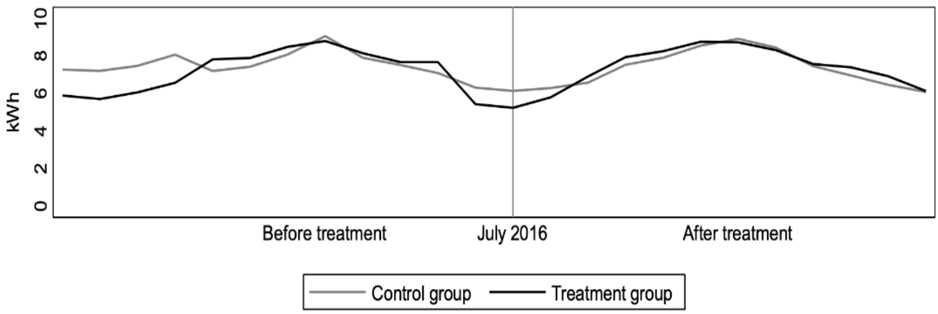

Figure 2.2: Daily average electricity use 12 months before and after the treatment

2.4.2 Average treatment effects (ATEs)

To estimate the ATE of descriptive information provision on electricity consumption, we employ the fixed-effects DID model as described in equation 2.1. The estimation results summarized in Table 2.3 reveal a significant treatment effect, namely an average daily reduction of 0.661 kWh (or about 8.6%). This effect is equivalent to an annual electricity saving of 241 kWh per average household.[8]

We would like to highlight that our estimated ATE of information provision on electricity use is much higher than ATEs found in other similar

[8] We multiply the coefficient of daily ATE (0.661 kWh/day) by the total number of days in a year (365 days) to find the annual electricity saving.

studies that use data from Western countries, such as the U.S. or Germany. For instance, our ATE estimate is higher than ATE estimates of Allcott (2011), Costa and Kahn (2013), and Ayres et al. (2013) who document ATEs of around -2 percent in the U.S, or Schleich et al. (2013) (-4.5% in Linz, Austria) and Andor et al. (2020) (-0.7% in Germany). The difference between our estimated ATE and ATEs of the above-mentioned studies could be explained not only by geographical and methodological differences, but also by the nature and intensity of interventions implemented. Unlike our study, these studies use informational interventions mixed with either energy saving tips, social comparisons or social norms. Interestingly, our ATE estimate is still higher than the ones from scant studies that employ a purely descriptive type of information provision. For example, Gleerup et al. (2010) find an ATE of between 0 and -0.3 percent in Denmark. The only exception is the study by Gans et al. (2013) who find a relatively higher ATE (a reduction in energy use between 11 and 17% in Northern Ireland). However, to understand whether descriptive information provision is more or less superior than other types of informational interventions require more studies that investigate the *isolated* effect of descriptive information provision.

Table 2.3: ATE on daily electricity consumption (in kWh)

Variables	Electricity
TREAT*POST	-0.661^{***}
	(0.139)
POST	0.292
	(0.177)
Temperature	-0.066^{***}
	(0.007)
Cloudiness	0.004^{***}
	(0.000)
Year-month fixed effects	Yes
Household fixed effects	Yes
No. of daily observations	654,903
No. of households	1,051

Notes: The standard errors clustered at the household level are in parenthesis. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

2.4.3 Quantile treatment effects

Recent developments in the impact evaluation literature stresses the importance of measuring the distributional effects of a treatment (see, e.g., Ayres et al., 2013; Bedoya et al., 2018; Havnes & Mogstad, 2015). To fully understand how personalized information provision affects households with different levels of electricity consumption, we estimate the quantile treatment effects (QTEs) following the specification of (Firpo et al., 2009).[9]

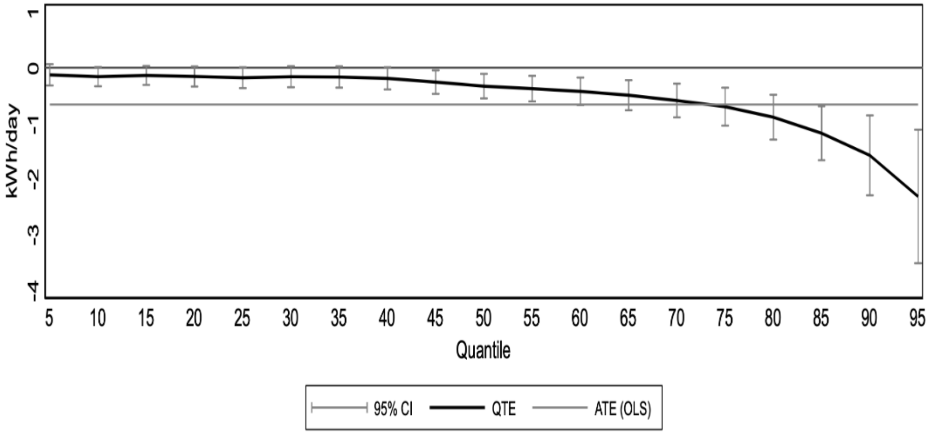

Figure 2.3: Quantile Treatment effects

Figure 2.3 presents the estimated QTEs together with 95 percent confidence intervals. For comparison, we also plot in the same figure the ATE estimated using equation 2.1. Figure 2.3 reveals that the treatment effects are largest at the highest percentiles of the electricity consumption distribution. Compared to the ATE, a significant and higher reduction in electricity use is observed for households with electricity consumption levels above the 75th percentile. Contrariwise, for electricity consumption levels above the 40th percentile and below the 75th percentile, the QTEs are smaller than the ATE. We do not find significant QTEs for electricity consumption levels below the 40th percentile. These results show the importance of addressing distributional effects of informational interventions, and that these types of interventions are more effective among higher electricity users. Similar findings were shown by Schleich et al. (2013) who reported the heterogenous ATEs of feedback information provision on electricity consumption in Austria.

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[9] To estimate the QTEs, we use the Stata command developed by Rios Avila (2019).

2.4.4 Persistency of treatment effects

Next, we investigate whether the treatment effect is persistent. Answering this question is crucial for understanding whether non-price instruments like behavioral interventions in the form of information provision could bring a long-lasting option for energy conservation. To examine the persistency of the treatment effect, we plot the ATEs for each month of the experiment for both treatment groups (see Figure 2.4). The monthly ATE's are estimated by using the following DID model:

$$y_{it} = \gamma_0 TREAT_i + \gamma_1 POST_{it} + \sum_{m=1}^{12} \beta_m (MONTH_m * TREAT_i) + \boldsymbol{\mu} X_t' + \alpha_i + \varepsilon_{it}, \qquad (2.2)$$

where $MONTH_m$ are the dummy variables representing a specific month (m = 1,…,12) in the post-treatment year. The remaining variables are the same as in the main model described above. The estimated coefficients of the interaction terms between the monthly dummies and the treatment variable, β_m, give the monthly ATEs. As before, the model is estimated by using OLS with household fixed effects, and clustered standard errors.

Figure 2.4 shows that the treatment reduces electricity consumption significantly in all months after the intervention. In line with similar studies, this result suggests that continuous treatment in the form of the provision of descriptive information could encourage persistent electricity saving choices. For instance, Schleich et al. (2017) for Austria, Allcott and Rogers (2014) and Brandon et al. (2017) for the U.S. find similar results by using other types of informational interventions. Interestingly, Byrne et al. (2018) argue that the persistency effect of information provision in the form of social comparison depends on household's beliefs in pre-treatment energy use and the actual level of consumption before the treatment. They find a persistent treatment effect only after accounting for pre-treatment energy use.

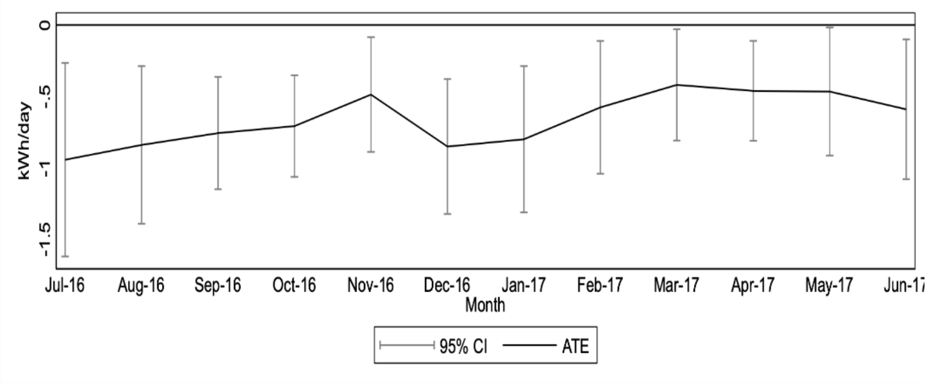


Figure 2.4: Persistency of the treatment, monthly ATEs over the period of the treatment

At this juncture, it is worth raising the question of what drives these persistent electricity savings? The literature suggests two explanations. First, a continuous provision of information could induce electricity conservation by influencing an individual's behavior. One example of such permanent behavioral change is the formation of a habits, which means that some actions, like switching off lights, or turning off appliances when they are not in use become automatic. Second, the provision of information could encourage households to invest in more energy efficient housing equipment (see, e.g., Allcott & Rogers, 2014). Both of these drivers could explain the persistent ATE on electricity consumption. We might think that providing continuous descriptive information about the household's hourly electricity consumption might enable the household to better understand its electricity consumption patterns, and to identify times of relatively high electricity consumption, caused by either inefficient appliances or sub-optimal behavior. This information would encourage the household to alter its electricity consumption patterns either by changing its habits or by changing its in-home capital stock, or both.

2.4.5 Heterogeneity analysis

An effective policy intervention requires identifying a particular segment of users or a geographical area, where the intervention effect could be more pronounced, and could bring a substantial change. For this purpose, we examine whether the ATEs vary among households (rural vs. urban households, households living in houses vs. apartments). Below we present and discuss the results of estimating models and exploring heterogeneity.

Table 2.4: ATE on daily electricity use by location and housing type

	Location (1)		House type (2)	
	Rural	Urban	House	Apartment
TREAT*POST	-1.423**	-0.465***	-1.078**	-0.515***
	(0.542)	(0.124)	(0.403)	(0.123)
POST	1.006	0.184	1.072*	0.0638
	(0.782)	(0.138)	(0.534)	(0.139)
Controls	Yes	Yes	Yes	Yes
Year-month f.e.	Yes	Yes	Yes	Yes
Household f.e.	Yes	Yes	Yes	Yes
No. of daily obsv.	113,495	541,408	162,723	492,180
No. of households	181	870	258	793

Notes: 1. The standard errors clustered at the household level are in parenthesis. ${}^{*}p < 0.05$, ${}^{**}p < 0.01$, ${}^{***}p < 0.001$. 2. “f.e.” stands for fixed effects.

Rural vs. urban households

First, we estimate the ATEs in rural and urban households. From the estimation results reported in column 1 of Table 2.4, it is evident that information provision significantly reduces energy consumption in both groups of households. However, the treatment-induced electricity conservation in rural households is higher by a factor of three: in rural households, electricity consumption decreased by 1.423 kWh/day, while in urban households, only by 0.465 kWh/day. We might think that rural households have more options available at hand to reduce their electricity consumption as, on average, they consume twice as much electricity as urban households (see Table 2.2).

Houses vs. apartments

Then, we explore the heterogeneity of the ATEs across households’ housing types. Column 2 in Table 2.4 shows that descriptive information provision significantly reduces electricity consumption for households living in detached houses and apartments, but the treatment effect is much larger for households living in detached houses (1.078 kWh/day) compared to households living in multi-unit apartments (0.515 kWh/day). As in the case of rural versus urban households, users living in detached houses consume twice as much electricity as households living in apartments. Again, this might suggest that households living in detached houses have more choice when it comes to electricity conservation.[10]

2.4.6 Robustness tests

Hourly analysis

Granularity in our data gives us an opportunity to estimate the intervention effect by using hourly data. We estimate the hourly ATE by using the same empirical model as in equation 2.1; we only add hourly fixed effects to it. We also exclude all observations with a zero level of hourly electricity consumption. The results presented in Table 2.5 show that descriptive information provision reduces electricity consumption by 0.027 kWh per hour. The estimated effect can be translated to a daily reduction of 0.648 kWh (8.4%), which is comparable to the ATE estimated with daily data (0.661 kWh or 8.6%).

Table 2.5: ATE on hourly electricity consumption (in kWh/hour)

Variables	Electricity
TREAT*POST	-0.027^{***}
	(0.006)
POST	0.009
	(0.007)
Temperature	-0.003^{***}
	(0.003)
Cloudiness	0.000048^{***}
	(0.000)
Year-month fixed effects	Yes
Household fixed effects	Yes
Hour fixed effects	Yes
No. of hourly obsv.	15,470,564
No. of households	1,038

Notes: The standard errors clustered at the household level are in parenthesis.
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

[10] We have investigated the interaction treatment effects in the case for households living in apartments but in rural area and in the case of households living in detached houses but in urban areas. Unfortunately, there are not so many households in our sample for this zooming-in analysis. There are only 22 households in our sample living in apartments in the rural areas and 98 in detached houses in the urban areas. Still, we run our triple interaction DID models to see if the treatment effects are different between apartments and detached houses given that they are located in rural or urban areas. We found no statistically significant different treatment effects between these groups.

Randomized inference

As a robustness test, we repeat our analysis by using randomization inference (RI). Since the assignment of households to the treatment group and the control group was not entirely random (see Section 2.3.2), and since we rely on a relatively small household sample, we think it is important to test for the causal effect of our treatment by using an RI approach. Originally developed by Fisher (1953) and later developed by Rosenbaum (2002), RI places no distributional assumptions on the errors and is valid even in small samples. This method is being increasingly applied to experimental data (Hess, 2017).

RI is a simulation method that computes the empirical distribution of the difference-in-differences estimate for a large number of randomly generated placebo treatments under the null hypothesis of no effect. From a large number of simulations, the critical value of the treatment effect can be determined for the inference test.[11] We randomize the assignment of households to the treatment and control groups and use the difference-in-differences coefficient (interaction term in eq. 2.1) as the test statistic. Our null hypothesis is that the provision of personalized descriptive information on web portals had no effect on electricity consumption, or $\beta_3 = 0$ in equation 2.1. We use 1000 replications in the "ritest" command developed by Hess (2017) to conduct the RI test in Stata. The estimated *p*-value (0.000) using the RI test confirms that the treatment effect on electricity consumption is significant. We report this result by including the *p*-value in square brackets in Table 2.6.[12]

[11] See Rosenbaum (2002) or Imbens and Rubin (2015) for more information.

[12] We also conducted the RI test for all the other models we estimated, and we did not find any different results. The computed *p*-values using the RI approach are consistent with the *p*-values generated using the cluster-robust method, except for low electricity users. The ATE for low electricity users is significant at 10 percent level, though it was insignificant before.

Table 2.6: ATE on daily electricity consumption (in kWh), RI method

Variables	Electricity
TREAT*POST	-0.661★★★/☆☆☆
	(0.139) **[0.000]**
Controls	Yes
Year-month fixed effects	Yes
Household fixed effects	Yes
No. of daily obsv.	654,903
No. of households	1,051

Notes: Randomization inference and clustered error methods were conducted to obtain alternative *p*-values. ★★★/☆☆☆ p<0.01, ★★/☆☆ p<0.05 and ★/☆ p<0.1 indicate significance levels, where filled stars ★ indicate significance levels preserved under randomization inference, while empty stars ☆ indicate significance levels that are sustained by the cluster-robust standard errors. The standard error clustered at the household level is in parentheses, and *p*-value obtained using randomization inference is provided in squared brackets.

2.5 Final remarks and Policy implications

Our daily energy consumption decisions are highly vulnerable to imperfect information problems. Households typically receive utility bills where all electricity use during a fixed period is lumped together. The lack of direct feedback potentially leads to mistakes in households' decision-making. In this study, we tested whether the provision of personalized information about hourly electricity use encouraged households to conserve electricity. Our analysis contributes to the existing literature in the two following ways. First, unlike previous studies, our field experiment was based in Lithuania, where a high share of households has been experiencing energy poverty. On the one hand, it could mean that these households might be already consuming low electricity levels and might have no room to reduce electricity use any further. On the other hand, households subject to energy poverty might be relatively more responsive to relevant information provision. So far, most experiments directed towards electricity conservation have been implemented in the U.S. and other rich OECD countries, where people on average consume more electricity. Second, our experiment aimed to estimate the effect of *pure* descriptive information provisions on households' electricity use without combining it with other normative types of information, such as energy saving tips or goal setting. To the best of our knowledge, only few experiments have tested this type of intervention. These studies used different modes for treatments, such as sending letters to the energy consumers or using expensive in-house displays. The postal, technological, administrative and psychological costs of such policy interventions are substantial (Allcott & Kessler, 2019; Andor et al., 2020). Digitalization of energy use information through smart metering does change the customer interface of utilities and extends the spectrum of possibilities for energy saving interventions. Clearly, more research is needed to gauge the potential of such information digitalization. Our study aims to fill this gap in the literature by showing how a *purely* descriptive type of information provision through web portals can be an effective way to achieve energy savings in the residential sector.

We found that, on average, descriptive information provision reduced electricity consumption by 0.661 kWh (or 8.6%) per day in Lithuanian households. This is equivalent to an annual energy savings of 241 kWh per household. Furthermore, our results revealed that most reductions in electricity use occurred among households at the highest percentiles of electricity consumption. On the other hand, the intervention had no effect in low-consumption households. This result confirmed our initial expectations: low electricity users are not able to reduce electricity even if they are exposed to more detailed information about their electricity consumption. The implication of this result is vital for policy makers, as it explicitly suggests which group of consumers policy makers should target to achieve energy conservation objectives. In similar vein, our heterogeneity analysis also shed some light on the effect of our intervention based on the type of house where the household lives in, and the location of the living place. We found that the treatment effect was more pronounced for households located in rural areas and living in detached type of houses than for household located in urban areas and living in apartment houses. Finally, our persistency analysis revealed that, on average, the treatment effect was persistent for the duration of the experiment. This finding supports the claim that non-price interventions in the form of descriptive information provision could serve as an effective tool for energy conservation even in less wealthy OECD countries.

Even though our study provides insightful policy implications and fills a clear gap in the literature, we cannot rule out some of its limitations. First, as we do not have information about the frequency of logging into the web portal, the estimated treatment effects are contingent upon the intensity of viewing the provided information. Second, our study does not delve into the channels through which the ATE is derived. Finally, our informational intervention is purely descriptive, and we did not consider other types of interventions, such as energy saving tips or social comparisons, that would allow us to evaluate the additional potential to decrease electricity consumption. The recent meta-analysis by Buckley (2020) offers some insights about what we could expect by adding such information to our treatment. Buckley (2020) finds that providing households with generic advice or social comparison information did not have desired effect on energy conservation. Most studies analyzed by Buckley (2020) come from the U.S. and Western European countries. The future research could uncover how different modes and types of information provision alter energy consumption patterns among households in other less wealthy countries.

3. SPILLOVER EFFECT OF SOCIAL COMPARISON INFORMATION: EXPERIMENTAL EVIDENCE ON RESIDENTIAL ENERGY AND WATER USE

The field of behavioral economics has brought attention to promising ways of encouraging people to make better choices for themselves and society as a whole. The findings in the field have inspired a wide array of environmental policies in multiple areas, such as energy, water, and food consumption; transport and car choice; waste management and resource efficiency; compliance with environmental regulations; and participation in voluntary schemes.[13] Social (or peer) comparisons alluding to social norms are some of the most popular behavioral interventions that have been widely used to induce resource conservation actions, particularly for energy and water resources. A large body of literature provides evidence on social comparisons being effective in reducing residential energy and water consumption (for a review, see, e.g., Każukauskas et al., 2021). Most of these studies have focused on evaluating the effects of behavioral interventions on targeted resource outcomes. However, it is very likely that the intended social comparisons do not only affect the targeted resource domain but extend (spill over) beyond the targeted outcome to other resource domains, changing the cost-effectiveness and welfare implications of the intended intervention (see, e.g., Jessoe et al., 2021). So far, these "cross-domain" spillover effects are not well-understood and have received very little attention in the academic literature, presumably due to the lack of opportunities to perform analyses that can examine such effects.

This paper uses data from a natural field experiment to study whether social comparisons affect households' energy and water consumption. Our field experiment was designed to study main and cross-domain spillover effects in both resource domains. In particular, we examine whether electricity use-targeted social comparison spills over into the use of water and heating energy—and conversely whether water use-targeted social comparison spills over into the use of electricity and heating energy.

To the best of our knowledge, there are only two published field-experimental studies that have investigated cross-domain spillover effects of social comparisons (i.e. Carlsson et al., 2021; Jessoe et al., 2021). However,

[13] See Lourenço et al. (2016) for an overview of behavioral policy initiatives and institutional developments regarding the policy application of behavioral interventions in Europe.

these studies examined whether social comparisons targeting the residential water domain spill over to the residential electricity domain. That is to say, there exists no study that evaluates cross-domain spillover effects of water and electricity social comparisons in the same experimental setting. Furthermore, our study contributes to the behavioral economics literature by experimentally scrutinizing the spillover effect of social comparison interventions aimed at electricity conservation on hot water consumption and space heating energy use. To the best of our knowledge, it has never been tested in the experimental setting whether behavioral interventions targeting electricity use spill over into the hot water and space heating domains. The heating of space and water is a central resource domain that, for example, in the European Union (EU) in 2019 accounted for about 80% of total household energy consumption and significantly contributed to the EU's carbon footprint (Eurostat, 2020b). This means that even a small reduction in the use of hot water and heating energy induced by behavioral interventions like social comparisons may result in substantial environmental benefits.

Our field experiment was started in March 2016 in Umeå, a city in northern Sweden, and the continuous treatments lasted for 1 year. The treatments were delivered via preinstalled in-home displays, which were salient and updated in real time.14 We constructed two separate treatment groups—one for electricity use-targeted social comparison and another for water use-targeted social comparison. We find that electricity social comparison treatment induced not only direct electricity savings but also spillover savings of hot water and heating energy. On average, electricity use decreased by 6.6% (111 kWh per year), while nontargeted consumption of hot water and heating energy decreased by 9.7% (about 143 kWh per year) and 0.9% (about 90 kWh per year), respectively. Meanwhile, water social comparison induced neither direct nor indirect effects on the use of water, electricity, or heating energy. We argue that the difference in direct treatment and spillover effects between the water and electricity treatments might be explained by differences in preexisting social norms of resource utilization, showing that the social norm for conservation of energy is stronger than that for the preservation of (cold) water in our study area. Furthermore, moral dissonance could help explain spillover effects from the electricity domain to the water and heating domains. The rest of the paper is structured as follows. In Section 3.1, we present a brief literature review summarizing the findings of several field-experimental

[14]The dwellings of the participating households were already equipped with real-time displays prior to the experiment's start. Thus, we avoid the "new-gadget effect," that is, the effect that people pay attention to and play around with their new appliances.

studies that have empirically tested the spillover hypothesis in the context of various behavioral interventions. In Section 3.2, we describe our experimental design. In Section 3.3, we present the experimental data and describe and interpret the results of our empirical analysis. We conclude in Section 3.4.

3.1 Brief literature review

In this section, we briefly review results from previous field-experimental studies conducted to analyze the direct and spillover effects of various informational behavioral interventions, including social comparisons.

It is well established that social comparisons promote household resource conservation behavior, at least in the short run (see, e.g., review studies of Abrahamse et al., 2005; Darby, 2006; Ehrhardt-Martinez et al., 2010; Faruqui et al., 2010; Fischer, 2008). Psychologists argue that peer comparisons may activate social norms—descriptive and injunctive norms—that cause people to change their behavior (Cialdini et al., 1991; Reno et al., 1993).15 However, whether social comparisons "spill over" into untargeted resource domains is less well understood and has received very little attention in the behavioral environmental economics literature, presumably due to lack of opportunities to perform such type of analysis.

To the best of our knowledge, there are only three studies that examine cross-domain spillover effects of social comparisons, and all of them target the water resource domain (Carlsson et al., 2021; Goetz et al., 2021; Jessoe et al., 2021). All of these studies find that the treatment spilled over from the targeted resource domain to an untargeted resource domain. In other words, social comparisons induced conservation not only for targeted domains but also for untargeted ones. The size of average treatment spillover effects (SATE) ranges from 1.3% to 9%.

The largest SATE of 9% was found by Carlsson et al. (2021), who measured the spillover effect of water social comparison on electricity consumption in the town of Jericó in Colombia. Their treatment consisted of a monthly water consumption report that included peer comparison information of households with similar characteristics as well as injunctive messages about participating households' performance with respect to their

[15] Descriptive norms specify "what most people do in a particular situation, and they motivate action by informing people of what is generally seen as effective or adaptive behavior there. Injunctive norms . . . specify what people approve and disapprove within the culture and motivate action by promising social sanctions for normative and counter-normative conduct" (Reno et al., 1993, p. 104).

peers ("Excellent," "Average," or "Room to improve"). Carlsson et al. (2021) find no significant spillover effects for the full sample did find such effects for the sample of households that used water efficiently before the intervention. The authors argue that the cross-domain spillover effect could be explained by cognitive (moral) dissonance theory, that is, that people seek consistency in behaviors that are determined by the same underlying motives.

Jessoe et al. (2021) examine the cross-domain spillover effects on electricity consumption of a natural field experiment that provided social comparisons of water consumption for households residing in single-family homes in California, U.S. They find a significant average treatment effect (ATE) on water consumption and no significant SATE on electricity use for the entire duration of the treatment. However, a significant SATE of 2% is found in one utility during a severe drought in the study area. They also show that electricity savings occur during peak hours and are mainly driven by behavioral changes rather than mechanical ones.

Goetz et al. (2021) measure the spillover effect of hot water social comparison on households' heating energy use and cold-water consumption in 782 buildings in Switzerland. The intervention consisted of different behavioral instruments, namely own and social comparison information regarding the individual household's hot water consumption, saving tips, and 5% incentivized saving goal. Goetz et al. (2021) find a SATE on cold water consumption of 2.57% and a SATE on room heating energy consumption of 5.44 percent. While the authors note the presence of the mechanical link between hot water and cold water consumption, they claim that behavioral changes, namely strengthened environmental self-image, are behind the positive spillover effects.

There are also a few other studies that use other types of informational interventions to investigate spillover effects. Alacevich et al. (2021) find that the introduction of a new policy that requests households to engage in waste separation by providing information about the benefits and pro-environmental consequences of organic waste recycling had a positive spillover effect (8%) on treated individuals' total waste production in Sweden. In a similar setting, Ek and Miliute-Plepiene (2018) evaluate the spillover effect of food waste collection policy on the amount of packaging waste collected for recycling. They find a positive SATE of 8 percent. Tiefenbeck et al. (2013) study the spillover effect of weekly water consumption feedback on electricity consumption in the U.S. They find that the treatment reduced water consumption, but it increased electricity consumption by 5.6 percent. They argue that the negative spillover could be due to moral licensing.

Table 3.1 summarizes the findings of the previous studies in terms of targeted and untargeted treatment resource domains; type of treatment; whether the experiment designed bidirectionally that goes from the targeted resource domain to the untargeted resource domain and vice versa; and whether subjects/households have a pecuniary motive to conserve the untargeted resource or not. It also accounts for the mode of treatment provision, duration of the treatment, frequency of measurement, direct average treatment effects, the type (positive, negative, or no effect) and size of average treatment spillover effects, geographical location of the experiment, and sample size of the control and treatment groups.

Unlike the previous studies summarized in Table 3.1, our paper aims to expand the existing literature in the field of behavioral and environmental spillover effects in the following two unexplored directions. First, our field experiment allows us to examine the cross-domain spillover effects of water and electricity social comparisons in the same experimental setting. By looking at spillover effects of electricity and water social comparisons on two types of resource domains (energy and water) in the same social context, we can examine whether preexisting, resource-specific social norms of resource use led to different spillover effects. Second, our experimental setting allows us to explore whether non-monetary (moral) incentives mainly drive the spillover effects of social comparison by analyzing the spillover effects on the energy use that households do not need to pay. One common feature of all the studies summarized in Table 3.1 is the presence of a pecuniary motive to conserve the untargeted resource. As households are required to pay for the use of the untargeted resource directly, attention-increasing information might motivate them to save the secondary resource for the sake of monetary gains rather than moral incentives. Our study differs from the abovementioned studies in that we can test the spillover effects for energy use that households pay for (energy for heating water) and for energy that households do not pay for (energy for heating space).[16]

[16] Our field experiment participants have to pay for their smart meter-measured use of electricity, cold water, and hot water but not for space heating. Space heating costs are included in the price of apartment rents that are regulated by the state of Sweden.

Table 3.1: Summary of the field-experimental studies on spillover effects

Study[17]	Treatment resource domain	Untargeted (spillover) resource domain(s)	Type of treatment	Experiment designed bidirectionally?	Is there a pecuniary motive to save the untargeted resource?	Mode of treatment provision	Duration of treatment	Data frequency in measuring spillover effect	Direct average treatment effect (ATE)	Type and size of average treatment spillover effect (SATE)	Location	Sample size[18]
1	2	3	4	5	6	7	8	9	10	11	12	13
Our study	Electricity	Cold and hot water, indoor temperature	Social comparison	Yes	No, for energy for space heating Yes, for energy for water heating	In-house displays	12 months	Daily	-6.6%	Positive spillover on hot water (-9.7%), positive spillover on indoor temperature (-0.9%)	Umeå, Sweden	100 (T) 315 (C)
	Cold and hot water	Electricity, indoor temperature	Social comparison						No effect	No effect		110 (T) 315 (C)
Tiefenbeck et al. (2013)	Water	Electricity	Own feedback with saving tips[19]	No	Yes	Weekly flyers	6 weeks	Daily(water) and weekly (Electricity)	-6.0%	Negative spillover (5.6%)	Lynnfield, Massachusetts	686 (T) 676 (C)
Ek and Miliute Plepiene (2018)	Food waste collection	Amount of packaging waste collected for recycling	Introduction of a food waste collection policy	No	Yes	Policy shift	5 years natural experiment	Yearly	37%	Positive spillover (13%)	Sweden	244 (staggered)
Alacevich et al. (2021)	Waste separation	Waste production	Introduction of a waste separation policy	No	Yes	Mailed brochure	4 years natural experiment	Monthly	Not estimated	Positive spillover (-8%)	Partille, Sweden	4,324 (staggered)

17 The studies are listed in chronological order.

18 (T) refers to the number of households (subjects, municipalities) in the treatment group. (C) stands for the number of households (subjects, municipalities) in the control group.

19 By tips, we mean the treatment also includes general or customized advice on how to conserve the targeted resource.

Carlsson et al. (2021)	Water	Electricity	Social comparison	No	Yes	Monthly letters	12 months	Monthly	-6.2%	Positive spillover for efficient water users pre-treatment (-9.1%)	Jerico, Colombia	379 (C) 389 (T)
Jessoe et al. (2021)	Water	Electricity	Social comparison with saving tips	No	Yes	Bi-monthly letters by post and email	12.5 months	Hourly	-4.9% in the whole treatment time and – 2.9% in the summertime	Positive spillover in summer months (-2.2%)	City of Burbank, Los Angeles	4,559 (T) 2,782 (C)
Goetz et al. (2021)	Hot water	Cold water	Social comparison, own feedback, saving tips, 5% saving goal with a lottery for the attainment of the goal	No	Yes	email	4 months	Monthly	-6.02%	Positive spillover (-2.57%)	Switzerland	3,814 (T) 961 (C)
		Room heating						Annual percentage change in energy		Positive spillover (-5.44%)		

3.2 Design of the experiment

The field experiment was implemented in collaboration with a municipality-owned rental housing company, Bostaden Ltd, which is based in Umeå, Sweden. Bostaden Ltd owns and manages over 15,000 apartments and is in this respect the biggest actor in Umeå's rental housing market, with a market share of about 50% (60% if including student housing).

The field experiment included 525 newly built residential rental apartments equipped with real-time displays (RTD), which provide the tenants with information on their own electricity and water use, and indoor temperature. The RTDs are placed on the side of the front door and updated almost in real-time. The sampled households were divided into two treatment groups (one for electricity and one for water, numbering 100 and 110 apartments, respectively) and a control group (numbering 315 apartments).[20] The apartments were assigned to the different groups as follows: One "block batch" (a block of eight buildings) was assigned to the two treatment groups, and three block batches were assigned to the control group[21]. Each of the eight buildings in each treated block batch was then randomly assigned to one of the two treatments. The contiguous block group approach, that is, a random selection of buildings rather than of individual apartments, was applied for two reasons. First, to minimize the risk that the treatment spills over and contaminates the control group, which can happen if subjects in the control and treatment groups get in close proximity with each other (Harrison & List, 2004; Heckman & Smith, 1995). Second, our research partner had a strong preference to randomize households at the building level, expressing a concern that randomization at the apartment level might increase the risk of complaints from tenants about some apartments in a building having the new RTD design and some not.

[20] When performing the analysis, we assume that one household lives in one apartment.

[21] It is important to note that one “batch” of seven buildings containing 185 apartments in the control group were built in 2015 and fully accommodated only between 2 and 10 months before our treatment delivery. As these houses were not occupied at our experiment designing and randomization stage, our research partner Bostaden Ltd had a strong preference for keeping and assigning this batch of houses to the control group. Still, this group of seven houses is alike to other houses in our experiment. We perform the robustness check for the balanced sample by excluding this batch of seven buildings in Section 3.3.7.

Ideally, we would have liked to have a randomized trial setting that was as “clean” as possible. However, because of the above-mentioned strong preferences of our research partner, Bostaden Ltd on how to cluster the treatment and control groups, we could not conduct an ideal randomized control trial (RCT). Our experiment arguably resembles RCT, but we consider it to be more of a “natural field experiment” in line with the taxonomy of Harrison and List (2004). In the absence of a completely clean RCT, we must turn to natural experimental methods that try to mimic the randomized allocation setting under reasonable conditions. A major concern is that the control and treatment groups might be different in some ways, and these differences might be correlated with the outcome variables (electricity, water, and heating energy use). In principle, many unobservable characteristics that might confound causal identification are those that vary across households/apartments but are fixed over time. A common method of controlling for time-invariant unobserved heterogeneity is to use difference-in-differences (DID) models, which we specify in Section 3.3.2.

The decision to have two separate treatment groups was based on our objective to test whether the direct and spillover effects of the provision of peer-comparison information on different resources differ. The treated households were informed about the changes in their RTDs through printed letters distributed on March 1, 2016. The participating households were observed for 24 months—12 months before and 12 months after the treatment was introduced.

The key features of the RTD designs for the three groups (two treatments and one control) are shown and summarized in Figure 3.1. Before the experiment was introduced, all selected households had been exposed to the control RTD (top RTD in Figure 3.1), which displays the household's own current electricity and water (cold and hot) consumption in real time ("Actual consumption") and own cumulated 24-hour electricity and water use ("Last 24 hours"). The displays also show outdoor and indoor temperature and have some indicators of positive or negative consumption changes over time based on the household's past electricity and water consumption.

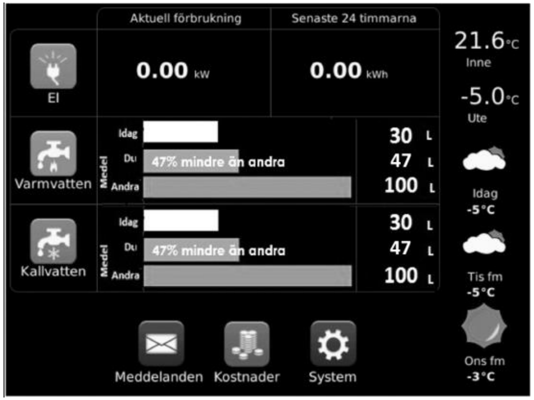
The middle and bottom RTD displays in Figure 3.1 show the new information provided by the treatment RTDs. As can be seen, three horizontal bars have been added to these displays. The top two bars, labeled “Idag and Du”, provide information about the household's consumption of the respective resource in the current 24-hour period (i.e., since midnight) and as a 7-day moving daily average, respectively. The electricity and water consumption are measured in kWh and liters, respectively. The third bottom bar, labeled

“Andra”, shows the 7-day moving daily average consumption recorded for all other RTD-equipped households in apartments of similar size. This new information allows the treated households to compare their own average consumption of electricity or water with the corresponding average consumption of similar households.

The experiment was not preannounced, and participation was nonvoluntary for the sampled households. Consequently, no monetary incentives were offered to the participants. We chose not to preannounce the experiment to the households to avoid the so-called social desirability bias, that is, that the treated subjects behave in line with the implicit objectives of the experiment even if these objectives are not explicitly communicated. During the 1 year after the treatment, not one single household contacted the landlord to express concerns or a wish to have the old design of the RTD back at any point during the experimental period.

When interpreting the results, it is important to know some features of the participating apartments. First, the participating tenants are subject to individual metering and billing of electricity and water. The costs of heating and some other utilities, such as garbage management and lighting of common areas, are included in the apartment rent. This means that households are aware of neither individual nor building-level heating costs but can increase or decrease their indoor temperatures as they wish by regulating each dwelling’s thermostats. Apartment-specific indoor temperature is provided on the RTD (see Figure 3.1). Second, Bostaden Ltd provides all its tenants with fixed electric appliances, such as fridges, freezers, dishwashers, and kitchen ranges. These appliances are the same or very similar in all new apartments in terms of energy performance and functions. Third, there is no obvious mechanical link between consumption of hot water, electricity, and heating as the heating system is based on district heating. The main mechanical link between electricity and (cold) water consumption is cooking. In the study area, district heating is mainly produced from biofuels and solid waste combustion by a local district heating plant.

	RTD front screen	Key features on the front screen
RTD, control group	 	*Aktuell förbrukning* (current consumption): the household's current electricity and water (hot and cold) consumption in real time *Senaste 24 timmarna* (last 24 hours): a household's total electricity and water (hot and cold) consumption in the last 24 hours *Inne*: current indoor temperature
RTD, electricity treatment	 	Information on current electricity consumption and electricity consumption in the last 24 hours is replaced with 3 bars: *Idag* (today): the household's total electricity consumption since midnight *Du* (you): the household's 7-day moving daily average of electricity use *Andra* (others): the 7-day moving daily average of electricity use of other households in apartments of similar size

<table>
<tr>
<td>**RTD, water treatment**</td>
<td>
</td>
<td>Information on current consumption of hot and cold water and the consumption of hot and cold water in the last 24 hours is replaced with 3 bars:

Idag (today): the household's total consumption of hot and cold water since midnight

Du (you): the household's 7-day moving daily average consumption of hot and cold water

Andra (others): the 7-day moving daily average consumption of hot and cold water recorded for other households in apartments of similar size.</td>
</tr>
</table>

Figure 3.1. RTD designs for the control group and the two treatment groups

3.3 Results

3.3.1 Descriptive statistics

Table 3.2 shows the descriptive statistics for the control group and the two treatment groups for electricity, water usage, and indoor temperature before and after the delivery of the treatments. There are 315 apartments in the control group, 100 apartments in the treatment group for targeting electricity use, and 110 apartments in the treatment group for targeting water use. We observed these groups for 2 years—1 year before and 1 year after the treatment delivery.

Table 3.2 Descriptive statistics

	Pre-treatment			Post-treatment		
	No. of daily observations	Average	Std. dev.	No. of daily observations	Average	Std. dev.
*Control group**						
Electricity, kWh/day	75,301	4.61	3.22	113,127	4.50	3.22
Water, l/day	76,508	176.2	151.4	113,782	172.5	152.9
Hot water, l/day	76,508	73.6	72.4	113,782	73.3	78.0
Cold water, l/day	76,508	104.5	90.3	113,782	99.2	86.9
No. of rooms**	76,517	2.4	0.7	113,820	2.3	0.7
Apartment size, m^2	76,517	60.4	18.7	113,820	59.1	19.0
Outdoor temperature (° C/day)	76,517	3.4	8.9	113,820	5.3	8.1
Sunlight (radiation intensity)	76,517	73.1	82.3	113,820	91.3	91.1
Precipitation (mm/day)	76,517	1.72	4.03	113,820	1.3	3.7
Indoor temperature (° C/day)	76,517	22.1	1.5	113,820	22.4	1.7
Electricity-targeted treatment group						
Electricity, kWh/day	35,217	4.53	2.69	33,734	4.30	2.5
Water, l/day	36,008	129.6	107.0	36,135	127.5	109.0
Hot water, l/day	36,008	54.6	56.4	36,135	52.8	56.4
Cold water, l/day	36,008	75.0	58.5	36,135	74.7	61.3
No. of rooms	36,009	2.3	0.4	36,136	2.3	0.5
Apartment size, m^2	36,009	59.3	9.6	36,136	59.4	9.7
Outdoor temperature (° C/day)	36,009	4.5	8.3	36,136	5.3	8.1
Sunlight (radiation intensity)	36,009	90.8	85.0	36,136	90.9	90.7
Precipitation (mm/day)	36,009	1.7	4.0	36,136	1.4	3.8

Indoor temperature (° C/day)	36,009	22.7	1.3	36,136	22.8	1.4
Water-targeted treatment group						
Electricity, kWh/day	39,636	4.89	3.02	39,894	5.00	2.9
Water, l/day	39,836	159.3	136.6	39,899	164.8	148.6
Hot water, l/day	39,836	69.4	72.8	39,899	70.7	74.6
Cold water, l/day	39,836	89.8	73.8	39,899	94.1	84.0
No. of rooms	39,839	2.4	0.6	39,894	2.4	0.6
Apartment size, m^2	39,839	62.3	11.7	39,894	62.3	11.7
Outdoor temperature (° C/day)	39,839	5.0	8.3	39,894	5.3	8.1
Sunlight (radiation intensity)	39,839	90.4	84.6	39,894	91.2	91.0
Precipitation (mm/day)	39,839	1.7	4.1	39,894	1.3	3.7
Indoor temperature (° C/day)	39,839	22.5	1.9	39,894	22.6	1.9

Notes: *The control group has a smaller number of observations before the delivery of the treatment due to the fact that seven buildings containing 185 apartments in the control group were built and fully accommodated between 10 and 2 months before the treatment. **In Sweden, the number of rooms means the number of living space rooms and bedrooms and does not include the kitchen or bathroom. Therefore, a two-room apartment means an apartment with a living room and a bedroom, a bathroom, and a kitchen. In the U.S. or U.K., this apartment would be called a "one-bedroom apartment." *** See covariate balance check in Table A3.1.

Our experiment delivers real-time data from smart meters and indoor sensors (indoor temperature). For our research purposes, we aggregate the hourly data on a daily basis. Our main outcome variables are electricity consumption, cold and hot water use, and daily indoor temperature over 2 years. We have 365 daily observations per year for most apartments.

We removed obviously flawed observations, such as abnormal electricity or water readings (more than 1,000 kWh or 1,000 l/day) from the analysis, along with daily observations with missing data for some hours. We also removed observations of daily electricity consumption when electricity was switched off (reported zero consumption), but not water (reported positive consumption). The dropped observations correspond to less than 2% of the total daily observations. The exact numbers of observations in each group for the pre-treatment and post-treatment periods, as well as other relevant descriptive statistics, are reported in Table 3.2.

Table 3.2 shows that the average daily electricity use in the electricity treatment group decreased by 0.23 kWh (from 4.53 kWh to 4.3 kWh), while in the control group, the decrease amounted to only 0.11 kWh (from 4.61 kWh to 4.5 kWh). The average daily water use in the water treatment group increased by 5.5 l (from 159.3 l to 164.8 l). In contrast, the control group displays the opposite development—an average decrease of 3.7 liters per day. Also, it is evident that average hot water consumption slightly decreased in the electricity treatment group (from 54.6 l to 52.8 l), while average cold water use remained constant. In the water treatment group, the average consumption of electricity slightly increased. The average indoor temperature slightly increased in all groups of households. All in all, when looking at the descriptive statistics of the targeted and untargeted resource use, it is not clear whether electricity and water social comparison treatments spilled over into the untargeted resource domains.

3.3.2 Spillover average treatment effects

To estimate the direct and spillover average treatment effects, we run the following difference-in-differences (DID) regression model:

$$y_{it} = \beta_1 TREAT_i + \beta_2 POST_{it} + \beta_3 TREAT_i * POST_{it} + \mu X_t' + \alpha_i + \varepsilon_{it}, \quad (3.1)$$

where y_{it} represents our outcome variables: daily electricity use (in kWh), hot or cold water use (in liters), and indoor temperature (in ^{o}C) in household i at time t; $TREAT_i$ is a dummy variable indicating whether household i is in the water- or electricity-targeted treatment group or the control group; $POST_{it}$ is a dummy variable indicating the pre- and post-treatment periods; X_t' is a set of the time-varying covariates (year-monthly fixed effects, Monday-to-Sunday fixed effects, and weather controls, such as outdoor temperature, sunlight, and precipitation); α_i represents household fixed effects; and ε_{it} is an idiosyncratic error term (unobserved household-specific shocks). This model is estimated in OLS using the standard fixed-effects estimator with Huber-White standard errors, clustered at the unit of the building to account for serial correlation (Bertrand et al., 2004). The estimated coefficient β_3 measures the direct average treatment effects and the average treatment spillover effects of provision of peer-comparison information on our outcome variables.

It should be noted that we estimate the SATEs of water and electricity treatments on apartments' indoor temperatures by estimating Equation 3.1 for the heating period only. In our study area, the heating season includes all months except June, July, August, and September. Thus, for this analysis, we have 8 heating months before the treatment and 8 heating months after the treatment.

The results from the estimation of the DID model are presented in Table 3.3. We find that water social comparison was ineffective in reducing targeted cold and hot water consumption and did not spill over into the electricity and heating domains (see Columns 1–3 in Table 3.3). Meanwhile, electricity social comparison had not only a direct positive effect on electricity conservation (see Column 7 in Table 3.3), but also a positive spillover effect on hot water consumption and space heating (see Columns 5 and 8 in Table 3.3). On average, treated households reduced their electricity use by 0.306 kWh per day and hot water consumption by around 7 liters per day. It should be highlighted that the spillover effect of electricity treatment on hot water use is stronger than the direct effect of water treatment itself, which is not significantly different from zero (see Columns 1 and 5 in Table 3.3). We find that electricity treatment, differently than water treatment, had a large spillover effect on apartments' indoor temperatures. On average, the electricity-targeted treatment group reduced their indoor temperature by 0.202 ^{o}C (see Column 8 in Table 3.3).

Table 3.3. ATEs and SATEs on daily electricity consumption (in kWh), water use (in liters), and indoor temperatures (in ºC).

	Water-targeted treatment				**Electricity-targeted treatment**			
	Hot water	Cold water	**Electricity**	**Indoor temperature**	**Hot water**	**Cold water**	Electricity	**Indoor temperature**
Variables	(1)	(2)	**(3)**	**(4)**	**(5)**	**(6)**	(7)	**(8)**
TREAT*POST	-3.800	7.114	**-0.048**	**-0.086**	**-7.151*** **	**2.166**	-0.306**	**-0.202*** **
	(4.377)	(4.682)	**(0.223)**	**(0.070)**	**(1.778)**	**(2.831)**	(0.130)	**(0.065)**
POST	5.314***	-2.728	**0.167***	**0.195*** **	**5.250*** **	**-2.710**	0.166*	**0.202*** **
	(1.492)	(2.645)	**(0.092)**	**(0.032)**	**(1.500)**	**(2.638)**	(0.093)	**(0.032)**
Outdoor temperature	-0.295***	-0.198***	**-0.014*** **	**0.022*** **	**-0.258*** **	**-0.189****	-0.013***	**0.021*** **
	(0.032)	(0.055)	**(0.002)**	**(0.002)**	**(0.040)**	**(0.066)**	(0.002)	**(0.002)**
Sunlight	-0.001	0.012***	**-0.002*** **	**0.003*** **	**-0.000**	**0.013*** **	-0.002***	**0.003*** **
	(0.003)	(0.004)	**(0.000)**	**(0.000)**	**(0.002)**	**(0.004)**	(0.000)	**(0.000)**
Precipitation	-0.009	-0.078**	**0.002**	**-0.004*** **	**-0.015**	**-0.077****	0.005***	**-0.003*** **
	(0.032)	(0.030)	**(0.002)**	**(0.001)**	**(0.030)**	**(0.027)**	(0.001)	**(0.001)**
Constant	78.793***	110.290***	**5.623*** **	**21.214*** **	**74.273*** **	**105.354*** **	5.479***	**21.320*** **
	(1.143)	(1.742)	**(0.099)**	**(0.049)**	**(1.253)**	**(1.760)**	(0.098)	**(0.049)**
Fixed effect Controls	Yes	Yes	**Yes**	**Yes**	**Yes**	**Yes**	Yes	**Yes**
No. of obsv.	270,015	270,015	**267,958**	**184,463**	**262,435**	**262,435**	257,379	**179,770**
No. of apartments	425	425	**425**	**425**	**415**	**415**	415	**415**

Notes: The estimated spillover effects on indoor temperature are for an 8-month heating period. Standard errors clustered at the building level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Sectoral spillover effects are in bold style.

3.3.3 Inference

In our main DID model (see Eq. 3.1), we rely on the building-level clustered robust standard errors to account for the correlation within buildings as our treatment was assigned at the building level. However, the consistency of the clustered robust estimation is subject to fulfilment of conditions like an infinite number of clusters and equal size of clusters. Since we have a small number of clusters and an unequal number of observations within each building-level cluster, the standard errors estimated using the clustered robust approach might not be consistent (see, e.g., Mackinnon & Webb, 2017).

Hence, we use randomization inference (RI) to test for the causal effects of our treatment. Originally developed by Fisher (1953) and later advanced by Rosenbaum (2002), RI places no distributional assumptions on the errors and is valid even in small samples. This method is being increasingly applied to experimental data (Asmare et al., 2021; Hess, 2017; Kažukauskas et al., 2021).

RI computes the empirical distribution of the DID estimate for a large number of randomly generated placebo treatments under the null hypothesis of no effect using a simulation method. The critical value of the treatment spillover effect to be used for the inference test can be determined from a large number of simulations. We randomize the assignment of buildings to treatment and control groups, and we use the DID coefficient (the interaction term in Eq. 3.1) as the test statistic. Our null hypothesis is that our water and electricity social comparison treatments had no effect on water consumption, electricity, and/or heating energy use, or $\beta 3 = 0$ in Equation 3.1. We conduct the RI test using 1000 replications in the "ritest" Stata command developed by Hess (2017). The results from the RI test confirm our initial results that electricity social comparison treatment significantly reduced not only targeted electricity consumption, but also hot water consumption and apartments' indoor temperatures (see Table 3.4).

Table 3.4: ATEs and SATEs on daily electricity (in kWh), water (in liters), and winter season indoor temperature (in oC) using RI method

	Water-targeted treatment				Electricity-targeted treatment			
	Hot water	Cold water	**Electricity**	**Heating season indoor temperature**	**Hot water**	**Cold water**	Electricity	**Heating season indoor temperature**
Variables	(1)	(2)	**(3)**	**(4)**	**(5)**	**(6)**	(7)	**(8)**
				12 months post-treatment				
TREAT*POST	-3.800	7.114	**-0.0484**	**-0.086**	**-7.151★★/☆☆☆**	**2.166**	-0.306★/☆☆	**-0.202★★/☆☆☆**
	(3.478)	(4.682)	**(0.223)**	**(0.044)**	**(1.778)**	**(2.831)**	(0.130)	**(0.065)**
	[0.342]	[0.170]	**[0.8060]**	**[0.216]**	**[0.030]**	**[0.617]**	[0.100]	**[0.027]**
Controls	Yes	Yes	**Yes**	**Yes**	**Yes**	**Yes**	Yes	**Yes**
Fixed effect Controls	Yes	Yes	**Yes**	**Yes**	**Yes**	**Yes**	Yes	**Yes**
No. of obsv.	270,015	270,015	**267,958**	**184,463**	**262,435**	**262,435**	257,379	**179,770**
No. of apartments	425	425	**425**	**425**	**415**	**415**	415	**415**

Notes: Randomization inference and clustered error methods were conducted to obtain alternative p-values. ★★★/☆☆☆ p < 0.01, ★★/☆☆ p < 0.05, and ★/☆ p < 0.1 indicate significance levels, where filled stars ★ indicate significance levels preserved under randomization inference, while empty stars ☆ indicate significance levels that are sustained by the cluster-robust standard errors. The standard error clustered at the building level is in parentheses, and the p-value obtained using randomization inference is provided in squared brackets. Sectoral crossover effects are in bold style.

3.3.4 Spillover quantile treatment effects

Motivated by recent impact evaluation studies that document the relevance of measuring the distributional effects of an intervention (see, e.g., Bedoya et al., 2018; Byrne et al., 2018; Havnes & Mogstad, 2015), we estimate the spillover quantile treatment effects (SQTE) of our social comparisons. This allows us to explore how the spillover effects vary among households with different levels of resource use.[22]

Following Rios Avila (2019) we estimate the following model to get the SQTEs.[23]

$$RIF\left(y_{it}; v\left(F_{y/TREAT,POST}\right)\right) = \beta_1 TREAT_i + \beta_2 POST_{it} + \beta_3 TREAT_i * POST_{it} + \mu X_t' + \alpha_i + \varepsilon_{it}, \quad (3.2)$$

where $RIF\left(y_{it}; v\left(F_{y/TREAT,POST}\right)\right)$ represents the RIF of the outcome variable; y_{it} is the daily hot water use in liters and indoor temperature in degrees of Celsius in household i at time t; $F_{y/TREAT,POST}$ is the cumulative distribution function; $TREAT_i$ is a dummy variable indicating whether household i is in the electricity treatment group or the control group. The remaining variables are the same as in the main DID model (see Eq. 3.1). The estimated coefficient β_3 measures SQTEs.

As we did not find any significant spillover effects of water social comparison, below, we present the SQTEs of electricity social comparison for hot water and indoor temperatures with 95% confidence intervals (see Figure 3.2).

We find that the SQTEs of electricity treatment on hot water consumption are significant at the higher percentiles of the hot water consumption distribution. Compared to the SATE (see Table 3.3), significant and larger reductions in hot water use are observed for households with hot water consumption levels above the 45th percentile. By contrast, for hot water consumption levels below the 60th percentile, the SQTEs are smaller (and insignificant below the 45th percentile) than the SATE, implying that the spillover effects of electricity social comparison on hot water conservation are

[22] We follow the specification of Firpo et al. (2009), which was extended to panel data application by Rios Avila (2019). We use the Stata command developed by Rios Avila (2019) to estimate the SQTEs.
[23] See Rios Avila (2019) for a detailed explanation of the approach.

heterogeneous and driven by households that consume hot water above the median level.

On the other hand, the SQTEs of electricity treatment on heating energy use are significant at the tails of the heating energy use distribution. As one can see from the lower panel of Figure 3.2, a higher and statistically significant reduction in indoor temperature is found for households with heating energy use levels below the 10th percentile and above the 90th percentile.

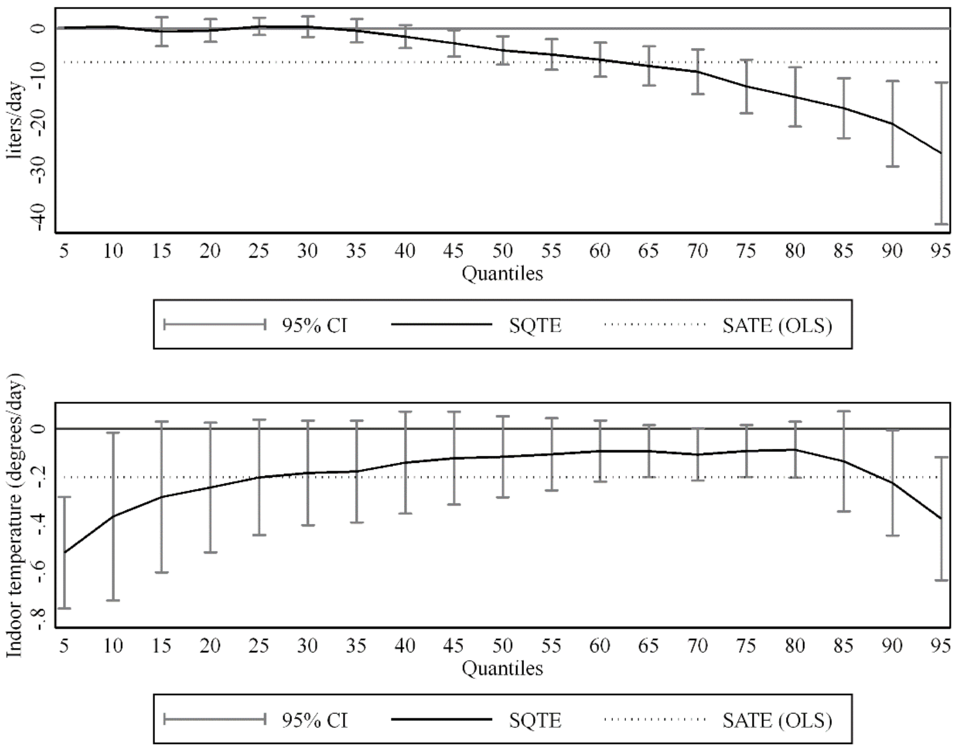


Figure 3.2: SQTEs of electricity social comparison on hot water consumption and apartments' indoor temperature

3.3.5 Persistency of the SATEs

To examine the persistency of the SATEs induced by electricity social comparison treatment, we estimate the SATEs for hot water use and indoor temperature for each month of the experiment. The monthly SATEs are generated by estimating the following DID model:

$$y_{it} = \gamma_0 TREAT_i + \gamma_1 POST_{it} + \sum_{m=1}^{12} \beta_m (MONTH_m * TREAT_i) + \mu X'_t + \alpha_i + \varepsilon_{it}, \qquad (3.3)$$

where y_{it} represents the daily hot water use in liters and indoor temperature in degrees of Celsius in household i at time t; $TREAT_i$ is a dummy variable indicating whether household i is in the electricity treatment group or the control group; and $MONTH_m$ are the dummy variables representing a specific month (m = 1,…,12) in the post-treatment year. The remaining variables are the same as in the main DID model (see Eq. 3.1). The estimated coefficients of the interaction terms between the monthly dummies and the treatment variable, β_m, yield the monthly average spillover effects. As before, the model is estimated by using OLS with household fixed effects and clustered standard errors at the building level. We plot the monthly SATEs for hot water and indoor temperature with 95% confidence intervals in Figure 3.3.

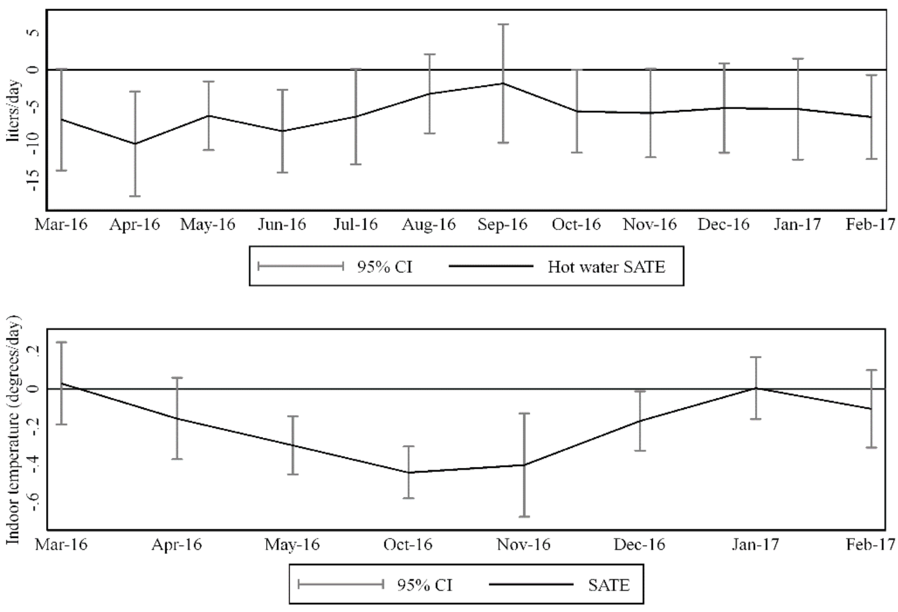


Figure 3.3: SATEs of electricity-targeted treatment on hot water use and indoor temperatures for each month over the period of the treatment (CI 95%)

Figure 3.3 shows that the electricity treatment caused a reduction in hot water use in the first 4 months of the experiment (April–July 2016) and then in October and November of the same year. In the case of indoor temperature, the monthly SATEs are significant for 4 out of 8 heating months (May–December 2016).

3.3.6 Interpreting the results

Here we aim to better understand the reasons behind the spillover effects of the electricity social comparison treatment by answering four questions. First, what drives the spillover effects of electricity treatment—a mechanical link between electricity use and hot water and heating use, or behavioral changes? Second, why did we find the positive spillover effects by targeting electricity use but not water use? Third, what actions underlie energy savings (direct and indirect) induced by electricity social comparison treatment? Finally, we want to understand whether the overall spillover effect is larger than the direct effect in terms of energy use.

What can explain spillover effects?

In previous studies, spillover effects induced by social comparisons are generally explained either by mechanical complementarities between appliances or other housing services that use both energy and water, or by changes in treated households' behavior (see, e.g., Jessoe et al., 2021). One exception is Carlsson et al. (2021), who show how cognitive dissonance facilitates the positive spillover effect of social comparison information provision. In our case, we reason that behavioral factors drive our found spillover effects, since there is no obvious mechanical link between treatment-targeted electricity use and hot water use or indoor temperature in our study area. Participating households live in apartments that are provided with hot water and space heating by centralized district heating, and electricity is mainly used for lighting, cooking, running the kitchen, and other appliances. Hot water is mainly used for showering. Thus, unlike in other studies, we can rule out mechanical complementarities among these resources and should focus instead on behavioral drivers that could explain the observed spillover effects.

As noted in Section 3.1, participating households did not have direct pecuniary motives to save energy used for space heating, unlike in other studies (see Table 3.1 for examples), but they had one for energy used to heat their water. In our study area, space heating expenses are included in the apartment rent payments that do not change over winter or summer months, and the state regulates these rents. Thus, only a non-monetary motive to save energy can explain the actions taken to reduce indoor temperatures. Specifically, we draw from the theory of moral dissonance. According to this theory, individuals want to avoid inconsistency in their beliefs and behaviors to reduce moral costs. Due to this, a strong correlation between behaviors in different domains is likely to exist (Festinger, 1962). Failure to maintain their primary resource domain consumption behavior in the secondary domain will result in a behavioral inconsistency. To avoid this inconsistency, individuals who reduce their primary resource use will also reduce their consumption of the secondary resource. We argue that, in our case, participating households' internal motivations to conserve electricity might translate into internal motivation to consume less energy for water and apartment heating in order to reduce behavioral inconsistencies.

Besides this intuitive explanation, we investigate the estimated quantile spillover treatment effects presented in Section 3.3.4 to find some supportive evidence for our claims. If the mechanism behind the spillover effects relates to individuals' ambition to be consistent in their behavior, we expect that households who reduced their hot water use or indoor temperature due to electricity-targeted treatment also reduced their electricity consumption. As can be seen in Figure 3.2, we find the significant spillover quantile treatment effects of electricity-targeted treatment on hot water consumption for households with hot water consumption above the 45th percentile. Therefore, we estimate the direct treatment effects on electricity use by splitting the sample into two groups. The first group consists of households above the 45th percentile, for which we find a significant spillover effect of electricity-targeted treatment on hot water. The second group contains households below the 45th percentile, for which we find no significant spillover effect on hot water consumption due to the electricity-targeted treatment. The results reveal that on average households who reduce their hot water consumption due to electricity-targeted treatment also reduce their electricity consumption (see Table A3.2 in the Appendix). Likewise, consistent with the cognitive dissonance theory, on average, we do not find a significant effect on electricity use for households in this subsample of households with no significant spillover effect on hot water. The corresponding results for heating are not as clear. While households who do not reduce the use of heating energy also do not save electricity, for households with significant spillover effects we find a larger but insignificant effect on electricity use (see Table A3.3 in the Appendix). Overall, these results provide supporting evidence for cognitive dissonance as the underlying mechanism.

Why did positive spillover effects results from targeting electricity but not water use?

The difference in the SATEs of the electricity and water treatments can be explained by differences in social norms regarding electricity and water use

that prevail in our study area. Kažukauskas et al. (2021) argue that in Sweden there is no social or political pressure to save water as this resource is abundant and cheap throughout the country. But this is not the case in other countries, where water shortages are prevalent; for instance, see the study by Jessoe et al. (2021) in California. Hence, there is reason to believe that people in Sweden are less concerned than people in many other places about the environmental impacts of water use and that social norms therefore do not provide a very effective tool to reduce residential water use in Sweden.
However, the same cannot be said about residential electricity consumption, since households living in Sweden associate electricity use with various environmental problems, including climate change. The results from an Organization for Economic Cooperation and Development (OECD) survey, which asked respondents about the seriousness of six specific environmental issues facing the world, show that Swedish respondents were aware of the negative environmental impact of energy use and perceived climate change as the most serious problem (OECD, 2014). The same survey also reports that Swedes were the second most likely to believe that climate change is partly caused by human activity, such as burning coal or gas for power generation. Thus, we think that these preexisting differences in social norms about the utilization of electricity and water are the reason the spillover effect was induced only by the electricity social comparison treatment.

What actions can explain positive direct and spillover effects on energy use?

The literature suggests two main explanations for energy conservation caused by social comparison information provision. The first is investments in energy-efficient house equipment, and the second is behavioral changes such as habit formation (see, e.g., Allcott & Rogers, 2014). Notwithstanding the first justification, we argue that it does not explain our findings, since all apartments in our study are equipped with very similar kitchen appliances, including fridges, dishwashers, and kitchen ranges, provided by the rental company, meaning that households' interest in investing in energy-efficient appliances is negligible. Instead, we claim that behavioral changes explain the observed electricity savings. For instance, to reduce electricity consumption, households might switch off the lights when they leave home and unplug different electronics when they are not in use. To reduce hot water use, households might shorten shower times and use cold water instead of hot water for other activities. Finally, households might reduce heating energy use by adjusting their thermostats and closing off unused rooms in their houses.

Could the spillover effects be larger than the direct effect in terms of energy use?

Another important aspect of our results is checking whether the energy savings from the spillover effects are higher than the energy savings from the direct effect. Thus, to better understand total energy savings from the direct and spillover average treatment effects induced by electricity social comparison, we use back-of-the-envelope calculations to compare the energy savings from the direct effect to the energy savings from the spillover effects.[24] We find that the energy savings from the untargeted resource domains (hot water and space heating) are by far higher than the energy savings from the targeted resource domain (electricity). We estimate that the energy savings from the reduction in hot water consumption and space heating are about 143 kWh per year[25] and 90 kWh per year, [26] respectively. In comparison, the energy savings from the directly induced reduction in electricity consumption amount to 111 kWh per year (0.306 kWh/day multiplied by 365 days).

3.3.7 Robustness tests

Parallel trends

The identification of the DID model relies on the fulfilment of the parallel trend assumption, which states that outcome variables should have similar trends for the treatment and control groups in the pretreatment period. We test this assumption by following two procedures. First, we visually inspect the trends of our outcome variables (electricity, hot and cold water, and heating energy) for the treatment and control groups before and after the treatment delivery (see Figures A3.1–A3.3 in the Appendix). It is evident that our

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[24] We do not aim to measure the welfare effects as is done in other similar studies (Allcott & Kessler, 2019) since it is not possible to elicit the demand curve for the social comparison information provision.

[25] We find that electricity treatment, on average, induced hot water savings of 7.1 liters per day or 2.6 m^3 per year. It is estimated that 55 kWh of energy is needed to warm up 1 m^3 of cold water (SEA, 2012). This means that hot water savings of 2.6 m^3 per year translate into energy savings of 143 kWh per year.

[26] We find that electricity treatment, on average, induced a daily indoor temperature reduction by 0.2 degrees Celsius. In Sweden, lowering the indoor temperature by 1 degree Celsius means around 5% lower energy use for heating, and the average annual energy use for heating is 9 MWh per apartment in Umeå. Thus, a reduction of 0.2 degrees Celsius translates into a 1% lower heating energy use, which corresponds to 90 kWh savings per year (Energiradgivningen, 2020; SEA, 2016).

outcome variables have similar pretreatment trends, providing initial evidence for the validity of the parallel trends assumption.[27]

Second, we conduct a formal placebo test considering a different treatment delivery date. Specifically, we hypothetically consider 2014 as a pretreatment year and 2015 as a posttreatment year. The results from this exercise presented in Table 3.5 reveal that our outcome variables do not indicate a statistical difference between the treated and control groups in 2014–2015.

[27] We also check the pre-treatment balance of the covariates by calculating the normalized differences and find that all the normalized differences are less than 0.5 (see Appendix Table A3.1). Imbens and Rubin (2015) indicate that normalized differences of less than one are good indicators of covariate balance.

Table 3.5: "Placebo" ATEs and SATEs on daily electricity, cold water, hot water, and heating energy use

	Water-targeted treatment				**Electricity-targeted treatment**			
Variables	Hot water	Cold water	**Electricity**	**Indoor temperature**	**Hot water**	**Cold water**	Electricity	**Indoor temperature**
TREAT*POST	2.731	3.950	**0.283**	**-0.040**	**2.949**	**2.424**	-0.068	**0.025**
	(3.963)	(5.305)	**(0.301)**	**(0.077)**	**(4.065)**	**(5.287)**	(0.301)	**(0.074)**
	[0.532]	[0.321]	**[0.203]**	**[0.716]**	**[0.108]**	**[0.573]**	[0.653]	**[0.641]**
Controls	Yes	Yes	**Yes**	**Yes**	**Yes**	**Yes**	Yes	**Yes**
Fixed effect controls	Yes	Yes	**Yes**	**Yes**	**Yes**	**Yes**	Yes	**Yes**
Number of observations	99,036	99,036	**98,780**	**99,111**	**71,264**	**71,264**	70,934	**71,278**
Number of apartments	150	150	**150**	**150**	**109**	**109**	109	**109**

Notes: Randomization inference and clustered error methods were conducted to obtain alternative p-values. The standard error clustered at the apartment level is in parentheses, and the p-value obtained using randomization inference is provided in squared brackets. Sectoral crossover effects are in bold style.

Balanced sample

Our analysis so far is based on an unbalanced sample of panel data (see Table 3.2). This is because seven buildings containing 185 apartments in the control group were built and fully accommodated between 10 and 2 months before the treatment delivery. Thus, we estimate our main model using a balanced sample to check how this affects our results reported above. As can be seen in Table 3.6, the ATEs and SATEs remain robust for the balanced data sample as well.

Table 3.6: TEs and SATEs on daily electricity, cold water, hot water, and heating energy use using the balanced sample

	Water-targeted treatment				**Electricity-targeted treatment**			
Variables	Hot water	Cold water	**Electricity**	**Indoor temperature**	**Hot water**	**Cold water**	Electricity	**Indoor temperature**
TREAT*POST	-3.874	4.004	**-0.054**	**-0.039**	**-6.820★★/☆☆**	**0.303**	-0.311☆	**-0.147★/☆☆☆**
	(4.086)	(4.632)	**(0.203)**	**(0.048)**	**(3.400)**	**(4.347)**	(0.184)	**(0.041)**
	[0.457]	[0.442]	**[0.821]**	**[0.600]**	**[0.048]**	**[0.942]**	[0.145]	**[0.068]**
Controls	Yes	Yes	**Yes**	**Yes**	**Yes**	**Yes**	Yes	**Yes**
Fixed effect controls	Yes	Yes	**Yes**	**Yes**	**Yes**	**Yes**	Yes	**Yes**
Number of observations	172,820	172,820	**172,640**	**115,815**	**165,442**	**165,442**	162,061	**111,122**
Number of apartments	240	240	**240**	**240**	**230**	**230**	230	**230**

Notes: Randomization inference and clustered error methods were conducted to obtain alternative p-values. ★★★/☆☆☆ $p < 0.01$, ★★/☆☆ $p < 0.05$ and ★/☆ $p < 0.1$ indicate significance levels, where filled stars ★ indicate significance levels preserved under randomization inference, while empty stars ☆ indicate significance levels that are sustained by the cluster-robust standard errors. The standard error clustered at the apartment level is in parentheses, and the p-value obtained using randomization inference is provided in squared brackets. Sectoral crossover effects are in bold style.

3.4 Concluding remarks

The behavioral environmental economics literature suggests that behavioral interventions may be part of a cost-efficient strategy to encourage households to act more in a prosocial way. While studies so far have focused mainly on measuring the direct effects of behavioral interventions, the effect of a particular behavioral intervention may go beyond the targeted resource domain, and failure to account for such indirect effects can lead to underestimations of their welfare implications.

In this paper, we present new results from a natural field experiment that contribute to the understanding of whether behavioral interventions in the form of social comparisons spill over beyond the targeted resource domains. We estimate the spillover effects of the provision of peer-comparison information on the consumption of two resources—energy and water—in the same experimental setting. This enables us to contribute to the existing literature by investigating whether social comparisons that target resources with presumably different preexisting social norms regarding conservation induce different spillover effects.

We find that only electricity-targeted social comparison is effective in reducing electricity consumption and that it induces conservation beyond electricity, leading to reductions in energy used for heating water and space. Water-targeted social comparison induces effects on neither the targeted water domain nor energy resource domains. We argue that the difference in direct treatment and spillover effects from the water and electricity treatments might be explained by differences in preexisting social norms of resource utilization. We reason that in the case of our study area (the north of Sweden), there is a stronger social norm for the conservation of energy than for the preservation of (cold) water. This potentially explains why our social comparison treatment is successful in affecting energy-intensive resource domains such as electricity, hot water, and space heating. Our findings suggest that behavioral interventions like social comparisons could bring significant energy savings beyond the targeted resource domains if society has strong preexisting social norms supporting conservation of the targeted resource.

Furthermore, we find evidence that the positive and significant spillover effects found in our study could be explained by other nonmonetary incentives such as moral dissonance. We find that our electricity-targeted social comparison treatment induced behavioral consistency—reduction in all energy-intensive resource domains but not in cold water—among treated households. This claim is further strengthened by the significant spillover effect on lower indoor temperatures, although there was no pecuniary incentive to save energy for heating.

4. ENERGY-RELATED FINANCIAL LITERACY AND RETROFITS OF SOVIET-ERA APARTMENT BUILDINGS: THE CASE OF LITHUANIA

The International Energy Agency (IEA) suggests that improvements in the energy efficiency of space heating and cooling in buildings could deliver more than half of the needed energy savings to stabilize climate change (IEA, 2018). Although there is considerable literature on barriers and drivers for energy efficiency investments, it has historically emphasized empirical applications in Western European and North American countries but not in less developed or emerging regions, such as the Soviet-era countries (Fowlie & Meeks, 2021).

Although it has been some 30 years since the communist system collapsed in Central and Eastern Europe, low energy efficiency in the residential building sector has remained a major problem in most Soviet-era countries (Sirvydis, 2014). Dwellings were designed at a time when energy efficiency was not a priority, as energy was abundant and cheap. Soviet mass housing provided multi-dwellings for tens of millions of families, and 170 million people still live in these mostly non-retrofitted and very energy-inefficient buildings (Meuser & Zadorin, 2015). Hence, improvements in energy efficiency and retrofits of multi-dwellings have been a key priority for most Soviet-era governments in dealing with fossil-based energy dependence, climate change, and social issues such as energy poverty. However, despite generous government subsidies and other measures that have been promoting energy retrofits, the pace of renewal of the residential sector in ex-communist countries has been slow (Paiho et al., 2013).

It is well-known that there are many barriers that prevent households from investing in energy efficiency solutions and adopting conservation behaviors in general. Besides market failures and financial constraints, there are behavioral failures associated with limited attention and bounded cognitive abilities that influence consumer decision-making and energy use (Allcott & Mullainathan, 2010; Broberg & Kazukauskas, 2015). Furthermore, large investments in energy efficiency, such as large-scale housing retrofits, require energy-specific knowledge and financial skills to process specific investment details to ensure net savings over their lifetimes. It has been shown that these processing costs are relatively high for a substantial share of individuals (Blasch et al., 2017b), meaning that the low level of knowledge about energy and investments, in general, might represent an important barrier preventing households from investing in large-scale energy efficiency measures.

Hence, a recent strand of literature has developed around the role of financial literacy and energy literacy in explaining households' energy-saving behavior. This literature has proposed an integrated concept of "energy-related financial literacy," which combines the energy-specific knowledge (i.e., energy literacy) and investment-specific financial skills (i.e., financial literacy) needed to evaluate investments in energy efficiency. Several studies have shown that low energy-related financial literacy is associated with low adoption of energy-efficient technologies and high energy consumption (Blasch et al., 2021; Filippini et al., 2020; Kalmi et al., 2021).

Trust facilitates decision-making by reducing uncertainties and fear of exploitation. The role of trust in economic outcomes has received considerable attention in the literature (see the review by Algan & Cahuc, 2014). This literature documents that trust improves different economic outcomes such as GDP per capita (Bjørnskov, 2012; Tabellini, 2010), stock market participation, and up take of micro-insurance (Cai et al., 2009; Guiso et al., 2008). Furthermore, individuals with a high level of trust are found more likely to buy green products (Gupta & Ogden, 2009) and recycle (Sønderskov, 2011). Similarly, we argue that households with limited financial knowledge and experience could seek advice and recommendation from other stakeholders to ease their renovation decision, which will be highly influenced by their level of trust in these stakeholders.

Therefore, in this paper we hypothesize that the low retrofit rate of multi-dwelling buildings in post-communist countries could be partially explained by the low level of energy-related financial literacy among households in these countries. Furthermore, we argue that the lack of energy-related financial literacy makes these households dependent on other stakeholders that are important in the house-retrofitting process, such as neighbors, national and local institutions, or supply-side actors in the construction industry. This leads to a focus on the role of trust in institutions, which is known to be low in Soviet-era countries (Hosking, 2013; Rapolienė & Aartsen, 2021). When homeowners view institutions as well as their house administrator as trustworthy and do not think that they will be cheated, they might be more willing to cooperate with them and provide consent for house retrofits. The same could be said about trust in neighbors: a collective decision to retrofit a multi-dwelling house may be easier to make if apartment owners of that house trust each other. Henceforth, in this paper we hypothesize that energy-related financial literacy and cooperation based on trust are the foundations for individuals in making sound collective energy retrofit investments, which is the focus of our study.

To the best of our knowledge, this is the first and only study that investigates the role of energy-related financial literacy and trust in explaining collective investments in energy efficiency, be it in the case of a Soviet-era country or any other country. Thus, herein we extend a large literature on the economics of energy efficiency investments by examining the determinants of homeowners' willingness to make collective investments in house retrofits in the case of a former Soviet country—Lithuania. We conducted an incentivized representative survey of households owning and living in Soviet-built multi-dwelling buildings to examine whether households' willingness to make collective housing retrofit decisions are affected by their energy-related financial literacy and trust in stakeholders that are directly involved in the process of house retrofits.

In particular, we seek to test the following hypotheses: (1) *Financial literacy* is positively related to an apartment owner's willingness to invest in a house retrofit; (2) *Energy literacy* has a positive association with an apartment owner's willingness to invest in a house retrofit; (3) *Energy-related financial literacy* is positively related to an apartment owner's willingness to invest in a house retrofit; and (4) *Trust* is positively associated with an apartment owner's willingness to make collective house retrofit decisions.

Our results lend support to all our hypotheses. We find that the probability of individuals' willingness to invest in house retrofits is positively associated with those individuals' general financial literacy, energy literacy, and energy-related financial literacy. Furthermore, we show that trust in institutions that are directly involved in house-retrofitting process is indeed an important predictor of house retrofit intentions.

The remainder of the paper is structured as follows. We present our conceptual framework that is used to support our empirical strategy in Section 4.1. With the help of this framework, we show how insights from the literature related to financial and energy literacy can be used to construct measures of energy-related financial literacy. In Section 4.2, we provide a short background about Lithuania's housing stock, policies directed towards residential multi-dwelling housing modernization, and other important indicators related to financial literacy and trust. In Section 4.3 we lay out our data and empirical strategy, and in Section 4.4 we summarize and discuss our results. Section 4.5 concludes the paper and provides several policy implications.

4.1 Defining the concept of energy-related financial literacy

Individuals' energy-related financial literacy, among many other retrofit decision drivers, such as trust in institutions and trust in other stakeholders related to retrofit processes, socioeconomic characteristics, and dwelling characteristics, can be an important predictor of homeowners' intention to retrofit their houses. In the following paragraphs, we explain how we define energy-related financial literacy and how it relates to the better-known concepts of financial literacy and energy literacy (see Figure 4.1).

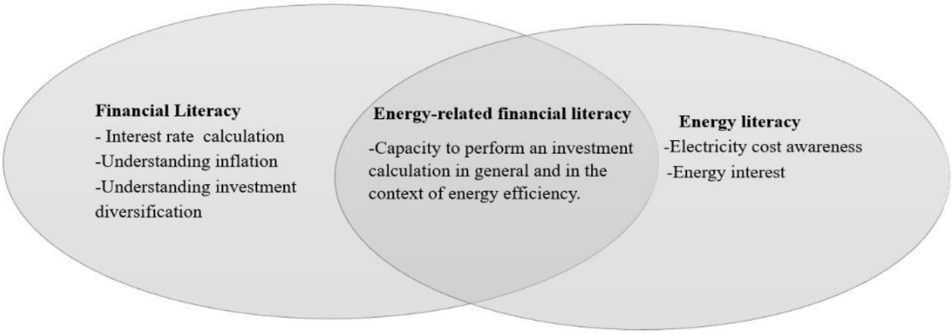


Figure 4.1: A concept of energy-related financial literacy

The first dimension of energy-related financial literacy is financial literacy. One of the most influential contributors to the literature on financial literacy, Lusardi and Mitchell (2014), define financial literacy as people's ability to process economic information and take informed actions about various financial issues in everyday life. Lusardi and Mitchell (2008, 2011) measure an individual's financial literacy with three questions related to people's capacity to perform compound interest rate calculations, understanding of inflation, and understanding of investment risk diversification. As these "big three" financial literacy questions have been widely used to measure adults' financial literacy across the globe (Klapper & Lusardi, 2020), we also use them in our study to elicit data on our respondents' financial literacy (see Table 4.1 for more details).

The second dimension of energy-related financial literacy is energy literacy, which, in contrast to the concept of financial literacy, does not share a commonly agreed-upon definition or metric. For instance, (DeWaters & Powers, 2011) define energy literacy across three domains: energy knowledge, attitudes or values, and behavioral domain. According to them, an energy-literate person is expected to have a sound energy knowledge base and is sympathetic to energy conservation and environmental protection. However, this definition is narrower compared to the most recent definitions of energy literacy that encompass the elements of cognitive ability to assess the financial viability of energy efficiency investments, energy cost awareness, and interest in energy efficiency (see, e.g., Blasch et al., 2019; Brounen et al., 2013; Kalmi et al., 2021). Therefore, in our study, the energy literacy dimension includes the elements of electricity cost awareness and interest in energy-saving opportunities. The first indicator could be seen as an objective indicator of energy literacy, and the latter as a subjective measure. Being interested in energy-saving opportunities could be considered as a subjective indicator of energy literacy as it shows the individual's subjective capacity to assess which investments are energy efficient, and which are not. For instance, if a particular individual has a low interest in energy-saving activities, we could think that this individual lacks knowledge about such activities and, hence, could be treated as energy illiterate. On the other hand, electricity cost awareness could be treated as an objective indicator of energy literacy as it measured the individual's knowledge about electricity prices that apply to his/her electricity bill. To elicit information on energy literacy, we ask our respondents to state the price of electricity on their electricity bills and rate their interest in energy-saving opportunities (see Table 4.1 for more details).

Similar to Filippini et al. (2020), Blasch et al. (2021), and Kalmi et al. (2021), we define energy-related financial literacy from the perspective of the financial literacy and energy literacy dimensions, meaning that energy-related financial literacy considers energy-related knowledge, financial literacy, and cognitive abilities that are needed to make intertemporal decisions concerning energy efficiency investments. Hence, to elicit data on energy-related financial literacy, we ask our respondents to perform investment payback period calculations in the context of a house retrofit and to evaluate and compare two investment options, of which one is a house retrofit project (for more details see Table 4.1). In this respect, our measurement of energy-related financial literacy compared to that of (Filippini et al., 2020) and (Blasch et al., 2021) is, on the one hand, narrower as it does not explicitly incorporate energy and financial literacy questions (we measure these dimensions separately), but on the other hand, more profound as it incorporates cognitive ability to perform more complex investment calculations in the context of a complex energy efficiency measure, which in the context of our study is an investment in a house retrofit.

4.2 Lithuanian context

In Lithuania, residential multi-dwelling buildings that were built in Soviet times comprised 72% and 55% of the total residential multi-dwelling building stock in the year 2019 (see Figure 4.2) in terms of square meters and the number of houses, respectively (Government of Lithuania, 2021). A typical feature of these multi-dwelling buildings is that, due to the lack of basic energy efficiency requirements at the time of construction, they have very low energy efficiency and are rated as E - or F- class in terms of building energy performance (NAOL, 2020).

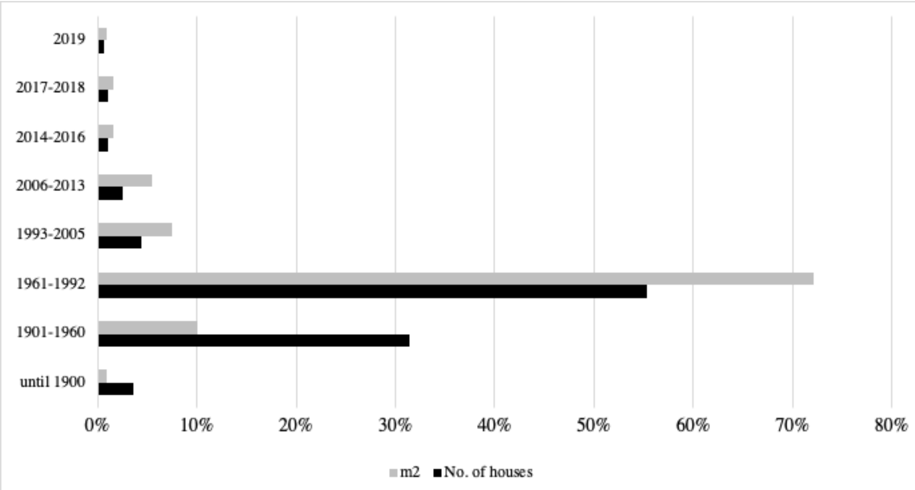


Figure 4.2: Multi-dwelling building housing stock in Lithuanian, year 2019

Lithuania has implemented several national and EU-wide policies aimed at improving energy efficiency in the residential sector. The national program for the modernization of multiunit apartment buildings was launched in 2004. All buildings built before 1993 were eligible to receive partial funding for retrofits, that is, a subsidy of 30% for investments in energy efficiency measures, such as insulation. If the decision to retrofit a particular multi-dwelling building is approved, governmental funding is provided if a simple majority of apartment owners approve the retrofit. Hence, the retrofit decision is a collective and binding decision for all apartment owners of the building. In addition, loans that finance retrofit projects are linked to buildings, not apartment owners. So, if a particular apartment is sold, the obligation to pay back the loan remains with the new apartment owner.[28]

However, despite various degrees of financial support, legal protection, and consumer information measures aimed at speeding up the retrofitting of old multi-dwelling houses, the rate of retrofits has been sluggish. According to the (Government of Lithuania, 2021), less than 10% of old apartment buildings (3,158 buildings out of a total of 35,000) were retrofitted during the implementation period of 2005 to 2019. For instance, between 2017 and 2018, 313 residential apartment buildings were retrofitted (NAOL, 2020). If this pace of retrofitting continues, it will take about a century to fully retrofit all energy-inefficient residential apartment buildings.

In Lithuania, there has been much discussion among policymakers and academics about barriers to building retrofits and how to overcome them. Inability to make collective decisions on retrofits due to lack of cooperation, reluctance to take out a loan, low state support, lack of understanding about the advantages and disadvantages of retrofits, and distrust in construction companies have been mentioned as the main reasons preventing retrofits of old apartment buildings (Aidukaitė et al., 2014; Streimikiene & Balezentis, 2020). Another recent study conducted by the European Commission surveyed various stakeholders related to building retrofits and similarly concluded that limited or absent resources to finance building retrofits, lack of interest because energy retrofitting does not pay off in an immediately evident way or takes too long to be noticed, different interests between a house's owner and its occupants, difficulties in planning building retrofit works, as well as limited or absent trust in building retrofit products and benefits are the main barriers to building retrofits (EC, 2020b). Overall, these survey-based studies suggest that the lack of interest or knowledge about the benefits of retrofitting is one of the most prevalent obstacles for retrofits, which suggests that residents themselves either lack the financial and energy literacy to estimate these benefits or are unwilling to do so.

In the context of Lithuania, incompetence in assessing the financial viability of a house retrofit project would not be surprising as Lithuania and other Soviet-era countries score very low in terms of financial literacy.

[28] Typical retrofit activities that take place in Lithuania are so-called deep renovation activities, which include the insulation of the walls, roof, and floors, the changing of windows and doors, the modernization of the heating system, the renewal of the ventilation system, the glazing of balconies, and the renewal of other systems – elevators, electrical system, etc. Thus, when we refer to retrofitted apartments, we mean apartments that underwent a deep renovation, and otherwise.

According to Klapper and Lusardi (2020), in Lithuania as well as in other Central and Eastern European countries, the financial literacy of adults is rather low compared to the financial literacy of adults living in the neighboring countries of Northern Europe and other developed countries. In Lithuania, 39% of adults were financially literate (the share of literate adults was much lower for adults older than 50), while in countries like Sweden and Denmark, the share of financially literate adults was over 70%. Low financial literacy means that adults lack the financial skills needed to deal with various economic challenges, which in turn could to some extent explain why a large share of the Lithuanian population is still living in energy-inefficient apartment houses and is not in a rush to retrofit them.

4.3 Data and Methods

4.3.1 Survey

In total, a professional survey company recruited 1,111 respondents from a representative online panel (out of 3,174 requests). The survey was conducted in May–June 2021 in Lithuania. The survey was directed to individuals who own and live in Soviet-era multi-dwelling buildings since, according to Lithuanian law, the decision to retrofit a multi-dwelling building should be made by the apartment owners of the particular building, not the tenants. Additionally, we intentionally oversampled homeowners who already live in retrofitted houses, making them represent about half of all our survey respondents. By doing it, we aimed to receive better data about the willingness to retrofit the house and to reduce variance in the responses as it is very likely that the responses provided by homeowners living in not-yet-retrofitted houses may suffer from hypothetical bias.

To elicit reliable data on the financial literacy and energy-related financial literacy of respondents, all their correct answers were incentivized in a similar way as (Brent & Ward, 2018) did in their study. Energy literacy questions were not incentivized because there are no objectively correct answers to these questions (see Q4 and Q5 in Table 4.1). The answers to the financial and energy-related financial literacy questions were incentivized by a reward of 20-euro cents per correct answer. The description of the tasks explains how respondents were paid (see questions 10 to 14 in Appendix C).

In addition, we also elicit data on each respondent's rate of time preference and risk aversion. Time preferences are estimated by asking respondents to choose between 80 euros received in 1 month or more money 7 months in the future, similar to how it was done by (Coller & Williams, 1999) and (Brent & Ward, 2018). See Question 18 in Appendix C for the complete description of the task and payoff for a randomly selected participant. We measure risk preferences based on the approach suggested by (Eckel & Grossman, 2002). In this task, respondents had to select any of the given lottery choices (see Question 17 in Appendix C for the complete description and payoff of this incentivized task). For time preference and risk aversion tasks, as explained in task descriptions, respondents were selected at random for the payoffs that depended on their preferred lottery and selected time preferences. The monetary incentives for the above-described tasks were on top of the standard survey participation incentives. After excluding observations with missing data, our final sample consisted of 1,041 valid responses.

4.3.2 Main variables of interest

Our outcome variable – the willingness to retrofit the house – is a dummy variable taking a value of one if the house owner is willing to retrofit his/her house and zero otherwise. We specifically measure it using the responses to the question that asks respondents about their vote in the last vote for retrofitting their houses or about their voting intentions in the future (see response options 1 and 4 to Question 6 of the questionnaire in appendix C). If respondents are living in an already retrofitted house, *"I was in favor (Yes vote)"* responses are coded as one, and if respondents are living in not yet renovated houses, *"we have had no such vote yet, but if asked I would be FOR it"* responses are coded also as one. All other responses to Question 6 are coded to zero, representing non-willingness to retrofit a house.

As discussed in the conceptual framework section, our main variables of interest are energy-related financial literacy, financial literacy, and energy literacy. In the following subsection, we describe how we measure and construct these variables.

To measure financial literacy, we asked the respondents three standard questions from the financial literacy literature (Lusardi & Mitchell, 2014) that evaluate the respondent's capacity to conduct compound interest rate calculations, understanding of inflation, and understanding of investment diversification (see Q1, Q2, and Q3 in Table 4.1). Most respondents performed well as around 72%, 65%, and 69% of respondents correctly answered the compound interest rate, inflation, and risk diversification questions, respectively (see Table 4.1). Based on these answers, we constructed a financial literacy score which takes on a value of 1 if the respondent answers all financial literacy questions correctly and a value of 0 otherwise. From Table 4.2, it is evident that about 44% of respondents correctly answered all financial literacy questions. In other words, we can claim that our survey participants' level of financial literacy can be considered high, especially when compared to the national level of financial literacy as reported by (Klapper & Lusardi, 2020).[29]

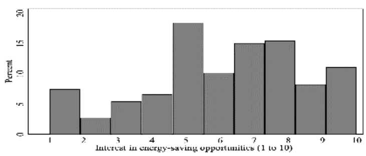
To measure energy literacy, we asked the respondents to state the price of 1 kWh of electricity that they paid last month without checking their electricity bills (see Q4 in Table 4.1).[30] A high share of the respondents (66%) were aware of their electricity price (see Table 4.1), which is not the case in other countries.[31] This could be explained by the fact that Lithuania is just about to start a country-wide rollout of smart meters, meaning that most households do not get automatically generated bills and therefore have to record their electricity consumption and related electricity expenditure on a monthly basis by themselves. Also, at the time of writing this article, most households faced regulated electricity prices. Based on the answers to the electricity cost awareness question, we construct an energy cost awareness score which takes on a value of 1 if the respondent reports the correct electricity price and a value of 0 otherwise.

[29] The difference between our found financial literacy rate and the rate reported by Klapper and Lusardi (2020) could be explained by monetary incentives offered to our respondents for correct answers, and the reasoning that individuals who own apartments are more likely to be more educated and more financially literate than the general adult population.

[30] When the survey was conducted, the price of 1 kWh of electricity ranged from 10 to 16-euro cents.

[31] For instance, Kalmi et al. (2021) report that only 12% of surveyed Finnish households understand well their energy bill, and Blasch et al. (2017a) find that 538 out of 1,994 surveyed Swiss households know the average price of electricity.

Table 4.1: Summary of scores for energy-related financial literacy dimensions

	Correct (%)	Incorrect (%)	Do not know (%)
Financial literacy			
Q1: Compound interest rate Suppose you had 100 euros in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow? ▪ More than EUR 102 ▪ Less than EUR 102 ▪ Exactly EUR 102 ▪ Do not know	71.66	15.47	12.87
Q2: Inflation Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account? ▪ More than today ▪ Less than today ▪ Exactly the same as today ▪ Do not know	65.03	15.28	19.69
Q3: Risk diversification Do you think that the following statement is true or false? "Buying a single company's stock usually provides a safer return than a stock in mutual fund." ▪ True ▪ False ▪ Do not know	68.78	8.17	23.05
Energy literacy			
Q4: Electricity cost awareness Without checking your electricity bills, state the price of 1 kWh of electricity last month. About ________ cnt/kWh	65.61	34.39	0
Q5: ERFL (energy-saving opportunities) Please state your interest in energy-saving opportunities. The question is answered on a 10-point scale ranging from 1 = "Very low" to 10 = "Very high."			
Energy-related financial literacy (ERFL)			

Q6: ERFL (payback) Suppose that the cost of heating a 2-room apartment in a not yet-retrofitted house is 500 EUR/year. The investment share of house renovation is 2,000 euros/apartment. After renovation, the heating costs will be 250 euros/year. How many years will it take to pay back the investment through savings in lower heating costs? ▪ 3 years ▪ 9 years ▪ 6 years ▪ More than 10 years ▪ 7 years ▪ Do not know ▪ 8 years	44.48	36.50	19.02
Q7: ERFL (investment choice) Now suppose that you have 2,000 euros in your savings account. Suppose that you can get 10% annual interest if you leave the money in bank account. Which option is better for you: leaving 2,000 EUR in the saving account or investing 2,000 euros into the house renovation as described in the above question? ▪ Leaving money in the saving account ▪ Renovating the house ▪ Do not know	63.88	19.98	16.14
No. of respondents		1,041	

We also expect that an individual's interest in energy conservation could indicate her/his level of energy literacy as a high interest in energy efficiency measures, which might reflect the individual's understanding of her/his suboptimal level of energy consumption and of potential benefits she/he would obtain by implementing different energy-saving actions. Hence, we asked our respondents to state their interest in energy-saving measures (see Q5 in Table 4.1). Based on the answers to this question, we construct an energy interest variable, which takes on a value of 1 if the respondent has above-average interest (6 and above) in energy-saving opportunities and a value of 0 otherwise.

As we described above, energy-related financial literacy shares the elements of both financial and energy literacy. Hence, in our survey, we ask two questions that enable us to capture the ability of the respondent to apply both her/his financial and energy literacy in the context of investment in a house retrofit. First, we measure energy-related financial literacy by examining whether surveyed individuals can perform investment payback calculations in the context of a house retrofit (see Q6 in Table 4.1). Second, we ask respondents to evaluate and compare two investment options of which one is a house retrofit project (see Q7 in Table 4.1). We find that respondents perform rather well in choosing a more financially viable investment (64% of respondents select the correct answer), but less than half of respondents (45%) correctly answer the question about the payback period needed to cover the initial investment cost through savings from investing in the house retrofit. Based on the answers to these questions, we construct an energy-related financial literacy score, which takes on a value of 1 if the respondent correctly answers both energy-related financial literacy questions and a value of 0 otherwise. The share of respondents that answer energy-related financial literacy questions correctly (36%) is lower than the share of respondents that answer financial literacy questions correctly (44%) (see Table 4.2). Presumably, this could be explained by the more complex nature of energy-related financial literacy questions.

Table 4.2: variable definition, measurement, and descriptive statistics

Variable name	Definition	Measurement	Willing to retrofit		Not willing to retrofit		Total		Mean differences ‡
			Mean	S.D.	Mean	S.D.	Mean	S.D.	
Financial literacy	The owner's level of financial literacy	1 = correctly answers all questions 0 = otherwise	0.438	0.496	0.440	0.497	0.438	0.496	-0.002
Energy cost awareness	The owner's level of energy literacy	1 = correctly answers the question 0 = otherwise	0.668	0.471	0.619	0.487	0.656	0.475	0.049
Energy interest	The owner's interest in energy-saving opportunities	1 = above average level of energy interest 0 = otherwise	0.543	0.498	0.350	0.478	0.495	0.500	0.193***
Energy-related financial literacy	The owner's level of energy-related financial literacy	1 = correctly answers all questions 0 = otherwise	0.380	0.486	0.307	0.462	0.362	0.481	0.073**
Index	All-encompassing energy related financial literacy index	Number	3.880	1.650	3.533	1.814	3.794	1.698	0.347***
Finance familiar	The owner's level of familiarity with using different financial instruments	1 = if the owner practices an above-average	0.758	0.429	0.696	0.461	0.743	0.437	0.062*

(saving and investment)		number of saving and investment activities 0 = otherwise							
Age	Age of the owner	Year	43.40	13.32	41.69	12.82	42.98	13.21	1.71*
Income	The household's total monthly income	Up to 499 euros	0.120	0.325	0.105	0.307	0.116	0.321	0.015
		500-999 euros	0.273	0.446	0.288	0.454	0.277	0.448	-0.015
		1000-1999 euros	0.389	0.488	0.370	0.484	0.384	0.487	0.019
		2000-2999 euros	0.154	0.362	0.163	0.370	0.157	0.364	-0.009
		> 3000 euros	0.063	0.245	0.073	0.262	0.066	0.249	-0.010
Gender	Gender of the owner	1 = male, 0 = female	0.265	0.442	0.292	0.455	0.272	0.445	-0.027
Education	Education level of the owner	1 = higher education degree 0 = otherwise	0.710	0.454	0.658	0.475	0.697	0.460	0.052
HH size	Number of people living in the apartment	Number	2.621	1.202	2.848	1.307	2.677	1.232	-0.227**
Apartment size	Size of the apartment	m^2	63.780	56.880	68.520	71.790	64.950	60.900	-4.740
Indoor temperature	If the level of indoor temperature is < 20 ºC	1 = yes, 0 = otherwise	0.369	0.483	0.346	0.477	0.363	0.481	0.023
Heating compensation	If the owner receives compensation for district heating expenses in the 2020/21 season	1 = yes, 0 = otherwise	0.081	0.274	0.062	0.242	0.077	0.266	0.019

Electricity expense	The amount of electricity expense in the last winter season (2021)	euros/month	36.440	39.340	34.110	38.320	35.870	39.080	2.330
Risk aversion	The owner's preference towards risky investment	The scale of 1 (high-risk aversion) to 6 (low-risk aversion)	3.125	1.726	3.016	1.807	3.098	1.746	0.109
Time preference (inconsistent)	Whether the respondent has inconsistent time preferences or not	1 = Yes, 0 = No	0.284	0.451	0.261	0.440	0.279	0.449	0.023
Time preferences	The owner's time preference	The scale of 1 (strong future preference) to 11 (strong present preference).	5.439	4.092	5.374	3.919	5.423	4.048	0.065
Environmental concern	If the owner believes that environmental concerns are the most serious issues facing the world today	1 = Yes, 0 = No	0.476	0.500	0.467	0.500	0.474	0.500	0.009
Energy bill burden	If energy bill is a burden for the owner	1 = Yes, 0 = No	0.450	0.498	0.444	0.498	0.449	0.498	0.006
Trust (neighbors)	If the owner trusts neighbors	1 = Yes, 0 = No	0.628	0.484	0.549	0.499	0.608	0.488	0.079**

Trust (institutions)	If the owner trusts different institutions, including government organizations promoting retrofitting, experts from science institutions, and construction firms.	1 = Yes, 0 = No	0.276	0.447	0.144	0.352	0.243	0.429	0.132***
Trust (house administration)	If the owner trusts house administrators	1 = Yes, 0 = No	0.491	0.500	0.350	0.478	0.456	0.498	0.141***
No. of observations			784		257		1, 041		

Notes: ‡ t-tests are performed to determine if the sample means are significantly different between those who are willing to retrofit and not willing to retrofit houses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3.3 Other variables

In addition to the energy related financial literacy dimensions discussed above, we also constructed an all-encompassing index following Blasch et al. (2021) and Filippini et al. (2020). As presented in Table 4.1, we asked three questions to measure financial literacy, one question to measure electricity cost awareness, and two questions to measure energy-related financial literacy. The index constructed using answers to these questions ranges from zero to six, depending on the total number of questions correctly answered by the given respondent. The index equal to zero indicates that the respondent did not answer any of the six questions correctly, while the index equal to six means that the respondent answered all questions correctly.[32] This approach enables us to compare our findings with similar studies in the literature as well as estimate different model specifications to check the robustness of our results.

Following the existing empirical studies, we include a host of other variables that could explain an individual's intention to retrofit a multi-dwelling building. Specifically, we account for socioeconomic and behavioral factors (Blasch et al., 2017a; Brounen et al., 2013; Kalmi et al., 2021; Mills & Schleich, 2012; Schleich et al., 2019), dwelling characteristics (Blasch et al., 2019; Filippini et al., 2020; Qiu et al., 2014; Trotta et al., 2017), and trust in different stakeholders, including government institutions, neighbors, and house administrators (Brown et al., 2014; Risholt & Berker, 2013). Table 4.2 presents the definitions and summary statistics of these variables. Additionally, as we are interested in understanding whether there is a significant difference between the respondents who are willing to retrofit their houses and who are unwilling to retrofit the house. For this we report the results of the t-test to determine if there is a significant difference between the means of these two groups in the same table.

[32] We check the internal consistency of different elements used in constructing each component of the energy-related financial literacy index following the approaches of Blasch et al. (2021) and Filippini et al. (2020). First, we look at the correlation coefficient between the components (50%) and next calculate Cronbach's alpha for the elements in each component (alpha ranges from 0.49 to 0.63). A higher Cronbach's alpha indicates the internal consistency of the scales used to measure each element of a given component, implying that the items in that component are closely related and justifying the reliability of the method used. See also Taber (2018) for a detailed discussion about Cronbach's alpha.

In general, we can conclude that respondents who are willing to retrofit their houses are, on average, very similar to respondents who are unwilling to retrofit their houses in terms of most socioeconomic characteristics. A high share of respondents (around 70%) from both groups report completion of higher education. Respondents, on average, are 43 years old, live-in apartments of 65 square meters, and spend 36 euros per month on electricity. Most respondents' (38%) household income ranges between 1,000–1,999 euros, and households average 2.6 individuals.[33] Furthermore, respondents who are willing to retrofit their houses are not different from respondents who are not willing to retrofit their houses in terms of the financial literacy score, as in both groups over 40% of respondents answered all financial literacy questions correctly. However, this is not the case once we consider energy-related financial literacy as we find that a higher share of respondents (38%) who are willing to engage in retrofitting their houses correctly answered energy-related financial literacy questions compared to the share of respondents who are unwilling to engage in house retrofitting (30.7%). This difference is statistically significant at a 5% significance level. Moreover, a significant share of respondents (54.3%) who are willing to retrofit their houses have above-average interest in energy-saving opportunities compared with the proportion of respondents who are unwilling to retrofit their houses (35.0%).

We also asked survey participants about their trust in different people in the community, like their neighbors and house administrators, and trust in institutions related to house retrofitting, including governmental organizations promoting house retrofits, experts from scientific institutions, and construction firms. In our survey, we measure the individual's trust in different stakeholders on a scale from 1 (absolutely trust) to 4 (absolutely do not trust). Based on the responses, we construct three dummy variables indicating trust in neighbors, trust in house administrators, and trust in retrofitting-related institutions (i.e., government organizations promoting retrofitting, experts from scientific institutions, and construction firms). These dummies take on a value of 1 if the answer is "absolutely yes" or "yes" for each respective trust question and a value of 0 otherwise. It is evident that respondents that express a willingness to retrofit their houses have significantly higher levels of trust in all stakeholders (see Table 4.2).

[33]According to Statistics Lithuania, in 2019, the average monthly gross income in the country was 1,160 euros, and the average household size was 2.17 individuals (SL, 2020).

4.3.4 Empirical strategy

As stated in the introduction, our empirical strategy aims to test the following four hypotheses: (1) There is a positive relationship between willingness to retrofit a house and financial literacy; (2) Energy literacy has a positive association with willingness to retrofit a house; (3) Energy-related financial literacy is positively related to willingness to retrofit a house; and (4) Trust in different stakeholders related to house retrofits is positively associated with intention to retrofit a house.

To test these hypotheses, we proceed as follows. First, we estimate a simple probit model since our outcome variable—the willingness to retrofit the house—is a binary variable, taking a value of 0 or 1. However, it is plausible that this model may suffer from endogeneity bias, which might be caused by different factors. First, the relationship between energy-related financial literacy (or financial literacy in general) and the willingness to invest in house retrofitting could be affected by reverse causality. For example, a person's energy-related financial literacy could have increased because she/she has already invested in a house retrofit or has already decided to do so in the near future. Second, energy-related financial literacy (or financial literacy) and the willingness to retrofit the house might be jointly determined by omitted factors like unobserved ability, personality traits, or different family member characteristics. For instance, a higher level of energy-related financial literacy (or financial literacy) in one or more of the family members could increase the energy-related financial literacy score of the entire household and, at the same time, influence the decision to engage in energy-efficient investment activities like house retrofitting. Finally, sample selection errors could be present. Hence, to address endogeneity problems, the second step of our empirical strategy is to identify suitable instrumental variables (IVs) and estimate multivariate probit (MVP)[34] and IV probit models. In estimating all models, we measure our variable of interest in two different ways. First, to explicitly test the effect of energy-related financial literacy components on the

[34] We use the MVP model in the IV framework since both the outcome variable (willingness to retrofit the house) and the endogenous variables (energy-related financial literacy and its dimensions) are binary categorical variables. Furthermore, this approach simultaneously estimates a system of different models allowing for residual correlations to capture interdependence among different models. To estimate the MVP model, we use the *mvprobit* command in Stata. See Cappellari and Jenkins (2003), Wilde (2000), and Wooldridge (2010) for a detailed discussion of this approach.

willingness to invest in the house retrofit, we include them in our MVP model separately. Second, we use the all-encompassing index constructed from the energy related financial literacy components to estimate the IV probit model.

Following previous studies in the field of financial literacy, which is closely related to the newly emerging field of energy-related financial literacy, respondents' attainment of higher education degree and familiarity with financial instruments are used as the IVs for our potentially endogenous variables (Alessie et al., 2011; Calcagno & Urzì Brancati, 2014; Pesando, 2018; Van Rooij et al., 2011). We use the two instruments as the IVs for financial literacy, but for energy-related financial literacy, energy cost awareness, and energy interest, we use familiarity with financial instruments as an IV.[35] In principle, the IVs should be correlated with the endogenous variable but uncorrelated directly with willingness to retrofit the house. Intuitively, attaining higher education, for instance, directly affects the person's financial literacy but not necessarily her/his willingness to retrofit the house. Instead, education will affect energy efficiency investment decisions by improving the individual's financial knowledge. Similarly, the respondent's familiarity with using different financial instruments (in short, financial inclusion) could improve her/his financial knowledge and, eventually, could enhance her/his energy-related financial literacy, which should lead to a higher willingness on the part of the respondent to retrofit the energy-inefficient building. In the following section, we test the validity of the chosen IVs.

4.4 Results

4.4.1 Initial results from the simple probit models

In this subsection, we briefly present the initial results from estimating the simple probit regression models without considering the above-mentioned potential endogeneity issues. We start with regressing the willingness to retrofit the house on each energy-related financial literacy dimension (see columns 1 to 4 in Table 4.3). We then estimate a probit model, which includes all energy-related financial literacy dimensions together (see column 5 in Table 4.3). Finally, we estimate a probit model using an all-encompassing

[35] We conducted an overidentification test of weak instruments and found that education is a weak instrument for energy-related financial literacy, energy cost awareness, and energy interest but not for financial literacy. Therefore, we use education as an IV for financial literacy alone.

index as an indicator for energy related financial literacy (see column 6 in Table 4.3). In Table 4.3, we report the estimated average marginal effects.

Table 4.3: Probit regression models, average marginal effects

	(1)	(2)	(3)	(4)	(5)	(6)
Financial literacy	-0.004				-0.033	
	(0.028)				(0.028)	
Energy cost awareness		0.035			0.021	
		(0.028)			(0.028)	
Energy interest			0.137***		0.135***	
			(0.026)		(0.026)	
Energy-related financial literacy				0.066**	0.066**	
				(0.029)	(0.029)	
Index						0.024***
						(0.008)
Trust (neighbors)	0.018	0.017	0.015	0.015	0.013	0.014
	(0.029)	(0.029)	(0.028)	(0.029)	(0.028)	(0.029)
Trust (house administration)	0.069**	0.069**	0.071**	0.067**	0.069**	0.065**
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Trust (institutions)	0.114***	0.114***	0.095***	0.113***	0.096***	0.113***
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Apartment size	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Income	0.005	0.004	-0.003	-0.000	-0.005	-0.003
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Gender	-0.025	-0.027	-0.041	-0.030	-0.042	-0.034
	(0.030)	(0.030)	(0.029)	(0.030)	(0.030)	(0.030)
HH size	-0.031***	-0.031***	-0.031***	-0.029***	-0.030***	-0.028**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Electricity expense (ln)	0.036**	0.036**	0.033*	0.033*	0.030*	0.034*
	(0.018)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)
Risk aversion	0.005	0.006	0.004	0.006	0.005	0.008

	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Time preference (inconsistent)	0.021	0.023	0.043	0.033	0.050	0.037
	(0.031)	(0.030)	(0.030)	(0.031)	(0.031)	(0.031)
Time preference	-0.001	-0.001	-0.001	-0.001	-0.000	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Energy bill burden	-0.000	0.001	-0.001	0.005	0.002	0.006
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Indoor temperature	0.007	0.008	0.002	0.010	0.004	0.010
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Heating compensation	0.021	0.027	0.008	0.029	0.015	0.034
	(0.054)	(0.053)	(0.053)	(0.053)	(0.052)	(0.053)
Environmental concern	-0.012	-0.012	-0.019	-0.017	-0.022	-0.016
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
No. of observations	1,041	1,041	1,041	1,041	1,041	1,041
Wald chi-squared	46.38	49.60	68.73	49.92	73.37	53.55
Prob > chi-squared	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R-squared	0.039	0.040	0.061	0.043	0.066	0.046

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Looking at the components of energy related financial literacy, we find that there is no significant relationship between financial literacy and apartment owners' willingness to retrofit a house (see column 1 in Table 4.3). Likewise, respondents' energy cost awareness plays an insignificant role in explaining apartment owners' willingness to retrofit a house (see column 2 in Table 4.3). However, energy-related financial literacy is positively and significantly associated with willingness to retrofit a house (see column 4 in Table 4.3). The average marginal effect of the energy-related financial literacy variable is 0.066, which means that the probability of willingness to retrofit the house of individuals who did not answer all energy-related financial literacy questions correctly is lower by 6.6 percentage points. Furthermore, our results indicate that higher interest in energy-saving opportunities significantly contributes to willingness to retrofit a house (see column 3 in Table 4.3). Individuals who have an above-average level of interest in energy-saving measures are more likely to be pro-retrofit by 13.7 percentage points. Moreover, we find a significant and positive relationship between the all-encompassing index and the willingness to retrofit the house. A unit increase in this index is associated with about a 2.5 percentage point higher probability to retrofit the house (see column 6 in Table 4.3). Taking all these initial results together, we can state that there is support for our second and third hypotheses that energy literacy and energy-related financial literacy are positively associated with willingness to invest in a house retrofit.

The results from the simple probit models also give support to our fourth hypothesis that trust helps explain apartment owners' willingness to retrofit a house. Namely, we find that a higher trust in house administrators and institutions is significantly associated with a higher probability of willingness to make collective retrofit investment decisions (see column 5 in Table 4.3). This signifies an important role of institutions in the retrofitting process, as they are responsible for designing and implementing retrofitting regulations as well as for partially funding the retrofits of multi-dwelling buildings. Similarly, trust in house administrators is also associated with a higher chance of being pro-retrofit (see column 5 in Table 4.3). The latter result is not surprising given the fact that in Lithuania, house administrators play a central role in facilitating the house-retrofitting process, starting with the persuasion of apartment owners to retrofit the building, and finishing with the coordination of the entire retrofitting process once the decision to retrofit the house has been made. The initial findings from our simple probit models are confirmed by our main results using the multivariate probit models, except for the case of financial literacy, which we present below.

4.4.2 Main results from the multivariate probit (MVP) and IV probit models

In this subsection, we look into our main results obtained by estimating the MVP and IV probit models to address the potential endogeneity bias discussed in Section 4.3.4. We use attainment of higher education degree and familiarity with different saving and investment activities (i.e., financial inclusion) as the instruments for financial literacy, and we use financial inclusion as an IV for energy cost awareness, energy-related financial literacy, and interest in energy-saving opportunities. Table 4.4 presents the estimated results from these models.

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Table 4.4: MVP and IV probit model results

	Panel A	
	MVP	**IV probit Average marginal effects**
Financial literacy	0.664**	
	(0.277)	
Energy cost awareness	0.684***	
	(0.202)	
Energy interest	0.676**	
	(0.314)	
Energy-related financial literacy	0.820***	
	(0.198)	
Index		0.151***
		(0.056)
Trust (neighbors)	0.026	-0.011
	(0.073)	(0.034)
Trust (house administration)	0.155**	0.046
	(0.078)	(0.034)
Trust (institutions)	0.253***	0.109***
	(0.092)	(0.039)
Apartment size	-0.001	-0.000
	(0.001)	(0.000)
Age	0.003	-0.000
	(0.003)	(0.001)
Income	-0.163***	-0.044*
	(0.047)	(0.023)
Gender	-0.336***	-0.076*
	(0.094)	(0.039)
HH size	-0.003	-0.009
	(0.040)	(0.015)
Electricity expense (ln)	0.080*	0.029
	(0.045)	(0.019)
Risk aversion	0.030	0.016*
	(0.023)	(0.010)
Time preference (inconsistent)	0.467***	0.119**
	(0.098)	(0.048)
Time preference	0.010	0.003
	(0.010)	(0.004)
Energy bill burden	0.023	0.031

	(0.071)	(0.033)
Indoor temperature	0.018	0.026
	(0.070)	(0.031)
Heating compensation	0.082	0.081
	(0.133)	(0.059)
Environmental concern	-0.047	-0.040
	(0.066)	(0.031)
Constant	- 0.973***(0.304)	
Panel B: First stage results of instruments		
Finance familiar (saving and investment)	0.334***	0.467***
	(0.092)	(0.120)
Education	0.158*	0.346***
	(0.098)	(0.106)
Wald test of exogeneity (P-value)		6.48 (0.010)
No. of observations	1,041	1,041

Notes: Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Before we report the results, we check the validity of our instruments and the appropriateness of the IV approach in the following way. First, we present the estimation results from the first stage of the MVP and IV probit models, which shows whether our instrumental variables affect the endogenous variable. As discussed above, finding a significant relationship between the instrumental variable and the endogenous variable is one indicator for the relevance of our instruments. Second, we undertake a Wald test of exogeneity, which tests the null hypothesis that the correlations between the error terms of the first- and second-stage models is not significant for the IV probit model. For the MVP model we also use the Wald test to check for the absence of significant correlations between the error terms in the willingness to retrofit the house model and the models for each endogenous variable. In other words, it tests for the presence of endogeneity in the model. Accepting the null hypothesis of this test indicates the absence of endogeneity bias and that a simple probit model could be enough to measure the relationships of interest. The results of this exercise are reported in Panel B of Table 4.4 and Table A4.1 in the appendix.

The test results presented in the first column of Table A4.1 of the appendix shows the presence of significant correlations between the error terms of the willingness to retrofit model and those from the models for energy-related financial literacy components, implying the presence of endogeneity bias. Similarly, we find that the index used to measure energy related financial literacy is endogenous and that both education and familiarity with financial instruments significantly and positively affect it, meaning that both variables can be valid instruments for this index (see column 2 in panel B of Table 4.4).

While it is argued that the MVP model does not require an exclusion restriction as long as varying exogenous variables appear in both the structural and reduced form models, using IVs increases the power of parameter identification in this model (Balia & Jones, 2008; Wilde, 2000). Therefore, when we estimate the MVP model, we use both education and familiarity with financial instruments as the IVs for financial literacy, whereas familiarity with financial instruments alone is used as an IV for energy cost awareness, energy interest, and energy-related financial literacy.

The results from the first stage of the MVP model indicate that familiarity with financial instruments is a valid instrument for energy-related financial literacy and interest in energy-saving opportunities, but not for energy cost awareness (see column 1 in panel B of Table 4.4). The result from the same model also reveals that both education and financial inclusion are valid instruments for financial literacy.

The results from the MVP model, which measures the effect of each energy-related financial literacy dimension on willingness to retrofit a house, are reported in the first column of Table 4.4. The results from this model should be interpreted on their signs. Once we account for endogeneity bias using the IV approach, we find that financial literacy positively and significantly affects apartment owners' willingness to invest in a house retrofit (see column 1 in panel A of Table 4.4). This result lends support to our first hypothesis, which states that financial literacy is positively associated with willingness to invest in house retrofitting. Similarly, we find support for our second hypothesis that energy literacy, which is defined in terms of energy cost awareness and high energy interest, is positively associated with the willingness to retrofit a house (see column 1 in panel A of Table 4.4). Having an above-average level of interest in energy-saving opportunities significantly increases the willingness to invest in house retrofitting.

Furthermore, as before, we find that energy-related financial literacy helps to explain the probability of a person's willingness to retrofit a house. That means that compared with individuals who answer none of the energy-related financial literacy questions correctly, those who answer all of the questions have higher willingness to invest in house retrofitting. These results support our third hypothesis that energy-related financial literacy increases willingness to invest in retrofitting a house.

The second column in panel A of Table 4.4 shows that using an index to measure energy related financial literacy does not alter the effect of energy related financial literacy on apartment owners' willingness to invest in a house retrofit. A unit increase in this all-encompassing index leads to a roughly 15-percentage-point increase in the probability of willingness to retrofit a house.

Finally, our results lend support to our fourth and final hypothesis that trust increases willingness to invest in house retrofitting. We find that trust in house administrators and trust in institutions are associated with a higher probability of willingness to invest in a house retrofit. The estimated results for trust in house administrators are significant in only the MVP model. Our interpretation is that apartment owners who trust house administrators are highly likely to be pro-retrofit. On the other hand, the estimated effects of trust in institutions are significant in both the IV probit and MVP models. The result from the IV probit model indicates that the probability of being willing to retrofit a house among apartment owners who trust institutions is higher by about 11 percentage points than for individuals who do not trust institutions. All in all, our findings suggest that trust in stakeholders and institutions that are directly related to the retrofitting process matters considerably for apartment owners' house-retrofitting intentions.

When it comes to other variables that could help explain willingness to retrofit a house, we find that female respondents have a higher probability of being willing to retrofit than male respondents (see columns 1 and 2 in panel A of Table 4.4). Higher electricity expense is also associated with a higher probability of being pro-retrofit. However, earning a higher income reduces the likelihood of being pro-retrofit.

4.4.3 Robustness tests

As a robustness check, we estimate our model using Lewbel's method of heteroscedastic based identification (Lewbel, 2012). This approach allows us to address endogeneity in the absence of standard IVs exploiting the heteroscedasticity of the error terms in the first and second stage regressions. However, including additional exclusion restrictions (even if they are weak), improves identification and Lewbel's method provides estimated results with and without exclusion restriction for comparison. This approach has been also widely used by other studies in various domains, including the financial literacy literature (Grohmann et al., 2018; Guo et al., 2021; Le Moglie et al., 2015).

Thus, our estimation involves the use of education and familiarity with financial instruments as exclusion restrictions. Table 4.5 presents the estimated results following this approach using the aggregated index as our main variable of interest. For the sake of comparison, we report the estimated results using the standard IV approach (column1), using the generated instruments only (column 2), and using both the generated instruments and exclusion restrictions (column 3) in the same table.[36]

Consistent with the main finds reported above, robustness test results reveal that energy-related financial literacy significantly increases the willingness to invest in house retrofit. Individuals who correctly answered all the energy-related financial literacy questions have a 9 to 9.5 percentage points higher probability of retrofitting a house than those who did not correctly answer all the questions. Furthermore, the results related to trust in institutions also remain robust when we estimate our model following this approach.

Table 4.5: Robustness test results using Lewbel's method

	Standard IV	**Using only generated instruments**	**Using both excluded and generated instruments**
Index	0.094**	0.089*	0.088***
	(0.048)	(0.032)	(0.032)
Trust (institutions)	0.092***	0.094***	0.093***
	(0.031)	(0.031)	(0.031)
Trust (house administration)	0.057*	0.058*	0.058*
	(0.032)	(0.032)	(0.032)
Trust (neighbours)	0.001	0.000	-0.000
	(0.033)	(0.032)	(0.031)
Apartment size	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Age	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)
Income	-0.027	-0.027	-0.027

[36] We use the *ivreg2h* Stata command to estimate our models.

	(0.020)	(0.017)	(0.017)
Gender	-0.058	-0.054	-0.052
	(0.035)	(0.033)	(0.033)
HH size	-0.017	-0.018	-0.018
	(0.014)	(0.013)	(0.013)
Electricity expense (ln)	0.034*	0.032*	0.033*
	(0.019)	(0.019)	(0.019)
Risk aversion	0.013	0.013	0.013
	(0.009)	(0.008)	(0.008)
Time preference (inconsistent)	0.084*	0.075*	0.074**
	(0.043)	(0.037)	(0.037)
Time preference	0.001	0.001	0.001
	(0.004)	(0.003)	(0.003)
Energy bill burden	0.020	0.020	0.020
	(0.030)	(0.029)	(0.029)
Indoor temperature	0.020	0.015	0.014
	(0.029)	(0.029)	(0.029)
Heating compensation	0.054	0.087*	0.085*
	(0.047)	(0.045)	(0.045)
Environmental concern	-0.026	-0.017	-0.018
	(0.028)	(0.027)	(0.027)
Constant	0.337*	0.365	0.369***
	(0.172)	(0.181)	(0.139)
Weak identification test – Cragg-Donald Wald F statistic	18.877	1.895	3.579
Overidentification test (Hansen J-statistic-P-values)	0.346	0.967	0.979
Number of observations	1, 041	1, 041	1, 041

4.5 Summarizing remarks

Energy inefficiency is the distinguishing feature of multi-dwelling buildings in the Soviet-era countries. However, the rate of retrofitting of these energy-inefficient houses is sluggish. In this paper, we hypothesize that the low retrofit rate of multi-dwelling buildings in Soviet-era countries could be partially explained by the low level of energy-related financial literacy among households in those countries. Furthermore, we argue that these households' lack of energy-related financial literacy makes them dependent on other essential stakeholders in the house-retrofitting process, such as neighbors, national and local institutions, and supply-side actors in the construction industry. To this end, we examine the effect of energy-related financial literacy and trust on apartment owners' willingness to invest in retrofits of their multi-dwelling buildings. Our empirical analysis relies on incentivized representative survey data collected from apartment owners in Lithuania.

We find that energy-related financial literacy significantly increases apartment owners' willingness to retrofit their multi-dwelling buildings. This result is robust to different measurements of energy-related financial literacy and different model specifications. We also show that more trust in institutional stakeholders, in particular house administrators, significantly increases apartment owners' willingness to retrofit multi-dwelling buildings.

From a policy perspective, our findings have important implications for energy efficiency policymaking in Soviet-era countries. First, providing both the costs and benefits of a particular house retrofit project in a clear, trustworthy, objective, and understandable manner should be taken as an important policy option to increase energy efficiency investments where it is needed. This could be achieved in different ways, including automated calculators that enable house owners to easily identify the net benefit of investments in energy-efficient activities. Furthermore, just before house owners vote on whether to retrofit their multi-dwelling house, they could be provided with an opportunity to take a short (online or on-site) financial literacy education and training program tailored to improve their understanding of the costs and benefits of their financial investment decision. The educational program could enable individuals to make an informed energy efficiency investment decision rather than relying on simple decision-making heuristics. The positive effect of online calculators and short education programs on selecting an appliance with a lower lifetime cost in Switzerland has been shown by (Blasch et al., 2017b). Whether the provision of energy-related financial education programs can really improve retrofit decision-making needs careful investigation. Hence, future research focusing on evaluating the cost-effectiveness of these approaches by using randomized experiments in the context of Soviet-era countries could provide meaningful information for policymakers.

Second, another possible way to overcome the lack of financial knowledge and skills among much of the populace in making complicated retrofit investment decisions is by sharing good practice experiences among different communities. To facilitate such sharing, one needs institutions that can be trusted by these communities. Hence, our findings imply that the stakeholders (local or governmental institutions, house administrators, and others) aiming at reducing the energy efficiency gap through investment in energy-efficient activities, like multi-dwelling building retrofits, should build up their trustworthiness. Trust facilitates energy efficiency investment by reducing uncertainty and increasing cooperation among various stakeholders. This is especially critical for households living in the Soviet-era countries.

While our study provides new evidence on the role of energy-related financial literacy in multi-dwelling building retrofitting decisions in the context of Soviet-era countries, it is not without limitations. As we rely on self-reported survey data, the causal interpretation of our findings should be taken with some caution. Even if we use the IV approach to address possible endogeneity biases, there might be some uncontrolled confounding factors that could bias our results. Nonetheless, our study contributes to the field of energy literacy and trust in explaining collective decisions in energy efficiency.

5. CLIMATE CHANGE ADAPTATION AND PRODUCTIVE EFFICIENCY OF SUBSISTENCE FARMING

Climate change continues to be seen as a serious threat to the natural and human systems of the world. These wide-ranging effects include ecosystem shifts, species extinctions, and disruptions of agricultural production and water supply that endanger food security and welfare (IPCC, 2014). Many studies show that climate change effects are paramount in the agriculture sector, which is not only the sector most vulnerable to climate-related shocks—it is also the main source of economic growth in sub-Saharan Africa, including Ethiopia, and especially among smallholder farmers (Crost et al., 2018; Deressa & Hassan, 2009; Di Falco et al., 2012; Zhang et al., 2017).

Agriculture is at the heart of the Ethiopian economy in terms of employment, exports, and national income. It employs 80% of the country's labor force and contributes 75% to the merchandise export earnings and nearly 40% to GDP (NBE, 2016). Ethiopia's economy is highly vulnerable to climate change for two main reasons. First, the agriculture sector in Ethiopia is mainly at subsistence level, rain-fed, and dominated by cereal crops; smallholder farmers produce about 90–95% of the total agricultural output. Second, Ethiopia remains one of the world's least developed countries, with a per capita annual income of $660. Thus, the risk of food insecurity and poverty is highly likely to increase in Ethiopia unless proper measures are taken to mitigate the impact of climate change.

Numerous studies suggest that implementing adaptation strategies will help reduce the effect of climate change (Bradshaw et al., 2004; Di Falco et al., 2011; Huang & Sim, 2021; Lin, 2011; Teklewold et al., 2013). Increasing production efficiency is one way of improving sustainability and resilience (Lokina & Lwiza, 2018; Wassie, 2014). First, climate adaptation strategies abate the effect of climate change through increasing resilience capacity. Second, climate adaptation strategies increase farmers' productivity by introducing new or improved agricultural practices, thereby improving technical efficiency (TE). This will directly contribute to an increase in crop yield and farm income, which will in turn improve farm households' welfare and consequently enhance farms' adaptive capacity.

Addressing this issue is more critical in countries like Ethiopia, where reconciling food production and environmental sustainability is very challenging, partly due to the alarming growth in population and lower agricultural technology adoption rates, coupled with the persistence of traditional agricultural practices. In response, we explore the effect of climate change adaptation on the TE of farmers engaging in subsistence agriculture in the Nile basin of Ethiopia. Although there is extensive literature on climate adaptation's effects on subsistence farming, there are fewer studies on efficiency that account for selection bias and exploit panel data. We employ a selection-bias-corrected model under a stochastic production frontier (SPF) framework. Our approach jointly implements propensity score matching (PSM) to address selection bias due to observed farmers' heterogeneity and Greene's (2010) approach to deal with selection bias due to unobserved farmers' heterogeneity in a panel-data setting.

Most previous studies have investigated the effects of climate adaptation strategies from three interrelated perspectives. The first strand focuses on yield and income effects of climate adaptation (see, e.g., studies by Arslan et al., 2015; Di Falco & Veronesi, 2013; Suresh et al., 2021; Tambo & Mockshell, 2018; Teklewold et al., 2013). The other two strands base their analyses on effects of climate adaptation strategies on poverty and risk exposure (see, e.g., Di Falco & Veronesi, 2014; Di Falco et al., 2011; Farris et al., 2017; Kassie et al., 2015; Khanal et al., 2021) and welfare implications (see, e.g., Asfaw & Shiferaw, 2010; Asmare et al., 2019; Khonje et al., 2015). However, none of these studies use panel data, and hence do not capture dynamic aspects of adaptation to climate change.

Vijayasarathy and Ashok (2015) for India and Khanal et al. (2018) for Nepal find that various climate adaptation measures are associated with higher farmers' TE. By contrast, Otitoju and Enete (2014) report that multiple planting dates – one climate adaptation practice – in Nigeria have a negative effect on farmers' TE. However, these studies fail to account for selection bias: the fact that farmers who employ climate adaptation measures are different in many ways from farmers who do not. Furthermore, to the best of our knowledge, there is no study that examines the efficiency effect of climate change adaptation in the context of Ethiopian subsistence agriculture.[37]

We explore the impact of climate change adaptation on TE among subsistence farmers by using a plot-level panel dataset from rural smallholder farmers in Ethiopia. Furthermore, we examine the importance of accounting

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[37] The only studies we are aware of that relate to our analysis are by Di Falco et al. (2012) and Di Falco and Veronesi (2013), who explore the effect of climate change adaptation on Ethiopian household income. However, these studies do not analyze the efficiency effect of climate change adaptation.

for weather and soil factors when estimating farmers' plot-specific productive efficiency for specific crops.

The remainder of this study is organized as follows. In Section 5.1, we provide some background information on climate change adaptation together with our data. Section 5.2 presents the empirical strategy. The results are presented and discussed in Section 5.3. We conclude in Section 5.4.

5.1 Data and background information on the study area

5.1.1 Study area and data

The study uses a panel data collected using a survey from 929 farm households and 6,820 plots within the Nile basin of Ethiopia. The survey was conducted by the Environment and Climate Research Center (ECRC) at the Ethiopian Development Research Institute in 2015, 2016 and 2017.[38]

The Nile basin covers around 34% of Ethiopia's area and contains 40% of its population. In the study area, the average farm size per household is rather small—less than one hectare—is traditionally farmed with animal draught power, and relies heavily on manual labor. The employment of other inputs is rather limited (Deressa et al., 2009).

The dataset comprises various surveyed households' and associated land plot characteristics, households' perceptions of climate change, and climate change adaptation practices. The study also incorporates two climate variables: the average annual temperature (measured in °C) and average rainfall (measured in mm) of the *Belg* and *Meher* seasons[39] for the period from 1983 to 2015. Considering long-term averages of climatic variables as indicators of climate change is a common approach (see, e.g., Di Falco & Veronesi, 2013; Mendelsohn et al., 2007).

The precipitation and temperature data were gathered from every meteorological station in Ethiopia. The Thin Plate Spline approach for a spatial interpolation was utilized to attribute the plot-explicit precipitation and temperature values using each plot's geographic location data.[40] The advantages of this approach are that it is accessible, easy to apply, and

[38] A sample of households was selected in 2015 and continuously surveyed for the years 2016 and 2017.

[39] *Meher* is the main cropping season, ranging from April to December. *Belg* covers the time from February to September.

[40] This approach is the most common and widely used method to produce spatial climate data sets. See, for example, Wahba (1990) for more information.

accounts for spatially varying geographical relationships (Di Falco et al., 2011).

The variables used in this study, together with their definitions and main summary statistics, are presented in Appendix D, Table A5.1. A detailed explanation about the sampling frame and sample selection procedure can be found in (Asmare et al., 2019).

5.1.2 Background information on climate and climate change adaptation practices in the study area

Dynamics of average rainfall and temperature

Identifying whether farmers notice climate change is the first step in any climate change adaptation impact evaluation study. Therefore, we look at the dynamics of the geo-referenced rainfall and temperature data specific to our study area for the last 32 years. Then, we analyze surveyed farmers' personal perceptions about climate change, their observed climate-related shocks, and their actually implemented climate change adaptation strategies.

The dynamics of rainfall and temperature are presented in Figure A5.1 of Appendix D. It is evident that surveyed plots have been significantly affected by rainfall and temperature variability. We can identify at least three extreme periods when there was an acute shortage of rainfall: 1984, 2002, and especially 2011–2012. These three extreme periods were followed by the three main drought events experienced by Ethiopia after the 1970s (Gebremeskel et al., 2019). The 1985 drought was caused mainly by a lower level of rainfall in 1984. Low precipitation in 2002 also led to the second drought in 2003. The third and most disastrous drought—not only in Ethiopia but also in the Horn of Africa—was in 2011. In 2011, two consecutive rain failures (Belg and Meher seasons) in Ethiopia resulted in a devastating drought impacting the southern, eastern, and north-eastern parts of the country (Somali, Afar, eastern and southern Tigray, southern Oromia, and SNNPR) affecting 4.5 million individuals. It was the worst drought in 60 years in Ethiopia.

Farmers' perceptions of climate change and implemented climate adaptation measures

One section in the questionnaire collected information about farmers' climate change perceptions together with their implemented climate adaptation measures. Specifically, the ECRC asked the following questions: *Have you noticed any changes in climate over your lifetime? If you have* *noticed changes in climate over your lifetime, do you practice the following climate adaptation practices?* About 95% of surveyed farm households in the study area indicated that they had noticed some changing climatic conditions. From Table 5.1, it is evident that most observed changing climate conditions are related to rainfall, such as erratic nature of rains, late rains, and decreasing rainfall. About 60% of surveyed farm households stated that these changing climatic conditions had affected the productivity of their farm plots.

Table 5.1: Noticed climatic change and implemented climate adaptation strategies, pooled plot-level data

Noticed climatic change	**No. of obsv.**	**Percent**	**Climate-related shocks**	**No. of obsv.**	**Percent**	**Implemented climate adaptation strategies**	**No. of obsv.**	**Percent**
More hot days	317	4.65	Drought	853	13.57	Improved crop variety	2,636	38.68
More cold days	43	0.63	Flood	267	4.25	Agroforestry	964	14.15
Rainfall increasing	414	6.07	Erratic rainfall	1,658	26.38	Minimum tillage	229	3.36
Rainfall decreasing	1,351	19.81	Animal attack	216	3.44	Soil conservation	1,489	21.86
Rains are more erratic	2,200	32.26	Land slide	17	0.27	Intercropping	266	3.90
Rains come earlier	527	7.73	Hailstorms	543	8.64	Irrigation	288	4.23
Rains come later	1,428	20.94	No shocks	2,542	40.44	Crop rotation	4,579	67.21
Others	187	2.74	Others	190	3.02	Crop residue	1,943	28.52
No change	353	5.17	**Total**	**6,286**	**100**	Row planting	1,620	23.78
Total	**6,820**	**100**						

Source: Authors' calculations based on survey data.

As one can see from Table 5.1, crop rotation (reported by 67.2% of surveyed farm households), improved crop varieties (38.7%), crop residue (28.5%), row planting (23.8%), and soil conservation activities (21.9%) were the main climate change adaptation practices used by these farmers.

5.2 Empirical strategy

5.2.1 Identification of causal effects

The main challenge to inferring causal effects in impact evaluation studies is addressing selection biases that arise from observed and unobserved heterogeneities. For this reason, we measure the impact of climate change adaptation on surveyed farmers' TE following the recent works of Bravo-Ureta et al. (2011) and Villano et al. (2015) who combined PSM, to correct for selection bias arising from observable factors, with Greene's (2010) proposed SPF model with a correction for unobserved sample selection. We exploit a similar approach in the panel-data setting.

To deal with selection bias from unobservable variables (e.g., farmer's innate and managerial ability, risk preferences and motivation) within SPF formulations, we employ the approach introduced by (Greene, 2010),[41] which assumes that the unobserved characteristics in the sample selection equation (i.e., the error term, w, in Eq. 5.1) are correlated with the noise in the stochastic frontier model (i.e., the part of the noise term, v, in Eq. 5.2). Sample selection bias due to unobserved heterogeneity arises if the error term in the production function, v, is correlated with unobservable factors in the sample selection equation, w; that is, if $\rho = corr\ (w,v) \neq 0$. The sample selection and SPF models, together with their error structures, can be specified as follows:

Sample selection: $d^* = \boldsymbol{\alpha}' z + \mathrm{w}, d = 1(d^* > 0)$ (5.1)

[41] Heckman (1979) sample selection model, which uses the inverse Mills ratio as a bias correction factor, has been used by many studies over some three decades. However, this approach is inappropriate for non-linear models such as SPF (Greene, 2010). Recently, alternative approaches have been introduced to deal with this problem. The first two attempts were made by Kumbhakar et al. (2009) and Lai et al. (2009). The model developed by Kumbhakar et al. (2009) assumes that the selection mechanism carries on through the one-sided noise term in the production function; they used this model to assess the efficiency of dairy farming in Finland. On the other hand, Lai et al. (2009) developed a model that assumed that the selection is correlated with the composed error in the frontier; they implemented their model to explore wage determination. However, the log-likelihood of these two models is computationally cumbersome.

SPF: $\mathrm{y} = \boldsymbol{\beta}'\mathrm{x} + v - u$ (5.2)

where y and x are observed only when d = 1.

Error structure: $u = |\mathrm{U}|$ with $\mathrm{U} \sim N(0, \sigma_u^2)$ (5.3)

$(v, w) \sim$ bivariate normal with $[(0,0), (\sigma_v^2, \rho\sigma_v, 1)]$

For the panel data specification, it is assumed that the "selection" takes place only once, before the production model operates. In the specification of the model, d and w do not change from period to period. Thus, the selection model used here is a random-effects selection model (Greene, 2016).[42]

In the sample selection equation, d is a binary variable equal to one for plots that implemented adaptation strategies in the first wave of the survey period (2015) and zero for plots of non-adopters; z is a vector of explanatory variables included in the sample selection model; and w is an unobservable error term. In the SPF model, y is plot-level output, and x is a vector of plot-level farming inputs in the production frontier. In the same model, v and u represent the stochastic error term and the inefficiency term, respectively. The vectors of coefficients $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are the parameters to be estimated, while the characters in the error structure are the components of the errors parallel to those usually included in the stochastic frontier specification. It is important to highlight that a statistically significant ρ parameter indicates the presence of selectivity bias in unobservable factors.

5.2.2 Estimation procedure

Even though several methods can be employed to estimate propensity scores, we base our analysis on a "1-to-1" nearest neighbor matching technique with replacement (Caliendo & Kopeinig, 2008) wherein every plot adopter is matched with a plot non-adopter imposing the common support condition.[43] We conduct a plot-level analysis for the following reasons. First, in our dataset, adaptation strategies are recorded at the level of the farming plot. Second, there are many plot-level characteristics—such as plot fertility, slope, distance from homestead, plot-level rainfall, and temperature values—that are important in explaining plot-level agricultural efficiency and output.

[42] For details on model specification, see LIMDEP 11 econometric modeling guide, pp. 1500–1505.

[43] As a robustness test, we also used the radius matching technique to show that our main results do not depend on the choice of the matching approach. The result of this exercise is presented in Table A5.13 in Appendix D.

Failure to control for these plot-specific varying factors may yield misleading results. Other studies also follow similar approaches (see, e.g., Di Falco et al., 2011; Kassie et al., 2015).

In our modeling framework, a plot is considered as a climate adopter if one or two specific climate adaptation strategies (i.e., improved crop varieties and/or soil conservation activities) are practiced on that plot. To choose among the practiced adaptation strategies (listed in Table 5.1), we follow two approaches. First, we consider the correlations between farmer perceptions of climate change and the adaptation practices. Table A5.2, Appendix D shows that two adaptation strategies—improved crop variety and soil conservation—have the highest correlation with the climate notice variable. Second, we assume that the likelihood of implementing a given adaptation strategy should be positively and significantly affected by climate variables such as temperature and rainfall. Indeed, the results from a probit model reported in Table A5.3, Appendix D, show that the probability of implementing improved crop variety and soil conservation strategies are positively correlated with average temperature and negatively correlated with the standard deviation of rainfall. Hence, we select these two adaptation strategies—improved crop varieties and soil conservation activities[44]—for our analysis.[45]

To facilitate the selection of matching variables, we rely on results from previous studies that analyzed subsistence farmers' climate change adaptation decisions (Di Falco & Veronesi, 2013; Kassie et al., 2013; Khanal et al., 2018; Ojo & Baiyegunhi, 2020; Teklewold et al., 2013; Teklewold et al., 2019). The matching variables are (1) various socio-economic factors, such as age,

[44] Improved crop varieties include higher-yield crop varieties and drought-resistant crop varieties. Soil conservation activities include stone bunds and soil bunds.

[45] One question that may arise here is why we do not consider all climate adaptation strategies that farmers implemented. We are constrained to choose only two climate adaptation strategies because of the methodology we use. Greene's (2010) sample selection correction approach, developed for the SPF framework, is designed for only the binary selection equation. We believe that using a more appropriate methodology allows us to address selection bias, thereby obtaining more robust results than by using methodologies considering many adaptation strategies without addressing selection bias; therefore, we focus only on the two of them. In addition, there are some adaptation strategies that farmers practice habitually, regardless of changing climate conditions. For instance, it is a common practice to rotate crop type from year to year. Thus, we want to disentangle such practices from adaptation practices that are driven by climate change. Hence, in this study, when we refer to "adopters," we mean climate adopters, and when we refer to "non-adopters," it is intended to describe climate non-adopters.

income, gender, education, marital status, household size, and off-farm employment; (2) credit and institutional factors, including extension service, food aid, farmers' perception of whether to rely on government during bad harvest seasons, land ownership, land certification, market distance, and farm support; (3) various farming plot characteristics, such as slope, soil fertility, soil depth, and plot distance to the homestead; and (4) climatic variables, such as monthly average growing season rainfall and its square, annual average temperature and its square, standard deviation of growing season rainfall, standard deviation of temperature, and farmers' perception of whether the growing season rainfall was sufficient.

The matching procedure generates a total of 6,588 matched observations, of which 2,997 are adopters and 3,591 are non-adopters. Table A5.4 (Appendix D) presents the descriptive statistics of the variables used in the selection model across the matched and unmatched samples, as well as the *t* test of whether the means of plot adopters and plot non-adopters are equal. We find that before matching, this hypothesis is rejected for most variables, whereas after matching, this hypothesis is accepted for all variables—at the 5% level of significance, at least. In addition, we provide the distribution of the estimated propensity scores in Figure A5.2 in Appendix D. The majority of propensity scores for adopters and non-adopters are found under the region of common support; therefore, the overlap assumption is fulfilled.

We estimate the SPF model with this matched sample corrected for sample selection. This requires a probit model, which is assumed to be associated with a number of plot-specific variables of the adoption of climate adaptation practices on a plot, household characteristics and exogenous climate characteristics.

The SPF model is estimated using a log-linear Cobb–Douglas[46] specification as follows:

$$ln(OUTPUT_{it}) = \beta_0 + \beta_1 ln\,(LAND_{it}) + \beta_2 ln\,(LABOR_{it}) + \beta_3 ln\,(ASSET_{it}) + \beta_4 ln\,(SEED_{it}) + \beta_5 ln\,(UREA_{it}) + \beta_6 ln\,(DAP_{it}) + \beta_7 ln\,(TLU_{it}) + v_{it} - u_{it}, \quad (5.4)$$

where v_{it} and u_i are as defined in Eq. 5.3. The dependent variable, $OUTPUT_{it}$, is the total weight of harvested crops (wheat, teff, maize, and barley) from the i^{th} plot, measured in kilograms, in production period *t*. These particular four crops were chosen based on their importance in Ethiopian agriculture; they

[46] The likelihood ratio test suggests that the Cobb–Douglas functional form is preferred over the translog counterpart. LR $chi^2 = 34.67$, Prob > $chi^2 = 0.1795$.

account for about 75% of the total cultivated area and 70% of the total agricultural production (Taffesse et al., 2011). The explanatory variables include: plot land size, measured in hectares; total amount of labor in the plot measured in person days; total value of productive farm assets, measured in Ethiopian birr; total amount of seed used in the plot, measured in kilograms; total amount of UREA and DAP fertilizers used in the plot, measured in kilograms; and total amount of livestock owned by the household, measured in tropical livestock units (TLU).

The average log values of output and input variables used in the SPF models for the matched sample are presented in Table 5.2. It is evident that, on average, output is significantly higher for adopters than for non-adopters. Furthermore, adopters consume significantly more labor, use fewer seeds, and possess more assets than non-adopters.

Table 5.2: Descriptive statistics of output and input variables used in the SPF models for the matched sample

	Adopters		Non-Adopters		
	Mean	S. D.	Mean	S. D.	Difference in means ‡
OUTPUT (ln)	5.66	1.05	5.35	1.06	-0.31***
LAND (ln)	0.25	0.17	0.24	0.16	-0.01*
LABOR (ln)	5.62	1.05	5.39	1.14	-0.23***
ASSET (ln)	9.69	1.30	9.60	1.31	-0.09***
DAP (ln)	2.34	1.52	1.57	1.62	-0.77***
UREA (ln)	2.11	1.51	1.29	1.55	-0.82***
SEED (ln)	2.47	1.16	2.67	1.09	0.20***
TLU (ln)	1.60	0.61	1.59	0.62	-0.01
No. of obsv.	2,997		3,591		

Notes: ‡*t* tests are performed to determine whether the sample means are significantly different between adopters and non-adopters.

Before presenting and discussing the estimation results, following Bravo-Ureta et al. (2011), we summarize the main estimation steps we perform to obtain the selection bias corrected average TE scores for adopters and non-adopters.

1. First, we estimate a pooled unmatched SPF model (*Pooled-U*), which includes the dummy variable *Adaptation* (zero for non-adopters, one for adopters) as an explanatory variable of the climate change

adaptation decision. Hence, this model does not control for any type of biases.

2. Next, two separate SPF models are estimated with the unmatched dataset, again ignoring any biases: one for adopters (*Adopters-U*) and the other for non-adopters (*Non-Adopters-U*).
3. The impact of correcting for self-selection is analyzed next. Using all the available data, we conduct PSM to address the bias from observed factors by matching adopters with non-adopters. Then, the selection probit model for the matched sample is estimated.
4. The fourth step is to estimate two separate SPF models by using the unmatched data and by correcting for selection bias following Greene (2010): one for adopters (*Adopters-U-S*) and the other for non-adopters (*Non-Adopters-U-S*).
5. The pooled SPF model is re-estimated with the matched sample. It includes the *Adaptation* dummy variable (zero for non-adopters, one for adopters) as an explanatory variable to represent the climate change adaptation decision.
6. Without addressing selection bias from unobserved factors, two distinct conventional SPF models are estimated using the matched subsamples: one for adopters (*Adopters-M*) and the other for the non-adopters (*Non-Adopters-M*). At this stage, the model addresses biases from observed heterogeneities only.
7. Finally, two separate SPFs are estimated using the matched subsamples: one for adopters (*Adopters-M-S*) and another for non-adopters (*Non-Adopters-M-S*), correcting for selectivity bias. Thus, these models address both types of selection bias (from observed and unobserved variables).

Next to the baseline model (Eq. 5.4), we estimate several additional SPF models for the matched sample. First, we estimate a separate SPF model and evaluate the effect of climate adaptation for each type of crop (wheat, teff, maize, and barley) because we expect that climate adaptation strategies may be crop-specific. By estimating a separate SPF model for each crop, we will check whether the production of these crops is based on the same technology.

Second, we expand the baseline SPF model (Eq. 5.4) by including weather- and soil-related factors that could potentially affect output of harvested crops. Sherlund et al. (2002) claim that failure to account for these factors will underestimate efficiency and overestimate inefficiency, which could produce findings that may mislead policymakers. This SPF model includes climate and soil variables, such as average Meher season rainfall and average temperature for 32 years (1983–2015), soil fertility, soil depth, and plot slope. The inclusion of these important factors enables us to compare the discrepancy in input elasticities and level of efficiency (if any) with and without weather and soil variables.

5.3 Results and discussion

5.3.1 Main results from the baseline model

The maximum likelihood estimation results from the conventional SPF model and SPF model adjusted for sample selection are presented in Table 5.3 for the matched sample and in Appendix D, Table A5.5, for the unmatched sample. In line with our expectations, the estimates imply positive partial elasticities for all production inputs except DAP. However, the elasticities vary in magnitude and statistical significance across different models. In all models reported in Table 5.3 and Appendix D, Table A5.5, plot size (*LAND*) and labor contribute most to the total output of both plot adopters and plot non-adopters.

Table 5.3: Parameter estimates of the conventional and sample selection SPF models, the matched sample

	Conventional SPF			Sample selection SPF	
	(1)	(2)	(3)	(4)	(5)
	Pooled-M	Adopters-M	Non-Adopters-M	Adopters-M-S	Non-Adopters-M-S
LAND (ln)	2.13***	2.08***	2.17***	2.29***	1.87***
	(28.88)	(20.17)	(21.29)	(0.06)	(0.11)
LABOR (ln)	0.07***	0.07***	0.06***	0.06***	0.07***
	(7.04)	(4.90)	(4.88)	(0.02)	(0.01)
ASSET (ln)	0.04***	0.01	0.05***	-0.00	0.06***
	(5.14)	(1.10)	(5.24)	(0.01)	(0.01)
DAP (ln)	-0.001	0.05	-0.02	-0.01	0.00
	(-0.75)	(0.33)	(-1.52)	(0.01)	(0.01)
UREA (ln)	0.09***	0.11***	0.07***	0.13***	0.05***
	(9.08)	(7.96)	(5.38)	(0.01)	(0.02)
SEED (ln)	0.061***	0.02*	0.09***	0.07***	0.10***
	(6.84)	(1.91)	(7.57)	(0.02)	(0.01)
TLU (ln)	0.03*	0.04*	0.02	0.05*	0.03
	(1.86)	(1.67)	(0.85)	(0.03)	(0.03)
Adaptation	0.19***(9.29)	-	-	-	-

Constant	4.76***(59.15)	5.20***(44.03)	4.60***(42.88)	5.61***(0.15)	4.86***(0.12)
σ (u)	1.13***(0.02)	1.26***(0.02)	1.29***(0.02)	0.874***(0.06)	1.10***(0.04)
σ (v)	0.32***(0.02)	0.28***(0.03)	0.31***(0.03)	0.97***(0.03)	0.85***(0.02)
Λ	3.98	5.81	4.09	0.89	1.13
Log-likelihood	-8,156	-3,630	-4,502	-5,980	-6,740
Selectivity correction term (*ρ*)	-	-	-	0.92***(0.12)	-0.86***(0.02)
No. of obsv.	6,588	2,997	3,591	2,997	3,591

Notes: Standard errors in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

From the conventional pooled SPF models for the unmatched (*Pooled-U*) and matched (*Pooled-M*) samples, we find that the effect of climate change adaptation on agricultural output is positive and significant (see column 1 in both Table 5.3 and Appendix D, Table A5.5). This result suggests that plot adopters and plot non-adopters may use different agricultural production technologies. We perform the LR test to check whether there is a difference in the production technology among the two groups. The test result shows a test statistic of 32.77 (p = 0.00), implying that the null hypothesis—which predicts that adopters and non-adopters will have the same production technology—is rejected. Therefore, our test results confirm the appropriateness of fitting two distinct SPF models—one for adopters and the other one for non-adopters.

Next, we analyze the impact of correcting for self-selection. First, we look at the results from the probit model that estimates the determinants of a farmer's decision to implement climate change adaptation measures in their specific plot using the matched sample. The estimates summarized in Table 5.4 indicate that the likelihood of implementing climate change adaptation is influenced by many factors, including farm household characteristics, plot-specific covariates, institutional factors, and climatic variables. For instance, we find that extension service about climate change adaptation, farm support, and farmers' education increases the likelihood of implementing climate change adaptation measures. Furthermore, farmers are more likely to practice climate change adaptation on plots that they themselves own and manage, rather than on shared plots—suggesting that tenure security is a contributing factor in sustainable land management.

Also, we find that the effect of temperature is U-shaped; that is, at lower temperature levels, the likelihood of climate change adaptation is lower. However, this inverse relationship will cease beyond a certain temperature, as implied by the estimated coefficient of the squared term of temperature. A higher temperature beyond this threshold increases the likelihood of implementing a climate change adaptation measure, possibly because a temperature higher than the optimal level required for crop production will cause water shortages and other disasters, including drought and crop loss.

Table 5.4: Parameter estimates of climate change adaptation decision using the matched sample

Variable	Coefficient	Variable	Coefficient
AGE	0.02**	SHALDEPT	-0.023
	(2.23)		(-0.36)
AGE^2	-0.01**	PLOTDIST	0.01
	(-2.23)		(0.04)
GENDER	0.21**	FARMSUPPO	0.22***
	(2.55)		(3.04)
MARRIED	-0.10	HHSIZE	0.01
	(-1.43)		(0.81)
OFFEMP	0.01	LANDOWNER	0.14***
	(0.02)		(2.66)
CREDIT	-0.08**	AVMRF	0.04***
	(-2.15)		(5.09)
AID	-0.28***	SDMRF	-0.02***
	(-3.86)		(0.02)
RELGOV	-0.03	AVMRFSQ	-0.01***
	(-0.87)		(-2.99)
CERTIFICAT	0.01	AVTMPSQ	0.02***
	(0.40)		(4.32)
EDUC	0.02**	AVTEMP	-0.80***
	(2.52)		(-4.03)
FLATSLOP	-0.07	SDTEMP	0.11**
	(-0.86)		(2.41)
MEDMSLOP	0.03 (0.38)	ENOURAIN	0.02 (0.54)
MEDMDEPT	-0.03 (-0.84)	MKTDIST	-0.01 (-1.55)
MEDMSOIL	0.22*** (3.80)	CLIMEEXTE	0.08**(2.20)
		Location dummies	Yes
GOODSOIL	0.22***	Log pseudo-likelihood	-4, 207
	(3.49)	Prob > chi2	0.00
Constant	2.68 (1.35)	No. of obsv.	6,588

Notes: Robust standard errors clustered at plot level in parentheses; *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

We use plot-specific rainfall during the growing season (Meher) and its variability to estimate the effect of rainfall on climate adaptation decisions. Considering season-specific rainfall rather than the total amount of annual rainfall is appropriate because it will show farmers' real responses to changing climatic conditions. Unlike temperature, the effect of rainfall is an inverted U-shape. Initially, at lower levels of rainfall, the likelihood of adaptation increases as rainfall increases. However, beyond some level of rainfall, further rainfall is associated with a lower likelihood of adopting a climate adaptation strategy. Our results are in line with the results of Deressa et al. (2009) and Deressa et al. (2011), who showed that weather variables such as precipitation and temperature are significant influences on the decision to implement climate adaptation strategies.

The estimates of the sample selection SPF models show that the sample selection correction term (ρ) is statistically different from zero for both adopters and non-adopters in the matched and unmatched samples. This result implies the existence of selection bias from unobservable factors; thus, estimating the separate selection bias-corrected SPF models for adopters and non-adopters is justified. Even though the main objective of this study is to measure the impact of implemented climate change adaptation strategies on plot adopters' TE, we also aim to understand how addressing selection bias from observed and unobserved heterogeneities affects the estimated TE scores. In Table 5.5, we present the average TE scores for adopters and non-adopters estimated by using the conventional SPF and selection-bias-corrected SPF models for the unmatched and matched samples. In addition, Table 5.5 presents the differential (in percentage terms) between the TE for adopters and the TE for non-adopters.

The average TE scores reveal that plot adopters are more efficient than plot non-adopters and that this difference is statistically significant after addressing selection bias in both the matched and unmatched samples. After addressing both types of biases, the TE differential between adopters and non-adopters is 12.37%, which is significantly larger than the conventional counterpart (4.21%). This suggests that plots are becoming more efficient due to the implementation of climate change adaptation strategies. Furthermore, our results reveal that the conventional SPF models underestimate the impact of climate change adaptation on average TE.

Table 5.5: Average TE levels across different models

	Conventional SPF				**Selectivity-corrected SPF**		
	Unmatched sample						
	Pooled-U	Adopters-U	Non-Adopters-U	*t* test of means‡	Adopters-U-S	Non-Adopters-U-S	*t* test of means‡
TE	41.33	42.26	40.55	1.71***	48.88	40.23	8.65***
TE Differential	4.21%				21.50%		
	Matched sample						
	Pooled-M	Adopters-M	Non-Adopters-M	*t* test of means‡	Adopters-M-S	Non-Adopters-M-S	*t* test of means‡
TE	44.6	45.10	44.19	0.91*	53.03	47.19	5.84***
TE Differential	2.059%				12.37%		

Notes: ‡*t* tests are performed to determine whether the sample means are significantly different between adopters and non-adopters; $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

In line with the findings of Villano et al. (2015) and Azumah et al. (2019) , our results show that failure to correct for selection bias from observed and unobserved factors overestimates inefficiency, while it underestimates the TE gap between adopters and non-adopters. However, these results are contradicted by those of Bravo-Ureta et al. (2011), who found that the TE gap between treated and control groups decreased as the correction for bias was implemented.

Even though plots where climate change adaptation practices are implemented are more efficient, there remains enormous potential to increase production and the overall efficiency of these plots. For the matched sample, corrected for selection bias, the average TE of plot adopters is 53%; the average TE of plot non-adopters, corrected for selection bias, is estimated to be 47%, indicating that farmers lose 52.81% of their total output because of technical inefficiency.

Addressing selection bias from both observables and unobservables not only reduces the proportion of plots operating at lower levels of efficiency, but also increases the proportion of plots operating at higher efficiency levels. For instance, when we compare the proportion of plots operating with 51–60% TE without accounting for any type of biases (Fig. A5.3A, Appendix D) to its counterpart when accounting for biases (Fig. A5.3D, Appendix D), the proportion of plots increases from 6% to 11.63% for adopters and from 6.83% to 10.84% for non-adopters. The effect of controlling for selection bias is larger for adopters.

We also examine which of the two groups (plot adopters or plot non-adopters) has a higher level of output after addressing selection bias from both observed and unobserved heterogeneities. Towards this end, we compare the average predicted frontier output for adopters and non-adopters generated from the selection-bias-corrected SPF models. On average, plot adopters not only attain higher TE, but also show statistically significant higher predicted outputs (see Table 5.6).

Table 5.6: Predicted frontier output in kg after bias correction

Sample	Adopters	Non-adopters	*t* test in means‡
Average	724.46	608.76	115. 7***
Min	6.63	12.47	
Max	4,918.62	5,130.82	

Notes: ‡*t* tests are performed to determine whether the sample means are significantly different between adopters and non-adopters; $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Finally, we repeat the previous analysis using the balanced sample only. As we explicitly pointed out in Section 5.2.1, it is assumed that once plot adopters are selected as adopters in the first wave of the survey period, they will remain adopters for the next two survey years. To address this, we constructed the balanced sample, wherein a plot adopter is considered as an adopter if they adopt in all the three years and a plot non-adopter as a non-adopter if they do not adopt in all three survey years. The results from the analysis of the balanced data sample (see Table A5.6, Appendix D) are consistent with the main findings discussed above.

5.3.2 Determinants of technical inefficiency

Identifying the determinants of technical efficiency (inefficiency) could enhance policymaking by indicating the potential directions of agricultural policy. Table 5.7 presents the determinants of TE estimated from a selectivity-corrected maximum simulated log-likelihood SPF and inefficiency models. For comparison, Table 5.7 provides the results for the pooled sample (column 1), the sample of farming plot adopters (column 2), and the sample of farming plot non-adopters (column 3). In our estimation, we include different covariates that could explain TE, including socio-demographic factors, plot characteristics, as well as institutional and climate-related factors. A positive significant estimated coefficient indicates a positive (negative) effect on inefficiency (efficiency).

Table 5.7: Determinants of technical inefficiency

	1	2	3
	Pooled	Adopter	Non-adopter
Age	-0.003***	-0.002	-0.004***
	(0.001)	(0.001)	(0.001)
Gender	0.106*	0.015	0.067
	(0.055)	(0.088)	(0.081)
Education	0.005	0.003	-0.002
	(0.004)	(0.007)	(0.006)
HH size	-0.015***	-0.025***	-0.010
	(0.005)	(0.008)	(0.007)
MARRIED	-0.080*	-0.071	-0.058
	(0.047)	(0.070)	(0.070)
CREDIT	-0.068***	-0.053	-0.067**
	(0.023)	(0.037)	(0.033)
RELGOV	-0.061**	-0.072*	-0.029
	(0.025)	(0.041)	(0.036)
PLOTDIST	0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.000)
SHALDEPT	0.070*	0.073	0.022
	(0.041)	(0.069)	(0.057)
MEDMDEPT	0.040	0.062	0.025
	(0.028)	(0.042)	(0.040)
MEDMSLOP	-0.007	-0.016	0.016
	(0.069)	(0.097)	(0.097)
FLATSLOP	0.044	0.160*	0.003
	(0.068)	(0.095)	(0.095)
GOODSOIL	0.287***	0.139**	0.203***
	(0.040)	(0.067)	(0.056)
MEDMSOIL	0.192***	0.050	0.173***
	(0.037)	(0.061)	(0.053)
AVMRF	0.014***	0.020***	0.018***
	(0.002)	(0.003)	(0.003)
SDMRF	-0.001	-0.001	0.001
	(0.001)	(0.001)	(0.001)
AVTEMP	-0.027***	-0.018	-0.031**
	(0.010)	(0.016)	(0.014)
SDTEMP	-0.005	-0.038	-0.020
	(0.027)	(0.047)	(0.035)
AVMRFSQ	-0.000***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)
Location dummy	Yes	Yes	Yes
Constant	3.734*** (0.308)	4.409*** (0.470)	3.462*** (0.452)
Log-likelihood	-12,786	-5,837	-6,768
No. of obsv.	6,588	2,997	3,591

Table 5.7: Determinants of technical inefficiency

	1	2	3
	Pooled	Adopter	Non-adopter
Age	-0.003***	-0.002	-0.004***
	(0.001)	(0.001)	(0.001)
Gender	0.106*	0.015	0.067
	(0.055)	(0.088)	(0.081)
Education	0.005	0.003	-0.002
	(0.004)	(0.007)	(0.006)
HH size	-0.015***	-0.025***	-0.010
	(0.005)	(0.008)	(0.007)
MARRIED	-0.080*	-0.071	-0.058
	(0.047)	(0.070)	(0.070)
CREDIT	-0.068***	-0.053	-0.067**
	(0.023)	(0.037)	(0.033)
RELGOV	-0.061**	-0.072*	-0.029
	(0.025)	(0.041)	(0.036)
PLOTDIST	0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.000)
SHALDEPT	0.070*	0.073	0.022
	(0.041)	(0.069)	(0.057)
MEDMDEPT	0.040	0.062	0.025
	(0.028)	(0.042)	(0.040)
MEDMSLOP	-0.007	-0.016	0.016
	(0.069)	(0.097)	(0.097)
FLATSLOP	0.044	0.160*	0.003
	(0.068)	(0.095)	(0.095)
GOODSOIL	0.287***	0.139**	0.203***
	(0.040)	(0.067)	(0.056)
MEDMSOIL	0.192***	0.050	0.173***
	(0.037)	(0.061)	(0.053)
AVMRF	0.014***	0.020***	0.018***
	(0.002)	(0.003)	(0.003)
SDMRF	-0.001	-0.001	0.001
	(0.001)	(0.001)	(0.001)
AVTEMP	-0.027***	-0.018	-0.031**
	(0.010)	(0.016)	(0.014)
SDTEMP	-0.005	-0.038	-0.020
	(0.027)	(0.047)	(0.035)
AVMRFSQ	-0.000***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)
Location dummy	Yes	Yes	Yes

Constant	3.734*** (0.308)	4.409*** (0.470)	3.462*** (0.452)
Log-likelihood	-12,786	-5,837	-6,768
No. of obsv.	6,588	2,997	3,591

The results reveal that the determinants of the TE are similar for plot adopters and plot non-adopters. However, the size and statistical significance of the effects are different. For instance, the technical inefficiency of adopters is significantly influenced by family size, reliance on government, and climatic factors; for adopters, larger family size reduces inefficiency. Because implementing climate change adaptation measures require both monetary and non-monetary outlay including labor, large families could facilitate the effectiveness of the implemented adaptation strategy by providing the required labor. On the other hand, large family size could also serve as a source of diversified farming knowledge, information, and non-farm income.

We also find that a farmer's perception that they can rely on the government during a bad cropping season significantly enhances plot adopters' TE, possibly because government support during a bad harvest season serves as a partial source of insurance against crop failure. This may encourage farmers to implement new and improved agricultural technologies that increase efficiency. Looking at climatic factors, the amount of rainfall during the main harvesting season has a nonlinear effect on the efficiency of both adopter and non-adopter plots. A lower amount of rainfall during this season reduces TE, whereas a higher rainfall beyond some threshold improves efficiency. Because most farmers in the study area engage in rainfed subsistence farming, insufficient rainfall during the main harvesting season will inhibit production efficiency by causing crop failure, asset depletion, and welfare loss in general; this result is in line with the findings of Auci and Coromaldi (2021). Unlike rainfall, temperature appears to significantly improve the efficiency of plot non-adopters only. Beyond climate-related factors, non-adopter plots' TE is significantly affected by plot characteristics, age of the household head, and access to credit. Older farmers are more efficient than younger farmers, indicating the role of farm experience in boosting productive efficiency. On the other hand, access to additional financial resources may assist farmers in smoothing their consumption during bad harvesting seasons and also may serve as a source of finance to purchase improved agricultural inputs and technologies. Similar results are found by Abdulai and Abdulai (2017) for Zambia and Azumah et al. (2019) for Ghana.

5.3.3 Additional results

Even though the results from our basic model estimation show the general efficiency effect of climate adaptation and the problem of failure to account for selection bias, it comes with two caveats. First, the estimated SPF model does not account for weather and soil factors, which may be important. Second, we do not estimate a separate production function for each crop by accounting for technological differences involved in their cultivation.

To understand whether our main production function estimates are sensitive to climatic and soil factors, we estimate the SPF models, adjusted for sample selection, for the matched samples with weather and soil variables. We report the results from this estimation in Table A5.7, Appendix D (columns 3 and 4) next to the results from the baseline model (columns 1 and 2). It is evident that all models deliver similar partial elasticities for all main production inputs. The input elasticities of climate and soil variables are in line with our expectation. Higher rainfall and soil fertility positively contribute to the total output, whereas higher plot slope and temperature are associated with a decreasing level of output.

The availability of plot-specific data for each crop allows us to estimate a separate production function for each crop. The results from the estimated crop-specific SPF models adjusted for sample selection for the matched samples can be found in Appendix D, Table A5.8. We also measure the effects of climate adaptation strategies on each crop's TE; these are summarized in Table 5.8. The results reveal that climate adaptation strategies have a crop-specific effect. Among the crops studied, adopters of climate adaptation strategies achieve a higher level of efficiency in maize, wheat, and barley. On the other hand, climate adaptation measures appear to reduce efficiency for teff. This suggests that it is misleading to assume that climate adaptation strategies are equally effective for all crops. In the case of our study, climate adaptation in the form of improved varieties and soil and water conservation activities can boost productive efficiency for maize, wheat, and barley crops.

Table 5.8: Crop-specific TE estimation after accounting for weather and soil factors for the matched sample under different models

	Conventional SPF				Selectivity-corrected SPF		
	Pooled -M	Adopters -M	Non-Adopters -M	*t* test of means ‡	Adopters -M-S	Non-Adopters -M-S	*t test* of means‡
Maize							

TE	43.65	45.78	40.85	4.93***	59.01	38.24	20.77***
TE Differential	12.06%	-	-	-	54.31%		
Number of obsv.	2,006	1,150	856		1,150	856	
Wheat							
TE	47.72	47.64	47.82	-0.18	49.80	48.05	1.75**
TE Differential	-0.37%	-	-	-	3.642%		
Number of obsv.	1,501	778	723		778	723	
Teff							
TE	52.21	52.91	51.78	1.13	57.52	60.19	-2.67***
TE Differential	2.18%	-	-	-	-4.43%		
Number of obsv.	1,877	721	1,156		721	1,156	
Barley							
TE	45.03	44.73	45.15	-0.42	46.48	44.40	2.08*
TE Differential	-0.93%	-	-	-	4.68%	-	-
Number of obsv.	1,204	348	856		348	856	

Notes: [‡] *t* tests are performed to determine whether the sample means are significantly different between adopters and non-adopters; $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.00$.

5.3.4 Robustness tests

We perform four robustness checks. First, by considering the same adaptation strategies, we seek to check whether our main results on adaptation hold once the analysis is performed at the household level. This is important because farm households make the decision to implement particular climate change adaptation measures. Second, we check whether the results differ once we consider other climate adaptation strategies. Third, we look at the results performed for each wave of survey data. Finally, we modify our definition of "adaptation." As we discussed in the empirical strategy section, the selection bias correction model developed by Greene (2010) assumes that the selection takes place only once—in our case, in the first year when our survey data was collected. However, farmers' climate change adaptation decisions may vary from year to year, meaning that a farm plot might be considered as a plot non-adopter in the first survey year, but as a plot adopter in the second and/or third years of the survey period. As a robustness test to account for this possibility, we modify our definition of "adaptation" so that a farm plot is considered an adopter if the considered climate adaptation strategies are implemented in that specific plot in at least one of the three survey years.

The results from the different SPF models with the household-level data are reported in Appendix D, Table A5.9. We can see that household adopters have higher TE levels than household non-adopters across all models. The results from the SPF models based on plot-level data and using different adaptation strategies—crop diversification and agro-forestry—are summarized in the Appendix D, Table A5.10. The selection of these two adaptation strategies is based on the work of Deressa et al. (2011) and Di Falco et al. (2011), which showed that these two strategies are commonly used to curb climate-related shocks in their study areas. Our results show that plot adopters are more efficient than plot non-adopters. The efficiency difference becomes greater when we control for both types of bias. Moreover, the year-by-year TE estimates also reveal the same result, except for the year 2016 (see Appendix D, Table A5.11). Finally, we re-estimate our model using the modified definition of "adaptation" and find that, as in the main analysis, adopters attain a higher level of TE than non-adopters. The average TE difference between adopter plots and non-adopter plots is statistically significant (see Appendix D, Table A5.12).

5.4 Concluding remarks

In this study, we investigate the impact of climate change adaptation measures on farmers' TE. For this purpose, we estimate the selectivity-bias-corrected stochastic frontier models with the plot-level panel data collected by surveying rural farm households in the Nile basin of Ethiopia. We address selection bias from observed and unobserved heterogeneities by jointly implementing the PSM method with Greene (2010) sample selection model developed for the stochastic frontier framework under panel-data setting.

Our results show that the presence of selection bias (arising from unobserved factors such as motivation, risk attitude, and farmers' innate ability) affects farmers' climate change adaptation practices. Furthermore, we find that climate change adaptation significantly improves TE. That is, farming plots with climate change adaptation are more efficient than farming plots without climate change adaptation. The impact of adaptation becomes greater once we account for selection bias from observed and unobserved covariates, suggesting that failure to address selection bias under non-random assignment of an intervention significantly underestimates the level of TE. All these results are robust to the analysis performed with the data at the household level, to the inclusion of different climate change adaptation strategies, and to the year-by-year plot-level analysis. Furthermore, we show the importance of accounting for weather and soil factors when estimating farmers' plot-specific productive efficiency, and that the impact of climate adaptation is crop-specific. In the case of our study, climate adaptation in the form of improved varieties and soil conservation activities increases TE of barley, wheat, and maize crops.

We also find that different factors, including socio-economic characteristics, institutional factors, as well as plot- and climate-related factors, impact adopters' and non-adopters' TE differently. Whereas adopters' TE is significantly and positively affected by family size and perception of government support during bad harvest season, non-adopters' TE appears to be positively and significantly associated with the age of the farm's household head and access to credit. Regarding climate-related factors, average growing season rainfall has a U-shaped effect on the efficiency of both adopter and non-adopter plots. Lower rainfall in the growing season inhibits subsistence farmers' efficiency, whereas a higher level of rainfall that is enough for the crop boosts efficiency. However, temperature positively and significantly affects the efficiency of plot non-adopters only.

Moreover, we show that farmers' decision to implement climate change adaptation measures in their plots is significantly affected by socio-economic, institutional, and climate-related variables. Extension service about climate change adaptation, education level of the household head, and farm support significantly increase the likelihood of implementing climate change adaptation. Climate variables affect adaptation decisions non-linearly. Whereas the effect of plot-specific average temperature is U-shaped, the effect of the growing season's rainfall is an inverted U-shape.

The following policy implications are drawn from the results of this study. First, subsistence farmers are, on average, operating below their full potential, which calls for a special policy intervention that would unleash current farmers' productive potential. Second, because climate change adaptation measures have a positive and significant effect on farmers' productive efficiency, policymakers need to increase awareness among farmers, not only about the fact that climate change adaptation measures lessen climate-related shocks, but also about the fact that these measures can increase farmers' productivity. Thus, a robust and well-endorsed adaptation package could improve productivity and, consequently, improve food security in Ethiopia. Third, the efficiency effect of climate adaptation is crop-specific. Thus, agricultural policymakers should identify specific climate adaptation strategies suitable for each crop type rather than promoting climate adaptation as a general tool to curb climate-related shocks.

Fourth, we show that failure to address selection bias in the measurement of farmers' productive efficiency will yield biased results that are likely to mislead the decision-making of policymakers. Thus, policies aiming to increase agricultural productive efficiency and to reduce the impacts of climate change on agriculture should follow studies that use appropriate empirical techniques.

Fifth, various factors act as sources of subsistence farmers' inefficiency, and these factors differ between plot adopters and plot non-adopters. In particular, policymakers aiming to improve subsistence farmers' efficiency should focus on expanding credit access and ensuring water supply during the growing season.

Finally, policies seeking to create a climate-resilient agricultural sector should promote and expand tenure security, extension service about climate change adaptation, and financial farm support; these "ingredients" appeared to be important in explaining farmers' decisions to implement climate change adaptation strategies.

Although our study makes an important contribution to the literature, it is not without limitations. The selection bias correction model developed by Greene (2010) under a stochastic frontier analysis framework and used in our study is for binary selection only. To the best of our knowledge, no other method would allow the estimation of a multinomial selection model to address selection bias under a stochastic frontier analysis framework. However, the climate adaptation decision is multinomial, as farmers usually implement a combination of different adaptation strategies. Greene (2010) selection model further assumes that the selection takes place only once (in our case, in the first survey year). Thus, future studies could focus on relaxing the selection model to account for selection at different periods.

CONCLUSIONS

Climate change mitigation and adaptation are the two complementary climate policies of the 21st century. Residential energy conservation is one of the areas where there exists potential for climate change mitigation through reduced GHG emissions. According to IEA estimates, more than one third of the total GHG emissions reductions necessary to stabilize climate change could be attained through energy efficiency improvements (IEA, 2018). Equally important is climate change adaptation, a dominant policy tool designed to lessen the impact of climate change in the agriculture sector, which is highly vulnerable to climate-induced risks. In subsistence agriculture systems, where capital-intensive technologies needed to transform the sector are not accessible and farm inputs needed to provide sufficient food production are inadequate, improving production efficiency by implementing effective climate change adaptation strategies will provide a double benefit by increasing climate resilience as well as sustainable food production.

However, it is not yet well understood which interventions should be used to achieve energy efficiency in the residential sector and thereby mitigate climate change. Moreover, how climate change adaptation strategies impact the production efficiency of subsistence farmers is another crucial question that calls for appropriate empirical scrutiny. The central goal of this dissertation was to address these two broad questions. To this end, I conducted four standalone case studies, each of which was presented as a separate chapter in the thesis.

Using randomized filed experiments, I find that behavioral interventions in the form of pure personalized information feedback and social comparison not only have a direct impact on energy conservation, but also a spillover effect in secondary resource domains such as hot water consumption and heating energy use. In Lithuanian households, descriptive information provision reduced electricity consumption by 0.661 kWh (or 8.6%) per day. This is equivalent to an annual energy savings of 241 kWh per household. Furthermore, the results reveal that most reductions in electricity use occurred among households at the highest percentiles of electricity consumption. This suggests that policymakers should target households with high levels of energy consumption to achieve energy conservation objectives. Moreover, the persistency analysis reveals that the effect of the intervention was not short-lived. The intervention significantly reduced electricity consumption for 12 months post-treatment. This finding supports the claim that non-price interventions in the form of descriptive information provision could serve as an effective tool for energy conservation, even in less wealthy OECD countries.

The spillover effect of social comparison information depends on the type of resource targeted. I report that only electricity-targeted social comparison was effective in reducing electricity consumption and that it induced conservation beyond electricity, also leading to reductions in energy used for heating water and space. Indeed, the spillover effects were greater than the direct effects. The annual energy savings from the reduction in hot water consumption and space heating due to electricity-targeted social comparison were about 143 kWh and 90 kWh, respectively. In comparison, the annual energy savings from the directly induced reduction in electricity consumption amounted to 111 kWh. However, water-targeted social comparison induced effects on neither the targeted water domain nor energy resource domains.

I argue that the difference in direct treatment and spillover effects from the water and electricity treatments may be explained by differences in pre-existing social norms of resource utilization. I reason that in the case of the study area (northern Sweden), there is a stronger social norm for the conservation of energy than for the preservation of (cold) water. This potentially explains why social comparison treatment is successful in affecting energy-intensive resource domains such as electricity, hot water, and space heating. These findings suggest that behavioral interventions like social comparisons could bring significant energy savings beyond the targeted resource domains in societies with strong pre-existing social norms that support conservation of the targeted resource. Furthermore, I find evidence that the positive and significant spillover effects found in this study could be explained by other nonmonetary incentives, such as moral dissonance. This is because electricity-targeted social comparison treatment induced behavioral consistency—reduction in all energy-intensive resource domains but not in cold water—among treated households. This claim is further strengthened by the significant spillover effect on lower indoor temperatures, although there was no pecuniary incentive to save energy for heating.

To provide a broad perspective and deep understanding about the possible ways to improve energy efficiency in the residential sector, I extended the above discussion and examined the relationship between ERFL and large-scale energy-efficiency multiapartment retrofit investment. Although energy-efficient retrofit investments have been shown to provide positive financial and environmental payoffs, there is a very low level of investment in these activities. It has been claimed that households usually lack energy-related knowledge and cognitive capacity (bounded rationality) to conduct energy-related investment analysis. In the fourth chapter of this dissertation, I empirically assess the extent to which this claim is true.

I find that an increase in energy-related financial literacy significantly improves the likelihood of investing in Soviet-era multiapartment buildings retrofit in Lithuania. I also show that more trust in institutional stakeholders, in particular house administrators, significantly increases apartment owners' willingness to retrofit multi-dwelling buildings. The policy implication is that both the costs and benefits of a particular house retrofit project should be communicated in a clear, trustworthy, objective, and understandable manner through automated calculators; thus, by enabling homeowners to easily recognize the net benefit of investments in energy-efficient activities, energy-efficiency retrofit investment would increase. Furthermore, just before homeowners vote on whether to retrofit their multi-dwelling building, they could be provided with an opportunity to take a short (online or on-site) financial literacy education and training program tailored to improve their understanding of the costs and benefits of their financial investment decision. The educational program could enable individuals to make informed energy-efficiency investment decisions rather than relying on simple decision-making heuristics. Building trustworthy and transparent institutions is also needed to promote energy-efficiency retrofit investment.

Finally, in my explanation of how climate change adaptation strategies impact technical efficiency among subsistence farmers in Ethiopia, I find that implementing climate change adaptation strategies, such as improved crop varieties and water conservation activities, increased technical efficiency by about 12.37%. Using PSM and Greene's (2010) method of selection bias correction in the SFA framework, I also find that failure to account for selection bias underestimated the efficiency impact of climate change adaptation (4.21%). The crop-specific analysis reveals that climate adaptation improved TE of barley, wheat, and maize crops but not of teff. These findings have vital policy implications. Climate change adaptation can serve as a strategy to lessen the effect of climate change and improve subsistence farmers' production efficiency. However, maximum care should be given to its implementation. First, because the effects of climate change adaptation strategies are crop-specific, agricultural policymakers should identify specific climate adaptation strategies suitable for each crop type rather than promoting climate adaptation as a general tool to curb climate-related shocks. Second, complementary requirements, such as increasing farmers' awareness of the benefits of climate change adaptation measures, expanding credit access, promoting climate change adaptation extension services, and ensuring tenure security and water supply during the growing season, should be fulfilled to reduce inefficiency and increase positive decisions toward climate change adaptation.

Limitation and direction for future works

Even if the findings of this dissertation answer relevant policy questions and fill a clear gap in the behavioral environmental economics literature—specifically targeting energy and production efficiency—they are not without limitations.

First, the information intervention tested in chapter two is of a purely descriptive type without being combined with other types of behavioral intervention, such as social comparisons or energy saving tips. Even if this was a deliberate choice motivated by my interest in measuring the pure information intervention effect, it overlooks the effectiveness of other interventions. It should also be noted that I did not have data about how frequently participants logged in to the web portal to view the provided information. Thus, it should be understood that the treatment effects presented in this chapter are contingent upon the intensity of viewing the provided information. Therefore, future research could uncover how different modes and types of information provision alter energy consumption patterns among households in other less wealthy countries. The underlying mechanisms that derive the estimated treatment effects constitute a further caveat that warrants attention in future research.

Second, in chapter three, I argued that moral dissonance is the mechanism facilitating the positive spillover effect of electricity-targeted social comparison on hot water and heating energy use. However, this justification is merely suggestive evidence lacking in-depth analysis. For instance, it may be the case that social comparison information provided in one resource domain increased individuals' knowledge about how to conserve their resource and that they used this knowledge in other resource domains. A targeted study that aims to more precisely test such mechanisms would be needed to fill this gap. Moreover, in the analysis of the relationship between ERFL and Soviet-era multiapartment retrofit decisions, I relied on self-reported survey data. As a result, the causal interpretation of these findings should be treated with some caution. Even if I used the IV approach to address possible endogeneity biases, there might be some uncontrolled confounding factors that could bias the results. Future studies exploiting randomized experiments are necessary to further ascertain the causal relationship.

Finally, the selection bias correction model developed by Greene (2010) under a stochastic frontier analysis framework and used in this thesis is for binary selection only. To the best of my knowledge, no other method would allow the estimation of a multinomial selection model to address selection bias under the stochastic frontier analysis framework using panel data. However, the climate adaptation decision is multinomial, as farmers usually implement a combination of different adaptation strategies. Greene's (2010) selection model further assumes that the selection takes place only once (in my case, in the first survey year). Thus, future studies could focus on relaxing the selection model to account for selection at different periods as well as multinomial selections.

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APPENDIX

APPENDIX A: APPENDIX TO CHAPTER TWO

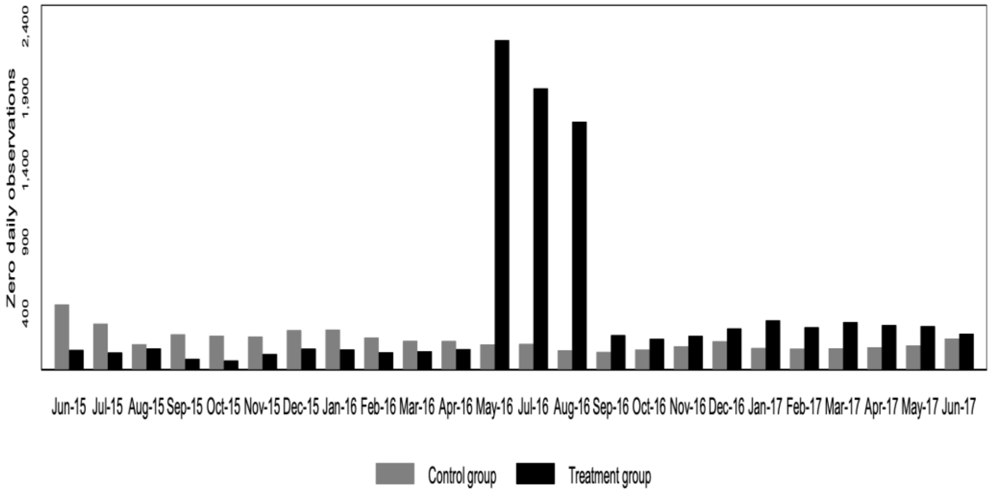


Figure A2.1: Number of zero daily observations by treatment status for each month of the experiment

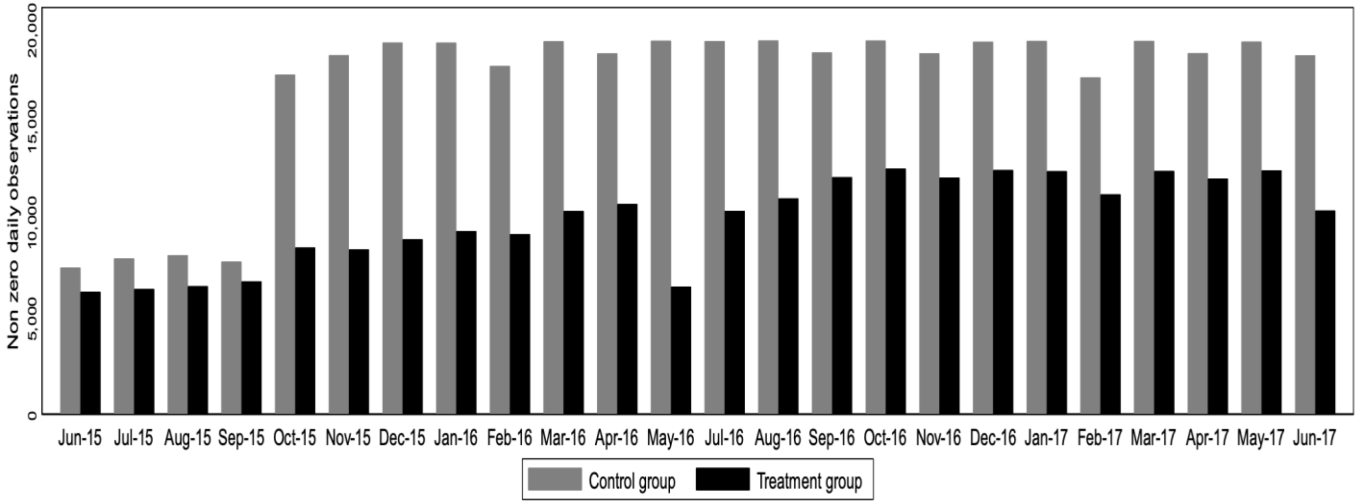


Figure A2.2: Number of non-zero daily observations by treatment status for each month of the experiment

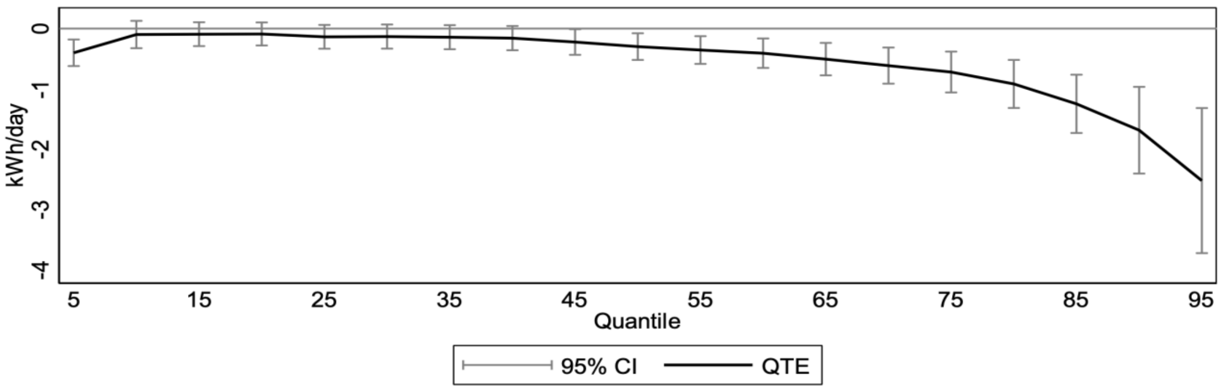


Figure A2.3: Quantile Treatment effects including zero consumption levels

APPENDIX B: APPENDIX TO CHAPTER THREE

Table A3.1. Covariate balance check before the treatment

	Control group		**Electricity-targeted treatment**		**Normalized differences**
	Mean	**Std. dev.**	**Mean**	**Std. dev.**	
Electricity, kWh/day	4.61	3.2198	4.525	2.6888	0.02793
Water, l/day	176.2	151.46	129.6	107.12	0.33582
Hot water, l/day	71.68	72.371	54.63	56.444	0.25197
Cold water, l/day	104.5	90.336	74.98	58.52	0.36268
No. of rooms**	2.379	0.71263	2.278	0.4479	0.15860
Apartment size, m^2	60.41	18.689	59.34	9.6262	0.06489
Outdoor temperature (ºC/day)	3.409	8.8807	4.991	8.3706	-0.18134
Sunlight (radiation intensity)	4.61	3.2198	4.525	2.6888	0.02793
Precipitation (mm/day)	176.2	151.46	129.6	107.12	0.33582
Indoor temperature (ºC/day)	71.68	72.371	54.63	56.444	0.25197
	Control group		**Water-targeted treatment group**		**Normalized differences**
Electricity, kWh/day	4.61	3.2198	4.887	3.0166	-0.08770
Water, l/day	176.2	151.46	159.3	136.59	0.11565
Hot water, l/day	71.68	72.371	69.47	72.792	0.03053
Cold water, l/day	104.5	90.336	89.81	73.875	0.17322
No. of rooms**	2.379	0.71263	2.381	.58839	-0.00327
Apartment size, m^2	60.41	18.689	62.27	11.698	-0.11239
Outdoor temperature (ºC/day)	3.409	8.8807	5.057	8.357	-0.18936
Sunlight (radiation intensity)	73.16	82.375	90.48	84.688	-0.20819
Precipitation (mm/day)	1.723	4.0368	1.739	4.1096	-0.00395
Indoor temperature (ºC/day)	22.17	1.528	22.49	1.8848	-0.19471

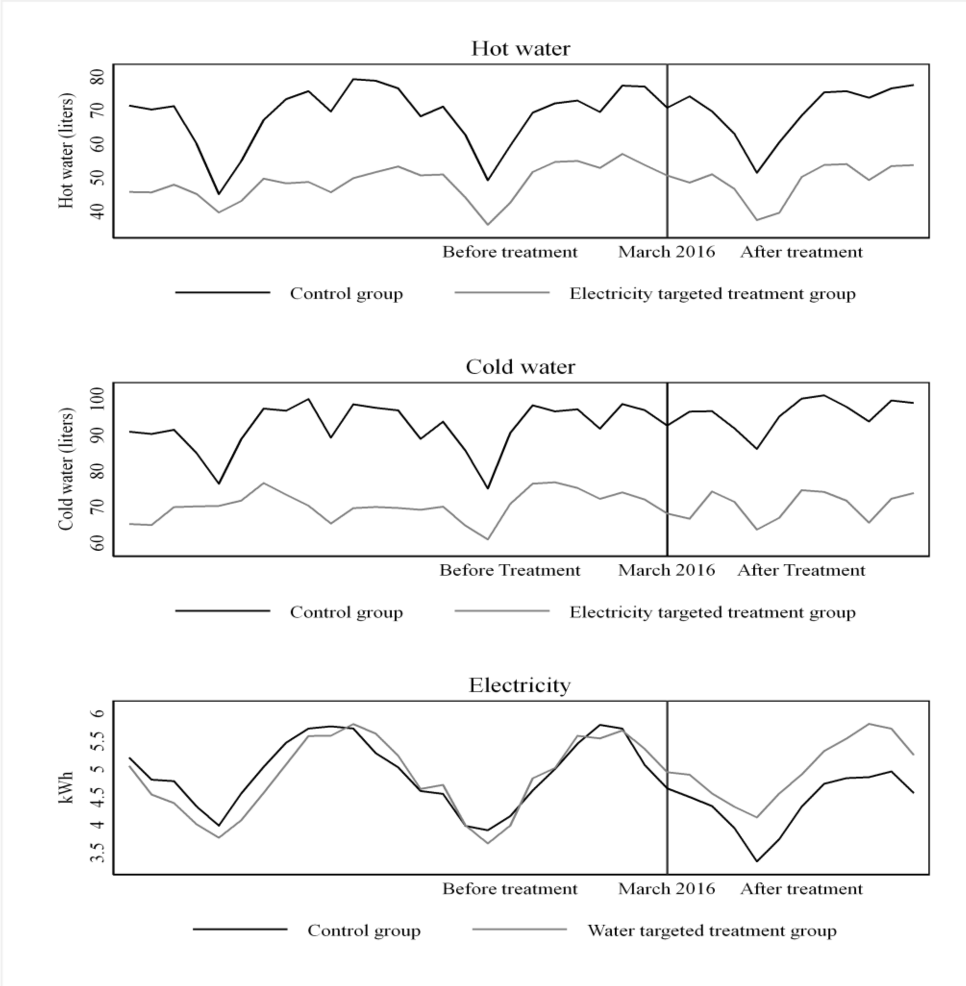


Figure A3.1. Dynamics of the treatment-untargeted monthly daily average electricity and water use before and after treatment delivery (March 2014 -February 2017)

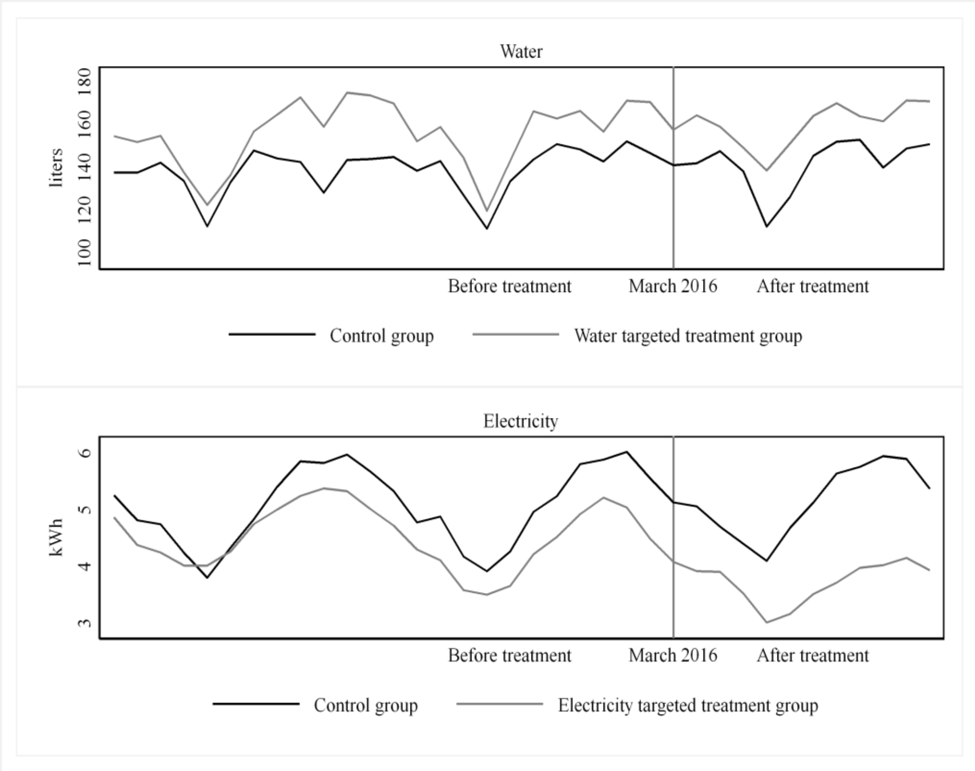


Figure A3.2 Dynamics of the treatment-targeted monthly daily average electricity and water consumption before and after treatment delivery (March 2014 -February 2017)

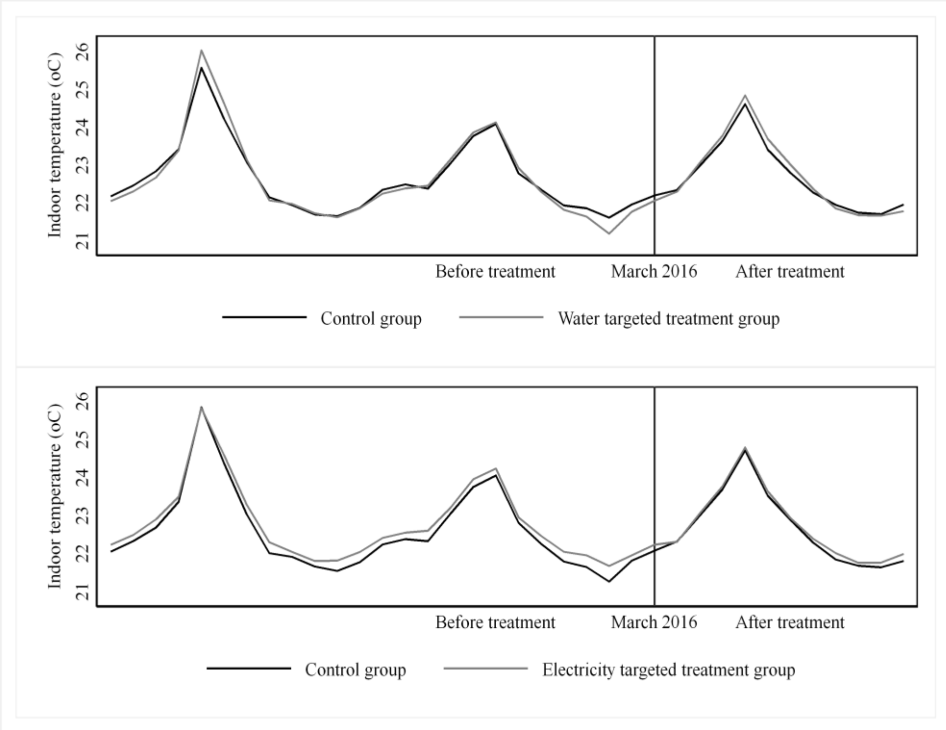


Figure A3.3. Dynamics of the monthly daily average indoor temperature before and after treatment delivery in two treatment groups (March 2014 -February 2017).

Table A3.2: Treatment effects on electricity consumption for the sub-sample with and without the significant spillover treatment effects on hot water

Variables	**Subsample with significant SQTEs**	**Subsample without significant SQTEs**
TREAT*POST	-0.385**	-0.145
	(0.149)	(0.114)
POST	0.232**	0.090
	(0.098)	(0.088)
Controls	Yes	Yes
Fixed effect Controls	Yes	Yes
No. of obs.	144,018	113,408

Notes: Standard errors clustered at the building level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3.3: Treatment effects on electricity consumption for the sub-sample with and without the significant spillover treatment effects on indoor temperature

Variables	**Subsample with significant SQTEs**	**Subsample without significant SQTEs**
TREAT*POST	-0.341	-0.185
	(0.369)	(0.143)
Controls	Yes	Yes
Fixed effect Controls	Yes	Yes
No. of obs.	37,554	138,704

Notes: Standard errors clustered at the building level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

APPENDIX C: APPENDIX TO CHAPTER FOUR

Table A4.1: Correlation matrix of the error terms in the multivariate probit model.

	Willingness to retrofit	Financial literacy	Electricity cost awareness	Energy-related financial literacy
Financial literacy	-0.731***			
	(0.257)			
Electricity cost awareness	-0.507***	0.167***		
	(0.155)	(0.053)		
Energy-related financial literacy	-0.646***	0.419***	0.109**	
	(0.162)	(0.056)	(0.054)	
Energy interest	-0.309	0.098*	0.135***	0.081
	(0.204)	(0.051)	(0.051)	(0.052)

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. $Chi^2(10) = 93.372$, Prob. > $Chi^2 = 0.000$.

Appendix A4.2 Survey questionnaire

Part1: About dwelling characteristics and energy use

1. How many years have you owned your current apartment?
   - Years___.
   - My family does not own it.
2. What is the approximate size of your apartment's living space (excl. cellar)? ______square meters.
3. **3.** How many people live in your apartment? ____ adults ___ children
   - What indoor temperature do you usually have set in your home when you are at home and not sleeping?Lower than 18 degrees
   - 18-20 degrees
   - 21-23 degrees
   - Higher than 23 degrees
5. I do not knowHow much did you pay for electricity per month on average last winter season? ________.
   - How did you vote in the LAST vote for retrofitting your house? I was in favor (Yes vote).

- I was against it (No vote).
- I was indifferent or/and abstained from voting.
- We have had no such vote yet, but if asked I would be FOR it.
- We have had no such vote yet, but if asked I would be AGAINST it.

7. Have you received compensation (subsidy) for district heating expenses in the 2020-2021 season?
   - Yes
   - No
   - Do not know
8. Was paying bills for energy (heating, electricity, and hot water) a significant burden for your household in 2020/2021?
   - Yes, I had delinquent bills.
   - Yes, but I managed to pay my bills on time.
   - No
9. Saving and investment measures in your household (you can select more than one)
   - We do not have sufficient income for savings or investments.
   - Investments in real estate
   - Equities
   - Life insurance
   - Savings in bank account
   - Cash
   - Investment funds
   - Deposit
   - Bonds
   - Pension fund
   - Lower than 18 degrees
   - 18-20 degrees
   - 21-23 degrees
   - Higher than 23 degrees
10. I do not knowHow much did you pay for electricity per month on average last winter season? ________.
11. How did you vote in the LAST vote for retrofitting your house?
    - I was in favor (Yes vote).
    - I was against it (No vote).
    - I was indifferent or/and abstained from voting.

- We have had no such vote yet, but if asked I would be FOR it.
- We have had no such vote yet, but if asked I would be AGAINST it.

12. Have you received compensation (subsidy) for district heating expenses in the 2020-2021 season?
    - Yes
    - No
    - Do not know
13. Was paying bills for energy (heating, electricity, and hot water) a significant burden for your household in 2020/2021?
    - Yes, I had delinquent bills.
    - Yes, but I managed to pay my bills on time.
    - No
14. Saving and investment measures in your household (you can select more than one)
    - We do not have sufficient income for savings or investments.
    - Investments in real estate
    - Equities
    - Life insurance
    - Savings in bank account
    - Cash
    - Investment funds
    - Deposit
    - Bonds
    - Pension fund

Part 2: About energy-related financial literacy and its dimensions

Instructions for this task

This task asks you factual questions about several investment decisions. In this task there are correct and incorrect answers. These questions are intended to be straightforward; there are no hidden tricks. You will earn 20 euro cents for each correct answer. Please select the "Do not know" option if you do not know how to answer a particular question. For this task you will earn nothing if you answer all questions incorrectly, and you will earn EUR 1 if you answer all questions correctly. Please select one answer for each question.

10. Suppose you had EUR 100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

    - **More than EUR 102**
    - Exactly EUR 102
    - Less than EUR 102
    - Do not know Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?More than today
    - Exactly the same as today
    - **Less than today**
    - Do not know
    - Do you think that the following statement is true or false? "Buying a single company's stock usually provides a safer return than buying in to a mutual fund."True
    - **False**
    - Do not know

13. Suppose that the cost of heating the 2-room apartment in the not-yet-retrofitted house is 500 euros per year. The investment share of house renovation is 2,000 euros per apartment. After renovation the heating costs will be 250 euros per year. How many years will it take to pay back the investments through savings in lower heating costs?
    - 3 years
    - 6 years
    - 7 years
    - **8 years**
    - 9 years
    - More than 10 years
    - Do not know

14. Now suppose that you have 2,000 euros in your saving account. Suppose that you can get 10% annual interest if you leave the money in bank account. Which option is better for you: leaving 2,000 euros in the saving account or investing 2,000 euros into the house renovation as described in the above question.

    - Leaving money in the saving account
    - **Renovating the house**

- **Do not knowPart 3: About attitude towards risky investment decisions.**

Instructions for this task

This task will help us understand your attitudes towards risky investment decisions. In this task there are NO correct or incorrect answers. In this task you select only ONE option you prefer the most from six available lotteries. Each lottery has two possible monetary rewards that are equally likely. Your compensation for this task will be calculated in the following way: We will randomly select 10 respondents who will earn money based on their preferred lottery. If you are selected, we will base your payment on your preferred lottery and on our randomly selected lottery outcome (A or B). For example, if you select lottery 4 and Outcome B is randomly selected, you will be paid 52 euros. Whereas if Outcome A is randomly selected, you will be paid 2 euros.

15. Please select one answer

Choice (50/50)	A	B	Select ONE lottery
Lottery 1	28	28	
Lottery 2	24	36	
Lottery 3	20	44	
Lottery 4	16	52	
Lottery 5	12	60	
Lottery 6	2	70	

Part 4: About time preference

Instructions for this task

This task will help us understand whether you prefer earnings from investments sooner than later for given interest rates. In this task there are NO correct or incorrect answers. You are asked whether you prefer 80 euros in 1 month or some amount more than 80 euros in 1 months. You are given several options where we gradually increase the amount of extra money you receive in 1 months. For EACH row choose whether you prefer 80 euros in 1 month (circle choice A) or 80 euros plus in 7 months (circle B). We will randomly choose one respondent who will earn money based on their decision. If you are selected, the money will be delivered for you either in 1 month or 7 months. To determine your earnings, we will randomly select a number from

1-10 with equal probability that selects which of the 10 decision rows will determine your payoff.

16. Select A or B

Payoff alternative	Payment option A (pays amount below in 1 month), in EUR	Payment option B (pays amount below in 7 months), in EUR	Annual interest rate (AR, in percent)	Preferred payment option (circle A or B)	
1	80	82	5	A	B
2	80	84	10	A	B
3	80	86	15	A	B
4	80	88	20	A	B
5	80	90	25	A	B
6	80	92	30	A	B
7	80	94	35	A	B
8	80	96	40	A	B
9	80	98	45	A	B
10	80	100	50	A	B

Part 5: Socioeconomic and attitudinal characteristics

17. Gender
    - Male
    - Female
    - Other
18. Age. I am […..] years old
19. What is your household's total monthly income after tax in EUR? (Income means job salary, unemployment benefit, sickness benefit, parental benefit, scholarship, and pension.)
    - EUR 0 – 499
    - EUR 500 –999
    - EUR 1000 – 1999
    - EUR 2000 – 2999
    - More than EUR 3000
20. What is your level of education?
    - Basic education
    - Upper secondary school

- Vocational school

21. Higher education degree Do you trust people from the following groups?

	Absolutely yes	Yes	No	Absolutely no
Family members	1	2	3	4
Your neighbors	1	2	3	4
House administrators	1	2	3	4
Experts from scientific institutions	1	2	3	4
Governmental organizations promoting renovation	1	2	3	4
Construction firms	1	2	3	4

22. In your view, do you believe that environmental concerns (e.g., pollution, waste, climate change) are the most serious issues facing the world today? ____.

    1 stands for the most important and 6 for least important.

23. Without checking your electricity bills, please state the price of 1 kWh of electricity last month.

    About ________ EUR cent/kWh

24. State your interest in energy-saving opportunities from 1 to 10:

    Very low 1 2 3 4 5 6 7 8 9 10 Very high

APPENDIX D: APPENDIX TO CHAPTER FIVE

Table A5.1: Definition and descriptive statistics of variables used in the study, based on three pooled waves of survey data.

Variable	Description	Mean (S.D.)	Variable	Description	Mean (S.D.)
OUTPUT	Harvested crop from main crops (wheat, teff, maize, barley, kg)	361.7 (341.2)	AVMRFPSQ	Square of average Meher season rainfall (1983–2015)	22,063.7 (11,306.9)
LAND	Land size of each plot (hectare)	0.3 (0.3)	AVTEMPSQ	Square of average annual temperature (1983–2015)	338.7 (76.5)
UREA	Amount of UREA fertilizer used in the plot (kg)	14.7 (29.4)	AVTEMP	Average annual temperature (1983–2015) in °C	18.3 (2)
DAP	Amount of DAP fertilizer used in the plot (kg)	18.1 (26.7)	SDTEMP	Standard deviation of annual temperature (1983–2015) in °C	2.6 (0.7)
SEED	Total amount of seed used in the plot (kg)	23.7 (28.3)	PLOTDIST	Distance of the plot from the homestead in minutes one way	14.7 (19.9)
LABOR	Total amount of labor used in the plot in production (person-days)	277.8 (210.7)	SHALDEPT	1 = if the plot has a shallow soil depth	0.1
TLU	Amount of livestock owned by the household (tropical livestock units, TLU)	4.9 (3.6)	MEDMDEPT	1 = if the plot has a medium soil depth	0.4
ASSET	Value of productive farm assets (Ethiopian birr, ETB)	30,191 (45,789)	MEDMSLOP	1 = if the plot has a medium slope	0.3
HHSIZE	Family size measured by adult equivalent (AE)	7.9 (2.4)	FLATSLOP	1 = if the plot has a flat slope	0.6
AGE	Age of the household head (years)	52.6 (12.7)	GOODSOIL	1 = if the fertility of the soil is good	0.3
MARRIED	1 = if the household head is	0.8	MEDMSOIL	1 = if the fertility of the soil is medium	0.5

	married and living together				
GENDER	1 = if the head is male	0.8	FARMSUPPO	1 = if the household receive any farm support in the last 3 years	0.1
EDUC	Years of education of the household head	1.7 (2.9)	CLIMEEXTE	1 = if the household receive an extension service about climate change last year	0.5
CREDIT	1 = if the household borrowed from any source (in kind or cash)	0.4	AID	1 = if the household receives food or other aid from the government or participated in government or NGO program in the past year	0.09
OFFEMP	1 = if the household participate in off-farm activities	0.1	RELGOV	1 = if the household perceive that it will rely on the government during bad cropping seasons	0.5
LANDOWNER	1 = if a farmer is the owner of the plot	0.8	ENOURAIN	1 = if there was enough rain during the growing season	0.7
MKTDIST	Distance of the plot from input market in minutes one way	50.7 (36.9)	CERTIFICAT	1 = if the specific plot is certified	0.87
SDMRF	Standard deviation of Meher season rainfall (1983–2015) in mm	115 (19.6)	AVMRF	Average Meher season rainfall (1983–2015) in mm	142 (43.4)

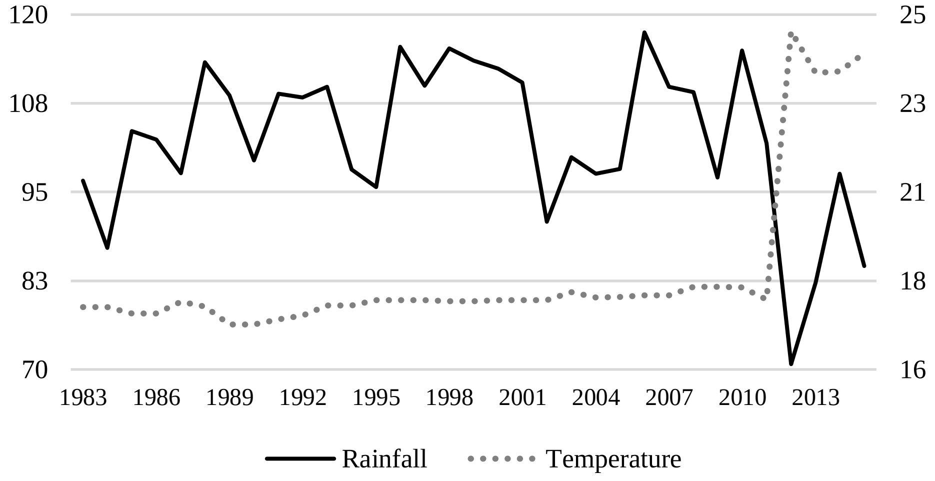


Figure A5.1: Dynamics of annual average rainfall (mm, LHS) and annual average temperature (°C, RHS) specific to the area analyzed in this study.

Table A5.2: Correlation matrix between adaptation strategies and farmers' notice of any climate variability.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Improved Variety	1.00									
(2) Agroforest	0.10*	1.00								
(3) Tillage	0.02	0.04*	1.00							
(4) Soil Conservation	0.05*	0.06*	-0.02	1.00						
(5) Intercropping	0.01	-0.02	0.02	-0.06*	1.00					
(6) Irrigation	0.01	-0.05	-0.01	-0.03*	-0.03*	1.00				
(7) Rotation	-0.05	-0.04	-0.02*	0.08*	0.06*	-0.06*	1.00			
(8) Crop Residue	-0.02	0.02*	0.01	0.10*	0.01	-0.02	0.13*	1.00		
(9) Row plant	0.32*	0.14*	0.01	0.06*	-0.01	0.04*	-0.03*	0.04*	1.00	
(10) Climate notice	**0.02***	0.02	-0.01	**0.03***	0.02	-0.04	0.01	-0.001	-0.01	1.00

Notes: * shows significance at the 0.1 level.

Table A5.3: Probit regression results of climate variables and adaptation strategies

	(1)	(2)	(3)
	Improved variety only	Soil conservation only	Both of two
AVMRF	0.06***	0.02*	0.05***
	(0.01)	(0.01)	(0.01)
SDMRF	-0.04***	0.01	-0.03***
	(0.01)	(0.01)	(0.01)
AVMRFSQ	-0.01**	-0.01	-0.01
	(0.00)	(0.00)	(0.00)
AVTMPSQ	-1.78***	0.81*	-1.14***
	(0.25)	(0.40)	(0.33)
AVTEMP	0.05***	-0.02	0.04***
	(0.01)	(0.01)	(0.01)
SDTEMP	0.17*	0.12**	0.13
	(0.07)	(0.07)	(0.08)
Constant	14.35***	-11.66**	7.01*
Other controls	Yes	Yes	Yes
No. of obsv.	1,606	961	528
Wald $chi^2(72)$ = 1,143***			
Log pseudolikelihood = -7,063			

Notes: Standard errors in parentheses; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table A5.4: Descriptive statistics of variables used in the sample selection model before and after matching, pooled sample

	Unmatched sample					Matched sample				
	Adopter		Non-adopters			Adopters		Non-adopters		
	Mean	S.D.	Mean	S.D.	Difference‡	Mean	S.D.	Mean	S.D.	Difference‡
AGE	52.6	12.4	52.7	13.0	0.07	52.5	12.3	52.7	12.9	0.15
EDUC	1.97	3.1	1.7	2.9	-0.32***	1.9	3.1	1.6	2.9	-0.34
AGE2	2922.5	1,342.8	2,946.1	1,444.2	23.6	2,911.4	1,340.4	2,947.22	1,434.8	30.63
GENDER	0.89		0.88		-0.01**	0.89		0.88		-0.012*
MARRIED	0.83		0.83		-0.00	0.83		0.83		-0.00
HHSIZE	7.89	2.54	7.82	2.31	-0.07	7.89	2.52	7.82	2.3	-0.07
OFFEMP	0.21		0.18		-0.03***	0.21		0.18		-0.03
CREDIT	0.41		0.41		-0.00	0.41		0.41		0.00
AID	0.12		0.07		-0.05***	0.11		0.07		-0.04
RELGOV	0.55		0.51		-0.04***	0.55		0.51		-0.04
CERTIFICAT	0.89		0.86		-0.03***	0.90		0.87		-0.03
FARMSUPPO	0.08		0.05		-0.03***	0.08		0.05		-0.03
LANDOWNER	0.85		0.84		-0.00	0.85		0.85		-0.00
ENOURAIN	0.75		0.75		0.00	0.75		0.75		0.000
MKTDIST	48.3	34.3	52.7	38.799	4.4***	48.36	34.348	52.71	38.8	4.35*
CLIMEEXTE	0.62		0.55		-0.07***	0.62		0.56		-0.07
FLATSLOP	0.62		0.64		0.01	0.62		0.64		0.01
MEDMSLOP	0.33		0.32		-0.02	0.33		0.32		-0.01
MEDMDEPT	0.44		0.45		0.01	0.45		0.45		0.00
MEDMSOIL	0.53		0.58		-0.01	0.53		0.52		-0.01
GOODSOIL	0.35		0.34		-0.01	0.35		0.34		-0.01
SHALDEPT	0.12		0.12		0.00	0.13		0.13		0.00

PLOTDIST	14.5	20.8	14.9	19.	0.43	14.5	20.8	14.8	18.8	0.3
AVMRF	142.0	46.1	142.1	40.9	0.06	141.6	44.8	141.7	41.3	0.18
SDMRF	113.8	20.5	115.9	18.8	2.2***	113.6	20.2	115.9	19	2.24
AVMRFPSQ	22,303	11,868	21,864	10,814	-439	22,188	11,592	21,785	10,833	-403
AVTEMPSQ	340.4	78.4	337.4	74.8	-2.9	339.8	79.9	336.8	69.4	-3.00
AVTEMP	18.3	2.1	18.2	1.9	-0.07	18.3	2.1	18.2	1.8	-0.01
SDTEMP	2.6	0.6	2.5	0.7	-0.07***	2.6	.700	2.5	0.770	-0.01
No. of obsv.	3,012		3,718			2,997		3,591		

Notes: ‡*t* tests are performed to determine whether the sample means are significantly different between non-adopters and adopters.

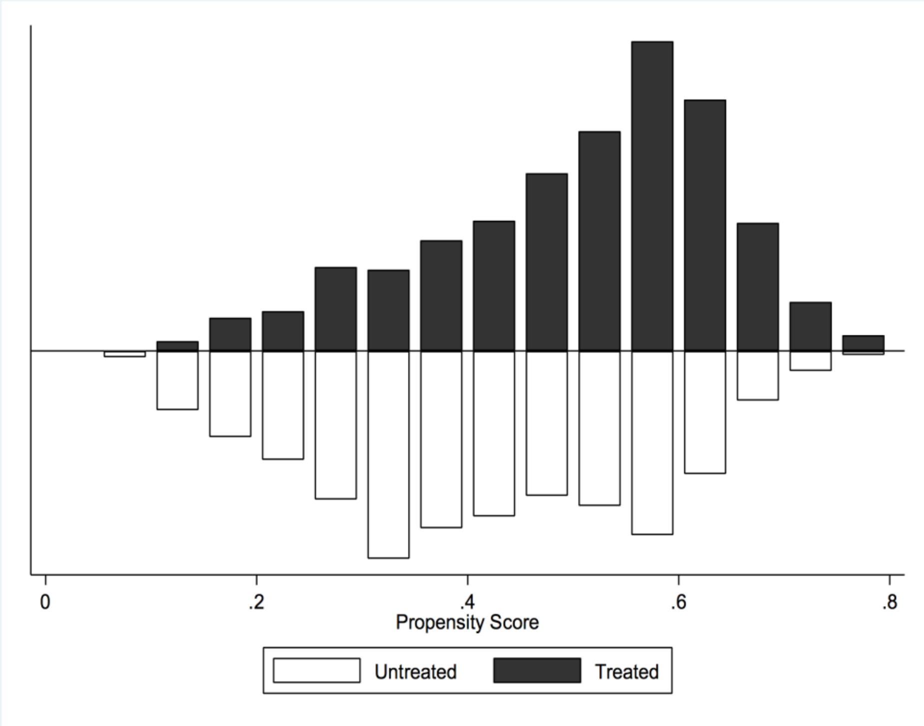


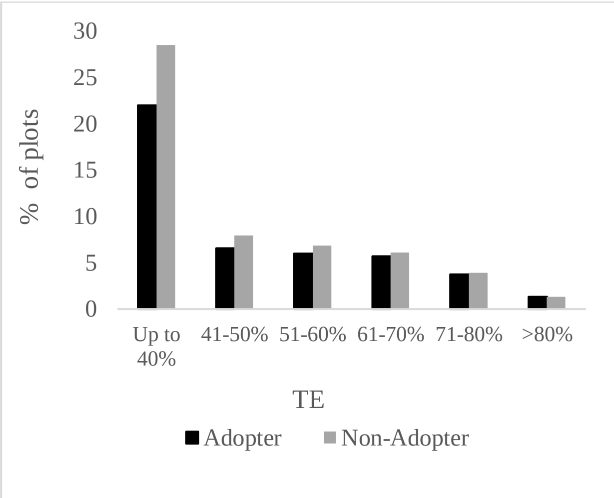
Figure A5.2: Distributions of the estimated propensity scores for plot adopters and plot non-adopters satisfying the common support

Table A5.5: Parameter estimates of the conventional and sample selection SPF models, unmatched sample

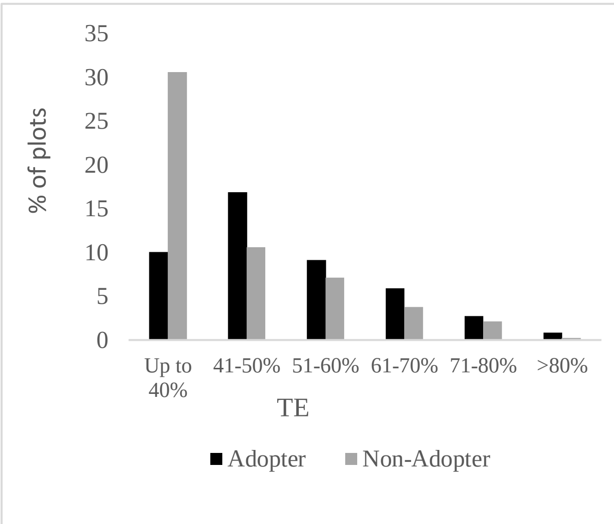
	Conventional SPF			Sample selection SPF	
	(1)	(2)	(3)	(4)	(5)
	Pooled-U	Adopters-U	Non-Adopters-U	Adopters-U-S	Non-Adopters-U-S
LAND (ln)	2.06*** (26.56)	2.08*** (19.44)	2.03*** (16.16)	2.28*** (0.07)	1.65*** (0.09)
LABOR (ln)	0.07*** (7.54)	0.08*** (5.44)	0.07*** (5.04)	0.09*** (0.02)	0.09*** (0.01)
ASSET (ln)	0.03*** (4.11)	0.01 (0.79)	0.04*** (4.03)	-0.01 (0.01)	0.05*** (0.01)
DAP (ln)	-0.01 (-0.26)	0.01 (0.41)	-0.01 (-1.03)	-0.01 (0.02)	0.02 (0.02)
UREA (ln)	0.08*** (8.23)	0.11*** (7.48)	0.06*** (4.66)	0.13*** (0.02)	0.06*** (0.02)
SEED (ln)	0.06*** (7.00)	0.02* (1.91)	0.10*** (7.36)	0.08*** (0.02)	0.08*** (0.01)
TLU (ln)	0.02 (1.43)	0.03 (1.16)	0.01 (0.34)	-0.06** (0.03)	-0.02 (0.03)
Adaptation	0.19***(8.99)	-	-	-	-
Constant	4.89*** (59.94)	5.26*** (45.29)	4.74***(39.09)	5.54*** (0.15)	4.72***(0.13)
σ (u)	1.49*** (0.02)	1.44*** (0.02)	1.54*** (0.05)	0.99*** (0.06)	5.17*** (0.04)
σ (v)	0.26***(0.02)	0.21*** (0.03)	0.32*** (0.03)	1.13*** (0.03)	0.96*** (0.02)
λ	5.67	6.72*** (0.03)	4.82	0.57	1.38
Log-likelihood	-9,114	-4,023	-4,734	-6,575	-7,440
Selection correction term (ρ)	-	-	-	- 0.95***(0.01)	-0.89*** (0.01)
No. of obsv.	6,820	3,012	3,718	3,012	3,718

Notes: Standard errors in parentheses; $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

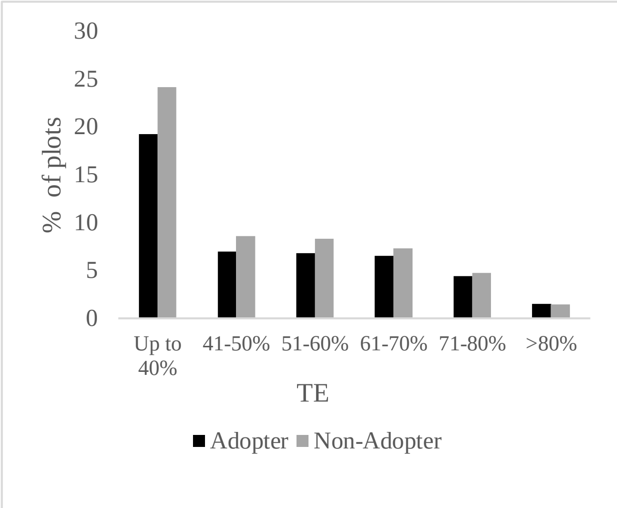
To better convey the effect of addressing selection bias from observed and unobserved heterogeneities on average TE estimation, we present the distribution of TE from the conventional SPF and selection-bias-corrected SPF models in Figure A3. It is evident that there is a significant improvement in the level of TE after accounting for selection bias. For instance, the percentage of plots operating below the efficiency level of 40% for the unmatched sample estimated using the conventional SPF approach, without addressing any biases (see panel A in Figure A3), is about 22% for adopters and 28.5% for non-adopters. When we account for selection bias from unobservable factors only (see panel B in Figure A3), it decreases to about 10.06% for adopters and increases to 30.6% for non-adopters. On the other hand, controlling for observed biases by using only the conventional SPF approach (see panel C in Figure A3) reduces the proportion for both adopters and non-adopters (to 19.23% for adopters and to 24.1% for non-adopters). Finally, as is presented in panel D of Figure A3, addressing selection bias from both observables and non-observables (i.e., TE estimated by using the bias-corrected SPF model for the matched sample) greatly reduces the proportion of plots operating below 40% efficiency level. For adopters, the proportion decreases to 8.21% and for non-adopters, to 18%.



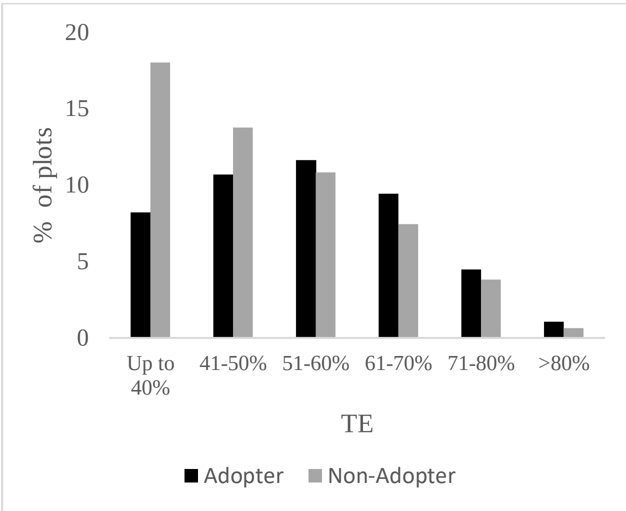
A: TE using conventional SPF for the unmatched sample



B: TE using selectivity-corrected SPF for the unmatched sample



C: TE using conventional SPF for the matched sample



D: TE using selectivity-corrected SPF for the matched sample

Figure A5.3: Distribution of TE across SPF model

Table A5.6: Average TE levels across different models using the balanced panel sample

	Conventional SPF				**Selectivity-corrected SPF**		
	Unmatched sample						
	Pooled-U	Adopters-U	Non-Adopters-U	*t* test of means‡	Adopters-U-S	Non-Adopters-U-S	*t* test of means‡
TE	41.33	45.46	42.86	2.60*	47.18	39.99	7.19***
TE Differential	6.06%				17.97%		
	Matched sample						
	Pooled-M	Adopters-M	Non-Adopters-M	*t* test of means‡	Adopters-M-S	Non-Adopters-M-S	*t* test of means‡
TE	46.6	47.03	46.23	0.80	55.05	49.25	5.8***
TE Differential	1.73%				11.77%		

Notes: ‡*t* tests are performed to determine whether the sample means are significantly different between adopters and non-adopters; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A5.7: Parameter estimates of the sample selection SPF model with and without climate and soil characteristics, matched sample

	Without climate and soil factors		With climate and soil factors	
	(1)	(2)	(3)	(4)
	Adopters-M-S	Non-Adopters-M-S	Adopters-M-S	Non-Adopters-M-S
LAND (ln)	2.30***	1.87***	1.89***	1.68***
	(0.06)	(0.11)	(0.07)	(0.11)
LABOR (ln)	0.06***	0.07***	0.06***	0.07***
	(0.02)	(0.01)	(0.02)	(0.01)
ASSET (ln)	-0.01	0.06***	0.01	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)
DAP (ln)	-0.01	-0.01	-0.02*	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
UREA (ln)	0.13***	0.05***	0.15***	0.06***

	(0.02)	(0.02)	(0.01)	(0.02)
SEED (ln)	0.10***	0.10***	0.17***	0.12***
	(0.02)	(0.01)	(0.07)	(0.01)
TLU (ln)	0.05*	0.03	0.04	0.01
	(0.03)	(0.02)	(0.03)	(0.02)
SOILFER (ln)	-	-	0.12*	0.27***
	-	-	(0.06)	(0.05)
SOILDEPTH (ln)	-	-	-0.07	-0.02
	-	-	(0.06)	(0.05)
SLOPE (ln)	-	-	-0.23***	0.07
	-	-	(0.05)	(0.05)
AVMRF (ln)	-	-	0.68***	0.30***
	-	-	(0.05)	(0.05)
AVTEMP (ln)	-	-	-0.42**	-0.35*
	-	-	(0.21)	(0.21)
Constant	5.61***(0.15)	4.86***(0.12)	3.21***(0.56)	4.12***(0.53)
σ (u)	0.87***(0.06)	1.10***(0.04)	0.70***(0.09)	1.06***(0.04)
σ (v)	0.97***(0.03)	0.85***(0.02)	1.01***(0.03)	0.85***(0.03)
Λ	0.89	1.13	0.70	1.12
Log-likelihood	-5,980	-6,740	-5,884	-6,699
Selectivity correction term (ρ)	-0.92***(0.12)	-0.86***(0.02)	-0.91***(0.01))	-0.86***(0.02)
Average TE (%)	**53.03**	**47.19**	**58.8**	**48.16**
No. of obsv.	2,997	3,591	2,997	3,591

Notes: Standard errors in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A5.8: SPF estimation after accounting for selection bias and soil- as well as weather-related factors for each crop type

	Maize		Wheat		Teff		Barley	
	Adopters-M-S	Non-Adopters-M-S	Adopters-M-S	Non-Adopters-M-S	Adopters-M-S	Non-Adopters-M-S	Adopters-M-S	Non-Adopters-M-S
LAND (ln)	1.81***	2.22***	1.85***	1.85***	0.99***	1.69***	1.67***	1.61***
	(-0.14)	(-0.28)	(-0.26)	(-0.25)	(-0.01)	(-0.15)	(-0.31)	(-0.28)
LABOR (ln)	0.12***	0.08*	0.03	0.06**	0.07**	0.01	0.15**	0.07**
	(-0.02)	(-0.04)	(-0.04)	(-0.03)	(-0.03)	(-0.02)	(-0.07)	(0.03)
ASSET (ln)	0.00	0.05	0.02	0.08***	0.06**	0.03	0.08*	0.12***
	(-0.02)	(-0.03)	(-0.03)	(-0.03)	(-0.02)	(-0.02)	(-0.04)	(-0.04)
DAP (ln)	-0.02***	0.00	-0.01	-0.03	0.09***	0.08***	-0.09	0.04
	(-0.03)	(-0.06)	(-0.04)	(-0.05)	(-0.02)	(-0.02)	(-0.10)	(-0.04)
UREA (ln)	0.13***	0.08	0.07**	0.08	0.09***	0.11***	0.12	0.06
	(-0.03)	(-0.06)	(-0.04)	(-0.06)	(-0.02)	(-0.02)	(-0.11)	(-0.04)
SEED (ln)	0.11***	0.11**	0.38***	0.24***	0.04	0.05*	0.27***	0.25***
	(-0.03)	(-0.05)	(-0.04)	(-0.04)	(-0.03)	(-0.03)	(-0.06)	(-0.04)
TLU (ln)	0.05	0.05	-0.02	0.12*	0.18***	0.03	0.20	-0.00
	(-0.04)	(-0.06)	(-0.07)	(-0.07)	(-0.06)	(-0.05)	(-0.13)	(-0.07)
SOILFER (ln)	0.13	0.00	0.07	0.37***	0.37***	0.00	0.08	0.33***
	(-0.11)	(-0.11)	(-0.12)	(-0.11)	(-0.09)	(-0.09)	(-0.24)	(-0.11)
SOILDEPTH (ln)	-0.06	0.05	-0.06	0.06	-0.10	0.09	-0.08	-0.13
	(-0.10)	(-0.10)	(-0.11)	(-0.12)	(-0.10)	(-0.10)	(-0.22)	(-0.10)
SLOPE (ln)	-0.05	-0.04	-0.41***	0.07	-0.13	0.08	-0.34*	0.00
	(-0.08)	(-0.12)	(-0.12)	(-0.12)	(-0.09)	(-0.08)	(-0.19)	(-0.09)
AVMRF (ln)	0.64***	0.25	0.71***	0.27***	0.81***	0.26**	0.91***	0.63***
	(-0.09)	(-0.21)	(-0.09)	(-0.10)	(-0.12)	(0.12)	(-0.23)	(-0.12)
AVTEMP (ln)	0.77***	0.62	-2.38***	-1.58***	-0.80**	-0.73**	-2.16**	-2.40***

	(-0.29)	(-0.48)	(-0.47)	(-0.52)	(-0.34)	(-0.31)	(-1.08)	(-0.53)
Constant	-0.50 (0.76)	1.50(1.19)	8.15***(1.39)	6.51***(1.59)	1.82*(1.05)	5.51*** (0.83)	6.15**(2.70)	7.06***(1.37)
σ (u)	0.71*** (0.07)	1.88*** (0.05)	1.05*** (0.10)	1.14***(0.07)	0.76***(0.08)	0.67*** (0.15)	1.16*** (0.21)	1.33*** (0.05)
σ (v)	0.70*** (0.02)	0.47*** (0.06)	0.72*** (0.07)	0.54*** (0.04)	0.56***(0.05)	0.74***(0.06)	0.99*** (0.18)	0.54*** (0.04)
Λ	1.04	4.03	1.46	2.10	1.35	0.91	1.17	2.46
Log-likelihood	-1817.49	-1795.32	-1366.41	-1305.53	-1353.25	-1830.53	-846.77	-1353.00
Selectivity correction term (ρ)	-0.66*** (0.08)	0.43**(0.28)	-0.90***(0.04)	-0.14(0.27)	0.38**(0.16)	-0.67***(0.06)	-0.95*** (0.03)	0.17 (0.45)
No. of obsv.	1,150	856	778	723	721	1,144	348	856

Notes: Standard errors in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A5.9: TE across different SPF models with the dataset aggregated at the farm household level

	Conventional SPF				Selectivity-corrected SPF		
	Unmatched Sample						
	Pooled	Adopters	Non-adopters	*t* test of means‡	Adopters	Non-adopters	*t* test of means‡
TE	47.41	48.42	45.27	3.15***	48.45	41.61	6.84***
TE Differential	6.95%				16.43%		
	Matched Sample						
TE	47.51	48.73	45.27	3.46***	53.82	42.99	10.83***
TE Differential	7.64%				25.19%		

Notes: ‡*t* tests are performed to determine whether the sample means are significantly different between adopters and non-adopters; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A5.10: TE level across different models considering crop diversification and agro-forestry

	Conventional SPF				Selectivity-corrected SPF		
	Unmatched Sample						
	Pooled	Adopters	Non-adopters	*t* test of means‡	Adopters	Non-adopters	*t* test of means‡
TE	41.01	41.35	40.88	0.47	41.38	39.23	2.15***
TE Differential	1.15%				5.48%		
	Matched Sample						
TE	44.38	45.24	44.06	1.18**	58.10	53.13	4.97***
TE Differential	2.67%				9.35%		

Notes: ‡*t* tests are performed to determine whether the sample means are significantly different between adopters and non-adopters; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table A5.11: TE across different SPF models for the three waves of the survey (2015, 2016, and 2017)

2015	**Conventional SPF**				**Selectivity-corrected SPF**		
	Unmatched Sample						
	Pooled	Adopters	Non-adopters	*t* test of means‡	Adopters	Non-adopters	*t* test of means‡
TE	46.10	42.44	48.31	-5.87	60.08	45.45	14.63***
TE Differential	-12.15%				32.18%		
	Matched Sample						
TE	47.30	50.88	44.40	6.48***	70.30	52.51	17.79***
TE Differential	14.69%				33.87%		
2016	**Conventional SPF**				**Selectivity-corrected SPF**		
	Unmatched Sample						
	Pooled	Adopters	Non-adopters	*t* test of means‡	Adopters	Non-adopters	*t* test of means‡
TE	41.21	37.41	43.03	-5.62**	60.08	45.45	14.63***
TE Differential	-13.06%				32.18%		
	Matched Sample						
TE	41.11	40.06	42.00	-1.94**	49.88	51.82	-1.94***
TE Differential	-4.61%				-3.73%		
2017	**Conventional SPF**				**Selectivity-corrected SPF**		
	Unmatched Sample						
	Pooled	Adopters	Non-adopters	*t* test of means‡	Adopters	Non-adopters	*t* test of means‡
TE	48.74	47.84	49.51	-1.67*	60.08	45.45	14.63***
TE Differential	-3.37%				32.18%		
	Matched Sample						
TE	48.88	47.95	49.72	-1.77**	75.04	65.04	10***
TE Differential	-3.55%				15.37%		

Notes: ‡*t* tests are performed to determine whether the sample means are significantly different between adopters and non-adopters; *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Table A5.12: TE across different SPF models following a revised definition of "adaptation"

	Conventional SPF				Selectivity-corrected SPF		
	Unmatched sample						
	Pooled-U	Adopters-U	Non-Adopters-U	*t* test of means‡	Adopters-U-S	Non-Adopters-U-S	*t* test of means‡
TE	42.49	42.26	43.00	1.71***	46.96	38.21	8.75***
TE Differential	-1.72%				22.89%		
	Matched sample						
	Pooled-M	Adopters-M	Non-Adopters-M	*t* test of means‡	Adopters-M-S	Non-Adopters-M-S	*t* test of means‡
TE	43.88	44.05	43.45	0.6	62.37	61.31	1.06***
TE Differential	1.38%				1.72%		

Notes: ‡*t* tests are performed to determine whether the sample means are significantly different between adopters and non-adopters; **p* < 0.05, ***p* < 0.01, ****p* < 0.001.

Table A5.13: Average TE levels across different models using the radius matching technique

	Conventional SPF				**Selectivity-corrected SPF**		
	Unmatched sample						
	Pooled-U	Adopters-U	Non-Adopters-U	*t* test of means‡	Adopters-U-S	Non-Adopters-U-S	*t* test of means‡
TE	41.33	42.26	40.55	1.71***	48.88	40.23	8.65***
TE Differential	4.21%				21.50%		
	Matched sample						
	Pooled-M	Adopters-M	Non-Adopters-M	*t* test of means‡	Adopters-M-S	Non-Adopters-M-S	*t* test of means‡
TE	44.6	45.10	44.19	0.91*	56.38	52.51	3.87***
TE Differential	2.059%				7.37%		

Notes: ‡*t* tests are performed to determine whether the sample means are significantly different between adopters and non-adopters; **p* < 0.05, ***p* < 0.01, ****p* < 0.001.

Conceptual framework for chapter five

In Figure A5.4, we present a simple conceptual framework showing that climate change adaptation could affect agricultural performance in different ways, and that climate change adaptation is a stepwise process. This conceptual framework has three main components: perceived changes in climate (left vertical box), adaptation processes (middle horizontal box), and farmers' welfare (lower horizontal box). The interaction among these components is represented using the dotted and straight lines. The straight lines show positive effects of climate change adaptation, such as increases in climate resilience, productivity, TE, and farmers' welfare. The dotted lines, on the other hand, represent adverse effects of climatic change and the absence of climate adaptation measures on crop productivity, resilience capacity, TE, and farmers' welfare.

As shown in Figure A5.4, the first step in the adaptation process is to notice climate change. Once farmers perceive a change in climate, either they will make a climate adaptation decision, or they will not. This decision will depend on a combination of factors, such as farming plot characteristics as well as socio-economic, institutional, and climate-related factors. Farmers may also implement different adaptation strategies at different points in time, and at different levels of intensity, for many reasons. Primarily, farmers implement a particular adaptation strategy if they perceive that it will abate climate-related shocks at a particular time. Thus, depending on the type and timing of climate-related shocks, farmers will adopt different climate adaptation strategies at different points in time. Furthermore, plot characteristics are different among different plots, and the type of crop planted in each plot requires different agricultural intensification strategies. Moreover, farmers usually plant multiple crops in a given plot. Thus, the intensity of climate adaptation measures will vary based on the type of adaptation required to improve the productivity of crops planted throughout the entire plot or in part of the plot.

Production is one major pathway by which climate change adaptation will improve farmers' welfare. Climate change adaptation will increase agricultural production by enabling farmers to produce a higher level of output, as well as by minimizing losses from climate-related shocks (Di Falco et al., 2011).

TE is the second pathway by which climate change adaptation will improve farmers' welfare. Climate change adaptation strategies may not only help mitigate the effects of climate change but may also help increase TE of farming production. A higher level of TE directly contributes to greater crop yield and farm income, which in turn improves farmers' welfare.

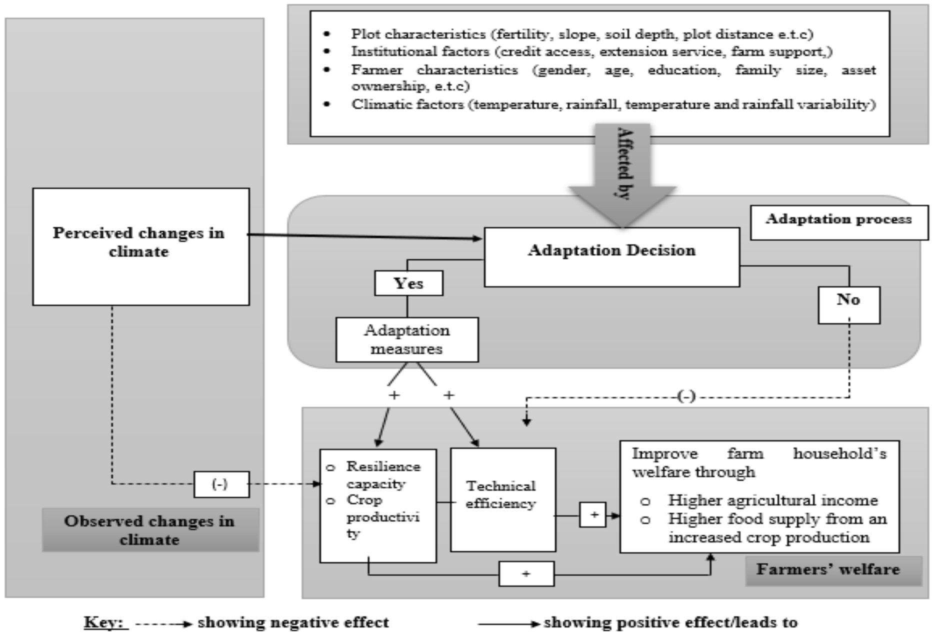


Figure A5.4. Conceptual framework of the study showing interactions among climate change, climate change adaptation, and farmers' welfare. Adapted from Abid et al. (2016).

SUMMARY (SANTRAUKA)

Klimato kaitos švelninimas ir prisitaikymas prie jos yra dvi viena kitą papildančios XXI a. klimato politikos kryptys. Energijos (vartojimo) efektyvumo didinimas namų ūkių sektoriuje padeda sušvelninti klimato kaitą, nes mažėja šiame sektoriuje išmetamų šiltnamio efektą sukeliančių dujų kiekis. Žemės ūkio sektoriuje gamybos efektyvumo didinimas, veiksmingai įgyvendinant prisitaikymo prie klimato kaitos strategijas, apsaugo nuo su klimato kaita susijusių rizikų.

Pagrindiniai šios disertacijos tikslai – išmatuoti nekaininių priemonių poveikį energijos taupymui namų ūkių sektoriuje ir įvertinti prisitaikymo prie klimato kaitos strategijų įtaką žemės ūkio gamybos efektyvumui. Šiems tikslams pasiekti atlikti keturi savarankiški tyrimai, jie aprašyti atskiruose šios disertacijos skyriuose. Atliekant tyrimus naudoti eksperimentiniai ir kvazieksperimentiniai metodai, tokie kaip skirtumų metodas (angl. difference in differences, DID) ir panašiausių atvejų analizę (angl. propensity score matching, PSM), o disertacijos rezultatai paskelbti (arba pateikti) keturiuose tarptautiniu mastu recenzuojamuose mokslo žurnaluose.

Antrame disertacijos skyriuje nagrinėjama, kokį poveikį Lietuvos namų ūkių elektros energijos suvartojimui daro informacijos apie valandinį namų ūkių elektros suvartojimą teikimas. Ankstesniuose tyrimuose dažniausiai informacijos teikimo poveikis buvo vertinamas derinant jį su įvairiomis socialinėmis normomis grįstomis elgsenos priemonėmis, pavyzdžiui, socialiniu panašių namų ūkių palyginimu bei jų vartojimo vertinimu, tikslų nustatymu ir patarimais, kaip taupyti energiją. Todėl jų autoriai negalėjo atskirti informacijos be socialinių normų poveikio nuo socialinių normų ar elektros energijos taupymo patarimų poveikio. Tai svarbu, nes dažnai dėl socialinių normų taikymo energijos suvartojimo elgsenai namų ūkiai patiria spaudimą - moralinius kaštus (angl. moral tax). Skirtingai nei ankstesniuose tyrimuose, šiame tyrime, naudojant duomenis surinktus iš pilotinio projekto keičiant seno tipo skaitiklius į išmaniuosius elektros energijos skaitiklius, vertinamas paprastos istorinės valandinės informacijos apie namų ūkių elektros suvartojimą teikimo poveikis elektros energijos taupymui be moralinio spaudimo sumažinti savo suvartojimą. Tyrimo rezultatai atskleidžia, kad šios informacijos teikimas sumažino Lietuvos namų ūkių elektros energijos suvartojimą 0,661 kWh (arba 8,6 proc.) per dieną. Tai atitinka 241 kWh per metus sutaupytos energijos vienam namų ūkiui. Be to, dėl šios intervencijos elektros energijos suvartojimas labiau sumažėjo tų namų ūkių, kurių elektros suvartojimas yra žymiai didesnis nei vidutinis.

Kita elgesio intervencija, kuri plačiai taikoma energijos taupymo elgesiui keisti, yra socialinė lyginamoji informacija. Nors nemažai mokslininkų tyrė tiesioginį socialinės lyginamosios informacijos teikimo poveikį energijai taupyti, mažai žinoma, ar ir kaip šios intervencijos taikymas elektros energijos vartojimui paveikia namų ūkių elgseną vartojant kitus gamtos resursus, pvz., vandenį.

Trečiame šios disertacijos skyriuje tiriamas socialinės lyginamosios informacijos, skirtos elektros energijai ir vandeniui, šalutinis poveikis vandens arba energijos suvartojimui toje pačioje eksperimentinėje aplinkoje. Mano žiniomis, yra paskelbti tik 3 tyrimai, kuriuose buvo atlikta panaši analizė (t. y. Carlsson et al., 2021; Jessoe et al., 2021; Tiefenbeck et al., 2013). Tačiau šiuose tyrimuose nagrinėjamas socialinės ribotas lyginamosios informacijos šalutinis poveikis siekiant taupyti tik vandenį arba elektrą. mano tyrime eksperimentiškai nagrinėjamas socialinių lyginamųjų intervencijų, siekiant elektros energijos ir vandens taupymo, šalutinis poveikis (karšto) vandens vartojimui, elektros energijos suvartojimui ir patalpų šildymo energijos suvartojimui. Atlikto tyrimo rezultatai rodo, kad socialinė lyginamoji informacija, skirta elektros energijai, daro reikšmingą šalutinį poveikį karšto vandens ir šildymo energijos suvartojimui Umeo mieste Švedijoje. Vidutiniškai namų ūkiai, kuriems buvo suteikta elektros energijos vartojimo socialinė lyginamoji informacija, sumažino karšto vandens suvartojimą maždaug 7 litrais per dieną, o patalpų temperatūrą – 0,20 ^{o}C. Dėl šalutinio intervencijos poveikio sutaupoma dvigubai daugiau energijos nei dėl tiesioginio jos poveikio.

Lietuvoje sovietmečiu statyti energetiškai neefektyvūs daugiabučiai sudaro 55 proc. visų 2019 m. šalyje esančių daugiabučių. Nors šie pastatai sunaudoja daugiau kaip 75 proc. visų pastatų pirminės energijos, investicijos į jų modernizavimą gana ribotos. Nuo 2005 m. iki 2019 m. modernizuota tik mažiau nei 10 proc. senų daugiabučių (3 158 pastatai iš 35 000) (NAOL, 2020). Jei tokia modernizavimo sparta išliks, prireiks maždaug šimtmečio, kad būtų visiškai modernizuoti visi energetiškai neefektyvūs daugiabučiai gyvenamieji namai Lietuvoje.

Ketvirtame šios disertacijos skyriuje nagrinėjamas su energetika susijusio finansinio raštingumo poveikis sprendimui investuoti į didelio masto energijos vartojimo efektyvumo modernizavimą. Esamoje literatūroje apie su energija susijusį finansinį raštingumą teigiama, kad su energija susijusių žinių trūkumas ir kognityviniai gebėjimai atlikti su energija susijusius investicinius skaičiavimus reikšmingai lemia sprendimus investuoti į energijos vartojimo efektyvumą ir energijos vartojimą (Blasch et al., 2021; Brounen et al., 2013; Filippini et al., 2020; Kalmi et al., 2021). Nepaisant to, daugiausia dėmesio šiuose tyrimuose skiriama arba mažesnėms investicijų rūšims, pavyzdžiui, elektros prietaisų keitimui, arba elektros energijos vartojimui. Mano atliktas tyrimas atskleidė, kad su energetika susijęs finansinis raštingumas reikšmingai padidina tikimybę investuoti į daugiabučių namų modernizavimą Lietuvoje. Taip pat nustatyta, kad didesnis pasitikėjimas instituciniais subjektais, ypač namų administratoriais, reikšmingai padidina butų savininkų norą modernizuoti daugiabučius namus. Šios išvados turi svarbių politinių padarinių. Pirma, aiškus, patikimas, objektyvus ir suprantamas konkretaus namo modernizavimo projekto išlaidų ir naudos pateikimas turėtų būti laikomas svarbia politikos galimybe siekiant padidinti investicijas į energijos vartojimo efektyvumą ten, kur to reikia. Tai galima pasiekti įvairiais būdais, įskaitant automatines skaičiuokles, kurios leistų namų savininkams lengvai nustatyti grynąją investicijų į energiją taupančią veiklą naudą. Be to, namų savininkams, prieš balsuojant, ar modernizuoti savo daugiabutį namą, galėtų būti suteikta galimybė dalyvauti trumpoje (internetu arba vietoje) finansinio raštingumo ugdymo ir mokymo programoje, pritaikytoje jiems geriau suprasti savo sprendimo dėl finansinių investicijų sąnaudas ir naudą. Antra, dar vienas galimas būdas įveikti daugelio gyventojų finansinių žinių ir įgūdžių trūkumą priimant sudėtingus investicinius sprendimus dėl modernizavimo – dalytis gerosios praktikos patirtimi tarp skirtingų bendruomenių. Norint palengvinti tokį dalijimąsi, reikia institucijų, kuriomis šios bendruomenės galėtų pasitikėti. Šios išvados reiškia, kad suinteresuotos šalys (vietos ar valdžios institucijos, namų administratoriai ir kiti), siekiančios mažinti energijos vartojimo efektyvumo atotrūkį investuojant į energiją taupančią veiklą, pavyzdžiui, daugiabučių namų modernizavimą, turėtų didinti savo patikimumą.

Keletas tyrimų rodo, kad prisitaikymas prie klimato kaitos žemės ūkio sektoriuje didina atsparumą klimato kaitai, nes didina pasėlių produktyvumą ir žemės ūkio pajamas (Arslan et al., 2015; Di Falco & Veronesi, 2013; Suresh et al., 2021; Tambo & Mockshell, 2018; Teklewold et al., 2013). Tikimasi, kad prisitaikymo prie klimato kaitos strategijomis bus įdiegta nauja arba patobulinta esama žemės ūkio praktika, kuri padės ūkininkams efektyviai naudoti ūkio gamybos priemones. Tačiau Etiopijoje trūksta tyrimų, kuriuose būtų tinkamai įvertintas prisitaikymo prie klimato kaitos strategijų poveikis gamybos efektyvumui naudojant panelinius duomenis. Šį labai svarbų klausimą reikia nuodugniai empiriškai įvertinti, ypač tokiose šalyse kaip Etiopija, kur dominuojantis žemės ūkio sektorius yra labai jautrus besikeičiančiam klimatui. Ankstesni tyrimai, kuriais bandyta įvertinti prisitaikymo prie klimato kaitos poveikį efektyvumui, buvo atlikti ribotoje geografinėje teritorijoje, naudojant skerspjūvio (angl. *cross-sectional*) duomenis, arba juose nebuvo tinkamai atsižvelgta į atrankos paklaidas, atsirandančias dėl esamo ir nesamo heterogeniškumų (angl. *observed and unobserved heterogeneity*).

Todėl penktame šios disertacijos skyriuje, naudojantis žemės ūkio sklypo lygmens paneliniais duomenimis, siekta užpildyti šią spragą, tiriant prisitaikymo prie klimato kaitos strategijų poveikį Etiopijos smulkių ūkių techniniam efektyvumui. Ankstesnių tyrimų metodologinės spragos autoriaus šalintos kartu taikant poveikio vertinimo priemones, t. y. panašiausių atvejų analizę (angl. *propensity score matching, PSM*) ir atrankos šališkumą koreguojančią stochastinę ribinę analizę (angl. *stochastic frontier analysis, SFA*). Disertacijoje atlikto tyrimo rezultatai rodo, kad, įgyvendinus prisitaikymo prie klimato kaitos strategijas, tokias kaip tobulesnės augalų veislės ir vandens išsaugojimo veikla, techninis efektyvumas padidėja 12,37 procento. Taip pat parodyta, kad, neatsižvelgus į atrankos šališkumą, nepakankamai įvertinamas prisitaikymo prie klimato kaitos efektyvumo poveikis (4,21 proc.). Be to, konkrečių pasėlių analizė rodo, kad prisitaikymas prie klimato kaitos pagerina miežių, kviečių ir kukurūzų, bet ne tefų (angl. *teff*) ūkininkavimo techninį efektyvumą.

Apibendrinant reikia pažymėti, kad mano tyrimo rezultatai rodo, jog prisitaikymas prie klimato kaitos gali būti klimato kaitos poveikio mažinimo ir natūrinių ūkių gamybos efektyvumo didinimo strategija. Tačiau jai įgyvendinti reikėtų skirti kuo daugiau dėmesio. Pirma, kadangi prisitaikymo prie klimato kaitos strategijų poveikis priklauso nuo konkrečių pasėlių, žemės ūkio politikos formuotojai turėtų nustatyti konkrečias prisitaikymo prie klimato kaitos strategijas, tinkamas kiekvienai pasėlių rūšiai, o ne skatinti prisitaikymą prie klimato kaitos kaip bendrą priemonę su klimato kaita susijusiems sukrėtimams pažaboti. Antra, siekiant sumažinti neefektyvumą ir padidinti prisitaikymo prie klimato kaitos priemonių naudą, reikėtų įvykdyti papildomus reikalavimus, pavyzdžiui, didinti ūkininkų informuotumą apie prisitaikymo prie klimato kaitos priemonių naudą, plėsti galimybes gauti kreditus, skatinti informavimo apie prisitaikymą prie klimato kaitos paslaugų teikimą, užtikrinti nuosavybės apsaugą ir vandens tiekimą vegetacijos sezono metu.

Taip pat reikia pabrėžti, kad su kainomis nesusijusios priemonės, pavyzdžiui, istorinės informacijos apie elektros energijos suvartojimą ir socialinės lyginamosios informacijos teikimas, gali būti veiksmingos politikos priemonės, skatinančios energijos (vartojimo) efektyvumą gyvenamųjų namų sektoriuje. Be to, veiksmingai įgyvendinant prisitaikymo prie klimato kaitos strategijas žemės ūkio sektoriuje, galima padidinti jo gamybos efektyvumą ir taip apsisaugoti nuo klimato kaitos keliamos rizikos smulkiems natūriniams ūkiams.

Nors remiantis šios disertacijos išvadomis atsakoma į politikai svarbius klausimus ir užpildoma aiški spraga elgsenos aplinkos ekonomikos literatūroje, konkrečiai skirtoje energijos ir gamybos efektyvumui, jos nėra be trūkumų. Pirma, antrame skyriuje analizuota informacinė intervencija yra tik aprašomojo pobūdžio. Ja neatsižvelgiama į kitų informacinių intervencijų – socialinių palyginimų ar energijos taupymo veiksmingumo patarimų. Todėl būsimi tyrimai galėtų atskleisti, kaip skirtingi informacijos teikimo būdai ir tipai keičia energijos vartojimo įpročius kitų mažiau turtingų šalių namų ūkiuose. Kokie pagrindiniai mechanizmai galėtų paaiškinti antrame ir trečiame disertacijos skyriuose išmatuotą nekaininių intervencijų poveikį, dar vienas svarbus klausimas, į kurį būtų svarbu atsakyti ateityje. Antra, ketvirto disertacijos skyriaus analizė yra paremta pavieniais apklausos duomenimis, todėl šios analizės išvadas dėl priežastinio ryšio reikėtų aiškinti atsargiai. Disertacijoje autoriaus naudotas instrumentinių kintamųjų metodas galimiems endogeniškumo nuokrypiams pašalinti, tačiau gali būti tam tikrų nekontroliuojamų klaidinančių veiksnių, kurie gali iškreipti rezultatus. Norint išsamiau išmatuoti priežastinį ryšį, būtina atlikti tyrimus, kuriuose būtų naudojami atsitiktinės atrankos eksperimentai.

Galiausiai, Greene (2010) sukurtas atrankos paklaidos koregavimo modelis, kuris naudojamas penktame skyriuje, yra skirtas tik dvinarei atrankai (angl. *binary selection*). Tačiau sprendimas dėl prisitaikymo prie klimato kaitos yra daugianaris, nes ūkininkai paprastai įgyvendina įvairių prisitaikymo strategijų derinį. Taigi būsimuose tyrimuose daugiau dėmesio galėtų būti skiriama šiam aspektui įvertinti.

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LIST OF PUBLICATIONS

The main findings of this dissertation are published (under revision) in four peer reviewed international journals.

I. Asmare, F., Jaraitė, J., & Kažukauskas, A. (2021). The effect of descriptive information provision on electricity consumption: Experimental evidence from Lithuania. *Energy economics*, *104*, 105687.

II. Asmare, F., Jaraitė, J., & Kažukauskas, A. (2022). Climate change adaptation and productive efficiency of subsistence farming: A bias-corrected panel data stochastic frontier approach. *Journal of Agricultural Economics*, *73*(3), 739-760.

III. Asmare, F., Giedraitis, V., Jaraitė, J., & Kažukauskas, A. (2023). Energy-related financial literacy and retrofits of Soviet-era apartment buildings: The case of Lithuania. *Energy Economics,* 106583.

IV. Asmare, F., Broberg, T., Jaraite, J., & Kazukauskas, A. (2023). Turbocharging Social Comparison Information: Experimental Evidence on Residential Energy and Water Use. Revised and submitted to the Journal of Environmental Economics and Management.

Conference presentations

The studies included in this dissertation have been presented in at least 15 dissemination events including conferences, seminars, and summer school. The following are some of them.

- The 25th and 26th Annual Conferences of the European Association of Environmental and Resource Economists (EAERE).
- Development and Research Conference (DevRes2021).
- The 96th annual conference of the Agricultural Economics Society (AES), Leuven- Belgium.
- The 9th European Association of Agricultural Economists PhD Workshop, Parma -Italy.
- The 40th International Energy Workshop (IEW)-Freiberg - Germany.
- The 10th Annual Lithuanian Conference on Economic Research, Vilnius Lithuania.

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