MISPERCEPTIONS AND INTEREST IN SOLAR PANELS INSTALLATION: EVIDENCE FROM UKRAINE

by

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Kyiv School of Economics

Abstract

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Ukraine is experiencing an energy crisis due to frequent power outages caused by constant shelling. One possible solution is to install solar panels so basic needs can be met during outages. However, the level of solar panel installation remains low across Ukrainian cities, and one possible reason is that people's beliefs about costs and payback are incorrect. Thus, this thesis investigates how misperceptions affect a proxy outcome: signing up for a webinar on solar panel installation. To examine this topic, a randomized survey experiment was conducted involving 222 respondents. The experiment includes four treatment groups: control, cost group, payback group, and combined text group. The main results showed that no treatment increased sign-ups for the webinar. The heterogeneous effects showed that results vary across overestimator and underestimator groups, but these results are imprecise due to small subgroups. Overall, a suggested interpretation is information overload in wartime, which is justified by the high-uncertainty conditions in Ukraine.

TABLE OF CONTENTS

Chapter 1. INTRODUCTION 1

Chapter 2. LITERATURE REVIEW 4

Chapter 3. METHODOLOGY 10

3.1 Statistical concerns 15

3.2 Main model specification 18

Chapter 4. DATA 23

4.1 General data description 23

4.2 Threats to identification 24

4.3 Analysis of socio-demographic and financial characteristics 27

4.4 Analysis of baseline perceptions 30

Chapter 5. ESTIMATION RESULTS 36

5.1 Main model results 36

5.2 Heterogeneous effects analysis 40

5.3 Results discussion 45

Chapter 6. CONCLUSIONS 47

6.1 Conclusions 47

6.2 Contribution and limitations 49

APPENDIX A. 54

APPENDIX B 65

APPENDIX C 67

TABLE OF CONTENTS — CONTINUED

APPENDIX D.....69

APPENDIX E.....71

APPENDIX F.....72

APPENDIX G.....73

LIST OF FIGURES

Number *Page*

Figure 1. The structure of the experiment 13

Figure 2. Correlation matrix 17

Figure 3. Assessing people's understanding of the text 25

Figure 4. Respondents' economic perceptions: cost and payback period 34

Figure 5. Respondents' willingness to sign up for a webinar 35

Figure 6. Comparison of respondents by cost and payback period misestimation (underestimation vs. overestimation) 44

Figure 7. Upper graph: levels of concern about power outages among Ukrainian region 46

LIST OF TABLES

Number *Page*

Table 1. Assessment of Variance Inflation Factor 18

Table 2. Summary statistics of socio-demographic variables 28

Table 3. Summary statistics of financial variables 30

Table 4. Summary statistics of perceptions 31

Table 5. Consumers sensitivity to cost errors 32

Table 6. Consumers sensitivity to payback errors 33

Table 7. Main results for LPM and Probit AME specifications 38

Table 8. Calculated marginal effects results for interactions 39

Table 9. Over- and underestimation among four treatment groups 42

Table 10. Balance table check 65

Table 11. Baseline vs Filtered sample robustness check 67

Table 12. Main results from the full model: LPM and Probit AME specifications with the electricity cost variable 69

Table 13. CI for cost underestimation and overestimation 71

Table 14. CI for payback underestimation and overestimation 72

Table 15. Full model: distribution of over- and underestimation among four treatment groups with housing status variable 73

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AI USE DECLARATION

In preparing this thesis, the author used additional AI tools: ChatGPT, Claude AI, and Grammarly to clarify concepts, improve how data is used, receive feedback on understanding of the material, and edit language, correct grammar, and spelling.

All substantive intellectual work, including the following sections, such as literature review, interpretation of the results, and conclusions, was done by the author throughout the academic year. The used AI does not replace the subsequent thesis. It was used to clarify material directly related to the thesis topic and to debug code, ensuring the data was formatted correctly and that regression results were obtained, which were interpreted only by the author.

LIST OF ABBREVIATIONS

RCT. Randomized Controlled Trial.

WTP. Willingness to Pay.

kW. Kilowatt

LPM. Linear Probability Model.

UAH. Ukrainian Hryvnia.

PV system. Photovoltaic system.

VIF. Variance Inflation Factor.

CI. Confidence Interval.

LPM. Linear Probability Model.

Chapter 1

INTRODUCTION

Over the past 20 years, Ukraine's path has changed: initially, Ukraine sought to break away from the Soviet system and align more closely with the EU framework. Russian aggression in 2014 only accelerated the transformation of Ukraine's energy market due to the partial loss of the Donbas region and access to the coal basin. Due to the Association Agreement with the European Union, Ukraine accelerated its development and created a more distributed renewable energy model. In 2022, Ukraine planned to change its development priorities toward energy storage to reduce the number of daily power outage hours, which includes the installation of solar panels.

During the full-scale invasion, Ukraine's energy system suffered extensive damage. Targeted missile and drone attacks on energy infrastructure have significantly damaged power plants, leading to prolonged and repeated power outages in most regions of the country. Considering Ukraine's energy crisis, decentralizing the power grid will enhance the resilience of the electricity supply against enemy attacks. One solution to the existing problem is to implement alternative energy production, such as solar panels. Therefore, Ukrainian President Volodymyr Zelenskyy announced that solar panels must be installed in every school and every hospital in 2024. Additionally, the President agreed that the government should develop simplified procedures for citizens to install solar panels and batteries, which are needed during the frequent blackouts that continue to occur.

Due to the full-scale invasion of Ukraine, we may ask: if renewable energy can improve people's lives to avoid constant power outages, are people unable or unwilling to install it? Even if people know about solar panels, they do not act

because of inaccurate beliefs about costs. According to the State Agency for Energy Efficiency, the number of solar panels installed in households has grown from approximately 24,000 units in 2020 to about 45,000 units in 2021, nearly twice as many, while in 2024, the number of installed household solar panels reached 52,000 units. The percentage change in the number of solar panels installed in households during the post-COVID period rose by 87.5%. After the full-scale invasion began, the rate of solar panel installation also increased, but the total number of solar panels installed over the three-year period grew by only 15%. A contributor to this slowdown is the difficulty households face in accessing practical and financial information needed to evaluate installation costs and expected returns. For instance, the results of a recent EcoDia survey[1] supported this interpretation: only 15% of respondents believe there is sufficient information, 44% say it is available but difficult to find, and 41% say the necessary information is not available at all.

This thesis includes a first randomized belief-correction experiment on solar engagement in a wartime economy to estimate a proximate behavioral outcome to understand the level of interest in installing solar panels. The purpose of this analysis is to determine whether informational interventions may affect respondents' interest in registering for a webinar on alternative energy under unstable conditions, such as wartime and frequent power outages. Thus, this thesis investigates how different types of financial information, such as cost and payback period, affect people's decision to sign up for a webinar. Webinar sign-up is used as a proxy outcome because it is hard to verify whether the solar panels are installed during the experiment, but it is possible to assess respondents' interest in solar panels after the survey. The use of a randomized experiment

[1] This data was provided by the research agency Info Sapiens. This survey was done for EcoDia with the aim to investigate what people think about renewable energy sources and whether are they ready to install them soon, as well as what barriers exist to their installation.

enables the establishment of a causal relationship between the information provided to consumers and their actual decision-making regarding solar panels.

Regression results indicated that the treatments have no statistically significant effect on decisions to register for the webinar. The analysis of interactions between the error and the treatment also shows generally insignificant results, but Text #4, which contains information about price and return on investment, yields a significant result. Additionally, when misperceptions are divided into two subgroups as >0 and ≤ 0, the difference is more visible. The results of the study showed that there was no significant effect of the treatments Text #2, Text #3, and Text #4. When we conducted a study on the interactions between the participants' errors and the cost and payback treatments, Text #4 (cost-only information) was the only one to show a significant result. No superadditive effect was found for Text #4, indicating that there is no reason to believe that the combined text has a greater effect than the sum of the effects of Text #2 and Text #3 separately.

Moreover, the experiment is essential because the heterogeneous analysis shows that, for a specific group of people who overestimated the cost of solar panels, their interest in the message increased. However, these results are based on small subgroups, and the confidence intervals are wide and include zero, making the results inconclusive.

This thesis is structured as follows: Chapter 2 presents a literature review. Chapter 3 provides a detailed methodology and limitations analysis. Chapter 4 outlines the data description, threats to identification, and variables. Chapter 5 presents the obtained estimation results and their discussion. Chapter 6 is focused on conclusions.

Chapter 2

LITERATURE REVIEW

The adoption and research on residential and small-scale PV systems remain limited, and the topic is still underdeveloped compared to other countries, including in terms of understanding behavioral factors, biases, and perceptions affecting adoption in Ukraine. One of the main goals of an individual in the economic environment is to make rational decisions for their own well-being based on economic conditions, their own beliefs, and available information. Solar panels could be one possible solution in the context of damaged infrastructure for ensuring energy supply due to the war in Ukraine and constant blackouts.

However, people are deterred from installing solar panels in their homes by unrealistic expectations, aggressive advertising, an unfavorable climate, potential installation errors, and financing issues (Rai et al, 2016). For instance, in the analysis of the U.S. renewable energy market, Ghimire et al. (2026) noted that the installation of solar panels is influenced not only by environmental concerns but also by institutional trust, social norms, cognitive biases, and demographic characteristics. This view is supported by authors Jenny Palm and Elina Eriksson (2018), and Jenny Palm (2018): the financial component remains the primary barrier, but uncertainty also arises from a lack of information or from information that is difficult to understand. The lack of information creates a problem when people are not sufficiently informed and they have distorted expectations that lead to irrational decisions. We identify the first gap: that informational and behavioral barriers remain significant even in the presence of economic incentives. This is classified as a key problem in economic experiments and field studies.

We started with foundations of decision-making. Simon (1955), whose work on bounded rationality earned him the Nobel Prize in Economics in 1978, argues that human cognitive resources are limited. Even complete information does not guarantee a "clear result" because the brain uses simplified strategies (Simon, 1955). While Haaland et al. (2023) noted, the effectiveness of information depends on its consistency with the agent's individuality. Undoubtedly, the new information obtained may have insignificant psychological impact on a person's decision due to their already established views. This results in the opposite effect, which will be statistically insignificant in the context of the study.

At the level of behavioral mechanisms, the literature also represents that respondents' decisions are constrained by systemic cognitive biases and individual preferences. Based on prospect theory, people experience losses more strongly psychologically than gains of similar magnitude (Kahneman and Tversky, 1979). People are afraid to make decisions not because of a lack of information, but because they are psychologically afraid of significant losses, a fear that is even more pronounced in the case of Ukraine. Therefore, the fear of losing money is currently preventing people from deciding to switch to solar energy. Based on fear of loss, Moncada et al., (2025) argues that the solar panels are long-term and valuable decision which is hard to implement because people fear to lose money due to uncertainty and unstable conditions. Additionally, another study shows a correlation: while Moncada (2025) supposed that fear of losses happened due to uncertainty impacts on decisions, Christine L. Crago and Rong Rong (2025) reflect that the decision is based rather on different preferences and motivation. In contrast to previous authors, Wolske et al., (2018) showed that different interventions did not provide a huge difference, and people immediately tend to be skeptical to provide information of the numbers, but this information increased their interest in solar panels and people would like to find more information about investments in solar energy by themselves. It depends

on personal motivation. This suggests that information must be clearly structured but tailored explicitly and simple to different audiences to increase the interest in solar panels. Also, this idea is supported by Bär et al., 2023 who shows that the effect of receiving clearly defined information in the context of a financial benefit that can translate into real action is stronger. Given that the presentation of information is very important, the authors Huang and Shen (2020) argued that people will trust information at the national level if the information is provided by the government, and the interest in transitioning to alternative energy sources will increase. Therefore, a decision depends not only on general information but mostly on the trustworthiness and credibility of the information, with the aim of providing clear information. Thus, the reviewed literature indicates that information interventions can be effective when respondents received clearly formulated information, and if the interventions correspond to a person's psychological type. Thus, this analysis represents the presence of heterogeneity, because the decision depends on who is reading and what preferences do they have.

Also, the literature frequently raises the question if the combination of different incentives indicates that people's willingness to make a decision will increase. In the study of Maris et al. (2025) various tools, such as financial incentives and reminders of environmental value should work together to achieve a stronger effect. The results showed that using psychological factors alone was ineffective. However, adding a financial incentive to the reminders doubled effectiveness. This work is an example of superadditivity. According to their experiment, the group that received a simultaneous combination of the two treatment methods showed a stronger effect than when the two methods were used separately. In other words, the synergy of the two simultaneous stimuli worked more effectively than the two methods used separately. This suggests that people perceive a connection between the two stimuli, which complement each other and yield a

stronger result. Viscusi (2023) supports this idea: the author supposed that financial incentives are more favorably than informational interventions it should provide a stronger impact than information campaigns. However, he supported the idea of including both types of approaches in the formulating public policy with the aim to formulate a foundational step before developing subsidy and loan programs, and information programs can amplify the effect when combined with subsequent financial incentives. In contrast to both authors, the idea of combining information is not supported by Alt et al. (2024). On the contrary, authors noted that combining policies, will have a weaker effect due to diminishing marginal utility, and such a combination of two tools will be difficult for people to accept.

However, it is also important to emphasize that policy effectiveness depends on the level of government, as people tend to trust the local authorities most (Huang and Shen, 2020). Zhao and Shi (2025) offered a different opinion, because conflicts may arise between different market players such as local authorities and businesses, while businesses may focus primarily on making money, local authorities will focus specifically on ecology and the environment. Both research focuses on how interventions can interact itself with local authorities to make effective policies for citizens.

A little research is available in the context of military and war-related context in terms of impossibility to hold a randomized experiment. For example, solar panels can serve not only as a technical solution to the problem of frequent power outages, but also as a means of shaping the relationship between the state and its citizens. Jamison et al., 2026, noted that installing solar panels during wartime has a dual effect. On the one hand, it enhances energy security and provides people with power during shelling, however, on the other hand, citizens may oppose such initiatives, as large-scale projects involving the solar panels installation can occupy significant part of land. Therefore, in this case, we can conclude that the

post-war reconstruction plan must be fully transparent. It is also worth noting the impact of the psychological trauma people have experienced due to the full-scale invasion. In one study, Callen et al. (2014) analyzed how violence (combat operations, shelling, frontline exposure) during the war influenced decision-making, and the authors concluded that people who were relatively close to the combat zone tended to avoid risks. This indicates that an exogenous environmental shock – such as the conflict in Afghanistan – altered people's preferences and increased their risk aversion, leading them to psychologically choose safer options.

Financial, informational factors and behavioral barriers formulate people's behavior. Research in the field of renewable energy shows that individual behavior is shaped by several factors, much like marketing strategies, namely the presentation of existing policies, financing opportunities, and support programs. Partially, empirical studies demonstrate that simply providing information through various channels does not fully shape a person's decision due to their pre-existing beliefs. Therefore, it is impossible to consider only the issue of a person's preconceptions in the context of psychology. It is also important to consider how the government provides financial support, which influences the formation of a person's final decision for the transition to alternative energy.

Hence, based on the reviewed literature, the gap is that there is a few research on war conflicts or unstable situations in the countries. However, there is no randomized experiments in war-related countries. Those articles represented the ecology issue and justification why implementing solar panels are important. Furthermore, the main focus and experiments of the analyzed experiments are based environmental issues, not on critical situations such as power outages.

Due to analyzed literature, we can identify following gap, which is going to be analyzed in this work: existing literature indicate that information interventions

impact peoples' decisions in terms of solar panels installation. However, the provided results in the research remain heterogeneous. Some research suggests that decisions are largely shaped by uncertainty and fundamental human characteristics, rather than by simple informational factors. Thus, the main gap which can be highlighted is limited behavioral evidence on intentions to act under wartime conditions in Ukraine.

Chapter 3

METHODOLOGY

The study is based on a question: how updating beliefs can strengthen Ukrainians' interest in renewable energy during the wartime. Therefore, for the research we used a randomized factorial experiment with the aim to show to what extent might new information influence people's interest in installing solar panels, given their prior biases. The study by Haaland, Roth, and Wohlfart (2023) was chosen as the basis for the design, where we adopted the model of belief updating by modifying it and adding interactions between cost, payback period and their errors to estimate how those mistakes influence people's behavior.

Based on the literature review, the following three hypotheses were tested in this study.

- H1: Each treatment including the text about price (Text #2), the text about payback period (Text #3), and the combined text containing both parts of information (Text #4) will increase the probability of webinar registration compared to the control group. This approach was used at least in the articles of Wolske, Bär, Huang and Shen, where the similar idea checked whether different information could provide an effect to adopt solar panels or increase the interest. Previous studies showed that different treatments had effects on an action across different contexts. However, this hypothesis examines if similar effects can be observed in Ukraine under wartime conditions.
- H2: Text #4 containing information about both price and payback period, has a stronger effect on the probability of webinar registration than the sum of Text #2 and Text #3. This hypothesis is based on the article of Maris et al., (2025), who were analyzing whether information

nudge and a financial incentive (voucher) have a stronger impact on involvement in volunteer activities, however Alt et al. (2024) who did not supported the idea that the combination of two types of information interventions provides a stronger impact than treatments separately.

- H3: Text #4 (cost information and payback group) is more effective for people who overestimated the cost. This hypothesis is supported by Christine L. Crago and Rong Rong (2025) and Wolske et al. (2018), which showed that adoption behavior is heterogeneous by the risk aversion and peoples' preferences, accordingly. Thus, the third hypothesis checks how the intention is going to be changed across individuals with different misperceptions.

To investigate all hypotheses, we developed the survey, including baseline (control) message and different messages with treatment effects. Each treatment has its own specific information about cost or payback period or both included information. We asked for help Info Sapiens to run the experiment. Info Sapiens conducted a survey in March 2026 comprising three sub-studies on solar panels, with 688 respondents in total. The present study includes data from one sub-study: n = 222.

The experiment was run through the Online Sapiens platform. Online Sapiens is an online service that allows various projects and new businesses to gauge public opinion on different issues, while also giving people the opportunity to share their thoughts on products or services. People receive rewards for their comments: they can accumulate points to top up their mobile accounts or donate money to a charity of their choice.

If people are interested in this initiative, they must register on the Info Sapiens Online platform and provide basic information about themselves, such as age, gender, and region of living. Info Sapiens has approximately 100,000 respondents

across Ukrainian cities on its platform to this initiative. Since KSE students prepared three different surveys, an agreement was reached with Info Sapiens that the platform would host a single survey with three parallel studies.

One of the objectives of the experiment was to ensure an even distribution of respondents. To achieve the randomization inside of the experiment, the data that people entered when registering on the platform – age, gender, and region of residence was used.

Treatment assignment followed a two-stage randomization procedure: assignment of a specific experiment within three studies and randomization inside the given experiment. First step is based on checking who is eligible for the experiment. This is checked by demographic quotas which are established by Info Sapiens. Respondents received invitations to the platform via a convenient communication app that they previously selected themselves: email, Telegram, or Viber. Once a person has received an invitation to the platform, the platform automatically checks whether they are eligible to participate in the experiment based on quotas as age, region and gender. If the quota is not filled and the person meets the criteria, they are randomly assigned to one of four groups: control, cost-only, payback-only and combined information group. Otherwise, if the specific quota for a group was already filled, the person received a message stating, "We have already received enough responses from the group you belong to (e.g., age, gender, and/or region)."

From the figure (see Figure 1 below), we see that the received data shows us a balanced group distribution: 28% for the control group, 20% for a treatment group with cost information, 25% for a treatment group with payback information and 27% for a treatment group with a combined effect. The experiment consists of 4 groups: a control group, a cost-only group, a payback-only group and combined effect group. The structure of the experiment lies in

interventions that provide accurate information about the solar panels for a better understanding how people react to new information.

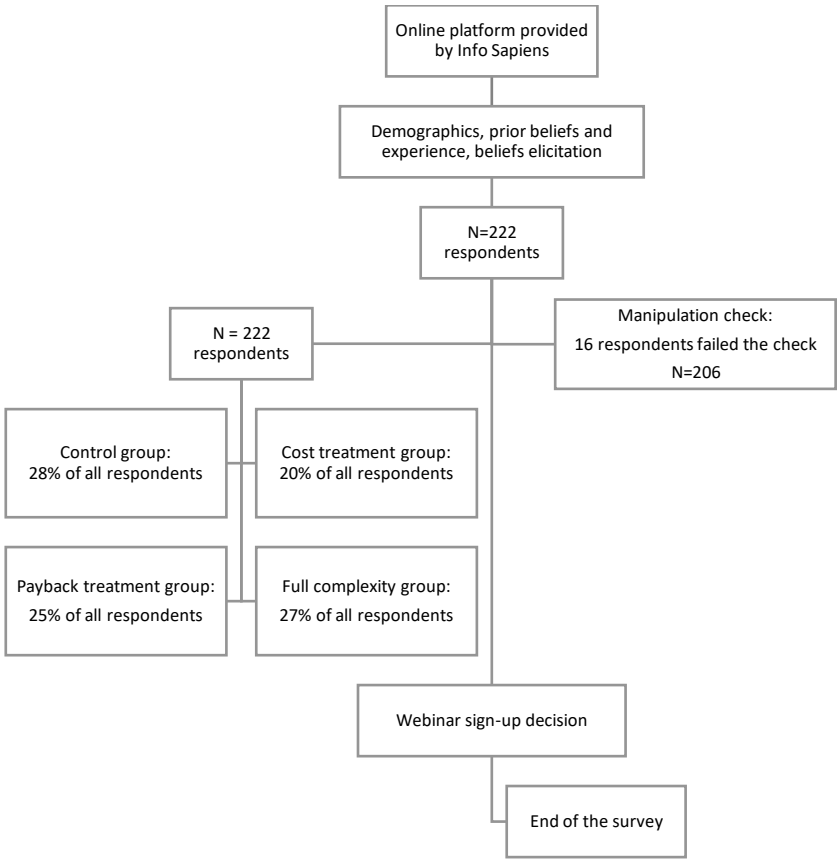


Figure 1. The structure of the experiment

Basically, the empirical analysis includes four levels of information that are intended for testing. Firstly, the LPM model is tested to examine the individual effects of cost and payback messaging. Secondly, we compared their relative magnitudes to identify which framing is stronger. Thirdly, we tested for superadditivity in the combined treatment group to estimate whether card with

cost and payback information has a stronger impact than the information separately. Finally, we tested the heterogeneous effects by using interactions between treatment text as a corrective mechanism and respondents' initial mistakes in cost and payback period.

Allcott and Taubinsky (2015) noted that information interventions work better on people who had misconceptions prior to the study. The authors also confirmed that a small sample size can greatly influence WTP – the result can be either very high or very low because people were focused only on market prices. At the same time, in surveys, people give inflated answers to hypothetical questions because, in their understanding, these answers will not be accompanied by anything additional.

List and Gallet (2001) add control variables to the analysis to distinguish hypothetical actions from real economic decisions to solve this problem. The control variables are used in the analysis to make the model more balanced. Also, Daniel Hausman (2011) was skeptical in his study about analyzing only respondents' answers. This suggests that additional tests and restrictions should be considered in the analysis. At the same time, Maris et al. (2025) suggested that financial incentives and environmental information work together and provide a stronger effect when the information is provided separately to respondents. The authors confirmed that both types of information provide positive synergy and, as a hypothesis of this thesis, tested superadditivity to see whether the two types of information would have a stronger effect.

The availability of information about solar panels to correct misperceptions are not always be able to change people's behavior, as people have stable preferences that they do not want to change and are not yet ready to invest (Allcott and Taubinsky, 2015). This is partly confirmed by Gillingham and Palmer (2014), who argue that the main driver of investment is not only the information received,

which can increase consumer valuation, but also a person's attitude to risk and how they perceive the prospects for long-term investment.

3.1 Statistical concerns

Before describing the methodology in detail, it is necessary to agree on the main risks that may arise when specification and estimation of econometric models.

The main risks are as follows:

- The high risk is a sample of 222 respondents. As it mentioned before, each group has to be distributed equally, and it is expected that for each group approximately 55 respondents are allocated. This number of respondents may not yield statistically significant results, and this sample will not reveal the effects of the treatments. Furthermore, issues may arise specifically in the heterogeneity analysis, because subgroups may be even smaller, and standard errors may be too large, which could skew the results. Additionally, the results should be interpreted with caution in the future.
- There is a risk of multicollinearity in the interactions. The model includes interactions between text and pricing error, as well as payback period. First, a high level of multicollinearity is expected between the two variables err_{cost} and $err_{payback}$ due to a possible pattern such as a lack of information. Therefore, if there is a strong correlation between two variables, there likely will be multicollinearity among the interactions between $Text_j \times err_{cost_i}$ and $Text_j \times err_{payback_i}$. If multicollinearity is present, the mean centering will be applied to proceed further regressions.

- The source of credibility. Respondents may not accept the information provided because it is overly optimistic in war-time period.

Since the risks are critical to the study, they need to be minimized. With the aim to minimize those risks, additional questions were included in the survey, which was created for the purpose of the research:

- A question about respondent's attentiveness was included in the survey with the aim to filter out answers and improve the quality of the data in the analysis.
- A separate multicollinearity test is be conducted. Before showing the study's results, one of the points of the analysis was diagnostic tests to confirm that regression coefficients are reliable, since model involves interaction terms. Dependent variables in the model may be strongly correlated, so a VIF test must be performed.

Thus, a two-step analysis is used for checking the multicollinearity. The matrix correlation is checked regarding the full regression model. VIF test which was conducted to find a multicollinearity shows that all variables fall within acceptable multicollinearity limits, so there is no point to apply mean centering. See the Figure 2 below representing the correlation matrix.

The correlation matrix contains the regressors used in the econometric model. The correlation between regressors does not exceed |0.7|. More regressors lie in the range [-0.22; 0.19], which is appropriate in terms of correlation. A modest correlation is observed between errors in cost and payback period (r=0.27). This can be explained by people's psychology, as respondents are prone to make mistakes in both costs and payback too. Also, a modest correlation is between prior experience and patience (r=0.36), as people can think more about future decisions regarding the level of power outages in the country. The highest

correlation coefficient is observed between the patience and risk tolerance variables (r = 0.63), but it remains within acceptable limits.

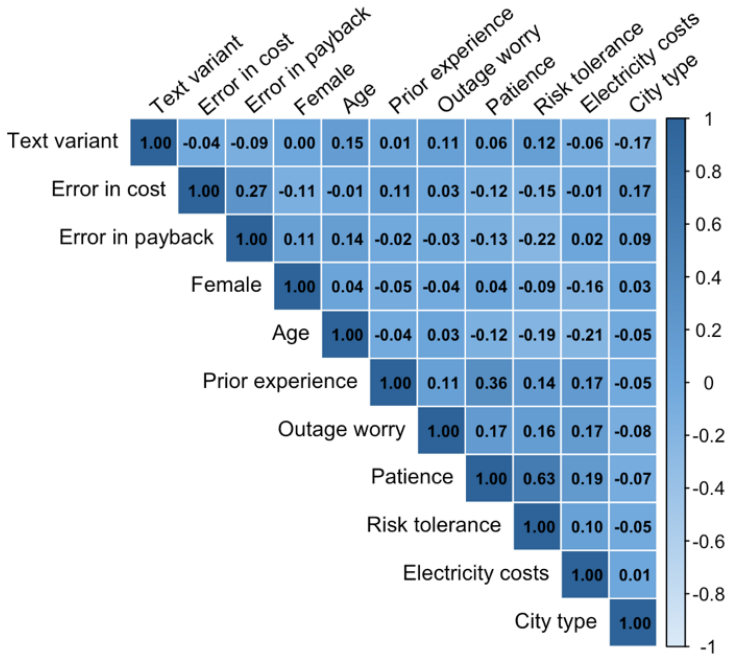


Figure 2. Correlation matrix

Additionally, all the variables which were used for regressions are checked by the Variance Inflation Factor below in Table 1.

Table 1. Assessment of Variance Inflation Factor

Statistic	GVIF	Df	GVIF^(1/(2*Df))
Text variant	2.066	3	1.129
Error in cost	4.484	1	2.117
Error in payback	4.535	1	2.130
Female	1.151	1	1.073
Age	1.242	1	1.114
Prior experience	1.306	1	1.143
Outage worry	1.149	1	1.072
Patience	2.183	1	1.477
Risk tolerance	2.140	1	1.463
Electricity costs	1.897	5	1.066
City type	1.331	2	1.074
Text variant × Error in cost	7.724	3	1.406
Text variant × Error in payback	8.337	3	1.424

The table represents that all variables have moderate multicollinearity: VIFs < 2, except error in cost and error in payback which are slightly >2. The results for error in cost and error in payback are appropriate. Thus no multicollinearity related to the model and no mean-centering is needed.

3.2 Main model specification

After the statistical concerns analysis, we specified a full model, which is going to be used in the thesis. Since the experiment is based on an RCT, one of the aims

is to estimate the Average Treatment Effect (ATE), which can be calculated by the LPM model (Angrist and Pischke, 2009). Hence, a LPM model was selected as the baseline model, where those coefficients are expressed in percentage points and display the change in the probability of registering for the webinar for this analysis.

$$Webinar_i = \beta_0 + \sum_{j=2}^{4} \beta_j Text_{j,i} + \sum_{j=2}^{4} \theta_j \left(Text_{j,i} \times err_{cost_i}\right) + \\ + \sum_{j=2}^{4} \delta_j \left(Text_{j,i} \times err_{payback_i}\right) + \gamma' X_i + \varepsilon_i \quad (1)$$

where:

$Webinar_i$ is a binary outcome which shows if a respondent is interested in registering for a webinar on installing solar panels (1 — if the respondent expressed willingness, 0 — otherwise).

$Text_{j,i}$ represents dummy variables for the informational texts (options: #2, #3 and #4), which shows how much people's psychological readiness to sign up for the solar panels course changes depending on the provided information. A variable displays four cards with its specific short text. Respondents in their assigned groups received following text that may affect individuals' prior beliefs. Each text is given in Appendix A.

err_{cost} and $err_{payback}$ are variables that indicate a human error about cost and payback. Errors are calculated as the difference between the user-estimated price and payback period and the baseline values. If the $err_{cost\ and\ payback} > 0$, it means that a respondent overestimated the cost and payback period, thus a

positive error shows an overestimation. While $err_{cost\ and\ payback} < 0$ means underestimation.

$Text_j \times err_{cost_i}$ and $Text_j \times err_{payback_i}$ demonstrate interaction terms where the effect of the text varies depending on the respondent's error is examined.

$\gamma' X_i$ is a set of additional control variables. Control variables help to examine which factors in the model would have the greatest impact on a person's interest to install solar panels. This approach serves to determine how much people's desires might vary depending on each person's situation. Control variables were selected by the following categories: demographic characteristics, expenses, experience and stages of consideration for installing solar panels, and time preferences. The control variables used in the regressions are listed below.

$gender$ – participant gender (coded as dummy: 1/0).

age – participant age in years.

$electricity\ costs$ – an ordinal categorical variable, which included six ranges, starting from "less than 500 UAH" to "more than 3,000 UAH", additionally added a "don't know" category.

$prior\ experience$ – an ordinal categorical variable, which included a range from "very poor" to "very good". The variable represents if respondents do have previous experience with similar technologies earlier.

$outage\ worry$ – an ordinal categorical variable, which included a range from "not worried at all" to "extremely worried". The variable displays whether individuals strongly feel anxiety about power outages in their region.

$patience$ – a 10-point Likert-type scale variable. The variable indicates if a person is ready to wait to receive the benefits.

$risk\ tolerance$ – a 10-point Likert-type scale variable. The variable suggests how willing a person is to take risks.

ε_i is a zero-mean error term.

LPM is a linear regression model with a binary variable with the aim to predict of probability to sign-up for a webinar. The OLS model assumes that errors are equally distributed, so this statement is violated in LPM. Thus, the error terms in are not normally distributed in the LPM. A variance formula for a binary outcome $Var\ (Y|X) = P(X)\big(1 - P(X)\big)$ shows that the variance of the binary outcome depends on the explanatory variables through the probability, the variance can be changed. The spread of errors predicts that the probability may fall outside the range [0;1] and be less than zero or greater than one in LPM. Therefore, one of the model's issues is the presence of heteroscedasticity, which is going to be tested by using the Studentized Breusch–Pagan test.

In general, LPM has limitations as fitted probability outside the [0;1] interval and partial effect of any explanatory variable is constant. These limitations can be overcome by using Probit model where Φ is a function taking on values strictly between zero and one: $0<\Phi<1$, for all real numbers. The probit model is provided below.

$$P(Webinar_i = 1|Z_i) = (\beta_0 + \sum_{j=2}^{4} \beta_j Text_{j,i} + \\ + \sum_{j=2}^{4} \theta_j \big(Text_{j,i} \times err_{cost_i}\big) + \\ + \sum_{j=2}^{4} \delta_j \big(Text_{j,i} \times err_{payback_i}\big) + \gamma' X_i + \varepsilon_i \quad (2)$$

Both models consist of interaction between $Text_{j,i} \times err_{cost_i}$, $Text_{j,i} \times err_{payback_i}$. The probit model does not account for interactions when calculating marginal effects; instead, it estimates the average value along an S-shaped curve, providing probabilities in the range [0, 1]. With proper randomization, the results of LPM and Probit AME should be similar, indicating robustness. Due to the existing interactions, the results of Probit AME may differ from LPM because Probit AME averages across the nonlinear structure of the Probit model; at the same time, interactions in Probit AME are not calculated. To assess robustness, the model's interactions will be calculated separately for comparison.

Chapter 4

DATA

We used the data from the research agency Info Sapiens. The study is based on a conducted survey. Together with the academic advisor, we developed survey questions to determine people's willingness to become more familiar with solar panel adoption and to understand how corrected perceptions of the cost and payback period affect the investment attractiveness of energy-efficient solutions for Ukrainian consumers. As of February-March 2026, Info Sapiens sent invitations to respondents via their preferred channel, such as email, Telegram, or Viber. Respondents must follow the link to get access to the online platform where the survey was conducted. The study was developed at the request of KSE students and their supervisor in both languages: Ukrainian and English. Respondents were taking the survey in Ukrainian.

4.1 General data description

The survey consists of 10 sections: screening and criteria selection, demographics, expenses, attention check, experience and stages of consideration for installing solar panels, information scenario (randomized – treatment effects), manipulation check, outcomes, post manipulation, and trust & data quality. The survey has 5 main parts for the analysis.

The first step was on demographics and decision-makers, afterwards respondents who do not meet our criteria were screened out. In the second part, the baseline was determined by assessing what respondents think about cost and payback period to providing information about solar panels. The third part includes randomization and information intervention with 4 groups as control, cost-only, payback-only and both effects. The fourth block is based on comparison of

changes in willingness to sign up for a course and the level of interest after reading the information. The last part is about data reliability and possibility for a session registration if respondents became interested in the proposal.

The second step after receiving the data was to verify that the randomization was correct. To analyze this, we ensured that all respondents were divided into 4 groups based on different informational incentives, and that none of these groups showed significant differences in demographic or socio-economic characteristics before they received treatment (Appendix B). The analysis in R showed that there was no significant difference between groups for various characteristics, such as age, education, and income ($p > 0.05$), but variable city type showed $p = 0.037$ and this variable is controlled and used in the regressions.

4.2 Threats to identification

Before conducting empirical analysis, it is necessary to verify that the experiment was correctly perceived by the participants. Previously, the attention check was provided to understand whether respondents do pay close attention when taking the survey. The data showed that 16 people gave a different answer than previously expected: respondents were asked about their favorite color, and it was important to choose a color that was given in the question, but 16 individuals chose another one. Consequently, 16 people were excluded because their responses could have negatively affected the results due to inattention for the further analysis.

Additionally, the respondents' text understanding was checked. The survey included a question about which text did the respondent read. The results are provided in Figure 3. Most people chose the correct provided text, however, the third of respondents chose the incorrect answer. The results of checking indicate that the incorrect answers lie in a range between 18.5% and 33.3%, which shows

that a part of respondents could not identified the correct text. The strongest result was observed in treatment group 4, where text included both cost and payback period information. Treatment groups 1 and 3 displayed slightly lower results 75.9% and 72.5%, but they also showed that people understood the needed information. The least result was provided by treatment group 2 – 66.7%. A small number of individuals believed the text was about cost and payback simultaneously, whereas it was only about the cost of solar panels.

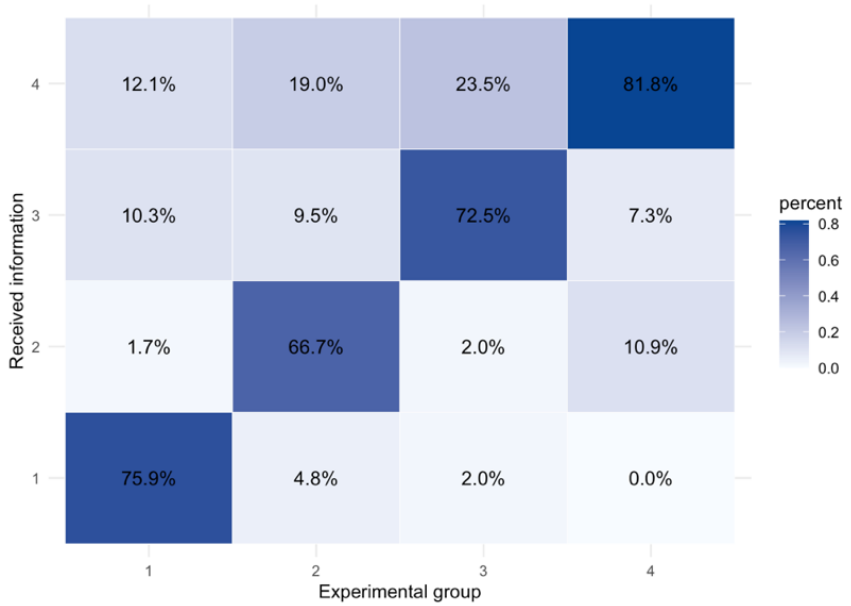


Figure 3. Assessing people's understanding of the text

Since the experimental conditions were designed to influence the respondents' behavior, it is important that the participants properly understand the content of the information provided. Only under this condition the presence of an effect of the experimental condition can be accurately assessed. According to the results of the manipulation check, approximately one-third of the respondents were unable to identify the text they had read. This is a substantial problem, and the

results of the experimental conditions may be underestimated which could cause the coefficients to shift toward zero.

As previously noted, the sample consisted of only 222 respondents, 206 of whom were included in the analysis because they failed the attention check. Since the proportion of respondents who failed the manipulation check is substantial and excluding them would have resulted in a significant reduction in the sample size and a loss of statistical power. We conducted an additional analysis with 206 respondents where those who failed the text comprehension test were excluded to verify the reliability of the results. After filtering, 154 respondents remained. A robustness check for the sample of 154 respondents showed that most variables in both models have the same sign, and the results can be considered reasonably robust. At the same time, after filtering, the model became statistically insignificant due to the small number of respondents whose responses cannot fully explain the dependent outcome (Appendix C).

Overall, the robustness check indicates that the results for all respondents and separately for the filtered respondents regarding text comprehension have the same direction in terms of signs and magnitude, suggesting that even after excluding data regarding incorrect text comprehension, the effect remains sufficiently unstable and fragile. The effect remains weak, showing that the treatment did not produce a stronger effect. Even after excluding respondents who incorrectly identified the text, they had read, the results are similar to those obtained when we did not exclude them from the sample. Therefore, the expected result – which would indicate the presence of a treatment – is absent. In other words, the participants who understood the task and answered correctly showed that there was no prior noise in the model, and the additional robustness check did not strengthen the result. We see that the probability of the webinar signs up did not increase after excluding all respondents who are did not proceed information correctly.

Additionally, regarding the survey, the social desirability bias also can be identified as a risk. Respondents may express their intention to sign up for a session to conform to the image of an environmentally conscious citizen, which is relevant in the context of the state's energy independence policy, but is not true in the context of the current environment.

4.3 Analysis of socio-demographic and financial characteristics

The sample of the respondents represents socio-demographic variables such as regions of residence distribution, settlement, accommodation, housing status and decision-making. The average age of respondents is 43 years, and approximately half of respondents are women. A significant proportion of the respondents who participated in the survey live in the northern (29.73%) and central (28.38%) parts of Ukraine, while a slightly smaller proportion live in the western part (22.07%). The smallest share is in the southern part (12.61%) and the eastern regions of Ukraine (7.21%). A major part of survey participants are residents of large cities (51.80%), while small cities and rural area residents accounted for 25.23% and 22.97%, respectively.

More than half of the individuals (54.5%) live in detached-private houses and around 42.79% of sample population live in apartments. The smallest shares are attributed to duplex and other categories: 1.8% and 0.9%. Regarding housing statuses, more than half of the sample (56.3%) are owners, and another 16.7% own their homes as co-owners. Also, some of participants are living with their families (18.47%). The two smallest shares are allocated to tenants (7.21%) and the "other" category (1.35%). A slightly more of survey participants are making decisions about home improvements. See Table 2 with the provided results. below.

Table 2. Summary statistics of socio-demographic variables

Statistic	Obs	Mean/Percent
Age	222	43.27
Gender (Female = 1)	222	52.25%
Geographic Distribution	**Obs**	**Percent**
North	66	29.73%
West	49	22.07%
Center	63	28.38%
South	28	12.61%
East	16	7.21%
Settlement Type	**Obs**	**Percent**
City (>100k)	115	51.80%
Small City (10-100k)	56	25.23%
Village/rural area (<10k)	51	22.97%
Accommodation Type	**Obs**	**Percent**
Detached private house	121	54.50%
Duplex (two-family house)/Townhouse	4	1.80%
Apartment in a multi-unit building	95	42.79%
Other	2	0.90%
Housing Status	**Obs**	**Percent**
Owner	125	56.31%
Co-owner	37	16.67%
Tenant	16	7.21%
Living with family (not an owner)	41	18.47%
Other	3	1.35%
Decision-Making	**Obs**	**Percent**
Yes, I make these decisions	118	53.15%

Table 2. Summary statistics of socio-demographic variables — Continued

Statistic	Obs	Percent
Yes, I make these decisions together with others	104	46.85%
No, someone else makes these decisions	0	0%
Education level	Obs	Percent
No education	1	0.45%
Basic secondary education	1	0.45%
Secondary education	13	5.86%
College	84	37.84%
Bachelor's degree	50	22.52%
Master's degree	72	32.43%
Doctor of Sciences	1	0.45%

The sample population displays financial variables as well. This includes financial status and electricity costs. According to the results, roughly half of the respondents (50.45%) answered that they live comfortably and can plan major purchases. A marginally smaller proportion (37.39%) belongs to those who can afford only the basics. Only 6.76% of individuals struggle with basics, while 4.5% and 0.90% has no difficulties with necessities and expensive purchases, respectively. However, electricity costs are quite volatile. About 53% of respondents pay between UAH 500 and 1,500 per month for electricity. Approximately 33% of all respondents pay between UAH 1,500 and 3,000 for electricity. The smallest share consists of those individuals who pay less than UAH 500 for electricity – 13.96%. 6.79% of respondents who paid a bill exceeding UAH 3,000. However, there are no survey respondents who do not know about electricity costs at all. A third part of respondents in a survey have master's degree – 32.43%. While college and bachelor's education took 37.84% and 22.52%, respectively. 5.86% is represented by people with secondary education, while the smallest shares (0.45% each) are those with no education,

basic secondary education, and a Doctor of Science degree. A Table 3 shows these results below.

Table 3. Summary statistics of financial variables

Financial Status	Obs	Percent
Struggling with basics	15	6.76%
Basics only	83	37.39%
Comfortable, plan big purchases	112	50.45%
No difficulty with necessities	10	4.50%
No difficulty with expensive purchases	2	0.90%
Electricity costs	**Obs**	**Percent**
< UAH 500	31	13.96%
UAH 500 – 1000	72	32.43%
UAH 1 000 – 1 500	46	20.72%
UAH 1 500 – 2 000	37	16.67%
UAH 2 000 – 3 000	21	9.46%
> UAH 3 000	15	6.76%
Do not know	0	0%

4.4 Analysis of baseline perceptions

Table 4 presents statistics on people's prior knowledge and perceptions of solar panels. The average for the estimation cost is UAH 239,115.15. However, the range of responses is between UAH 4,122 and 500,000, suggesting that people do not have a clear understanding of the investment appraisal metrics for solar panels. Additionally, the standard deviation is also high, at UAH 127,973.26, regarding a quite large range. The estimated average saving is UAH 3,390.80, with

a standard deviation very similar to the mean (2,658.17). The range is also variable: people's answers range from UAH 0 to 10,000. The average of a payback period estimation is 9.5 years, while the standard deviation is 6.48 years. Table 4 represents the results below.

Table 4. Summary statistics of perceptions

Statistic	Obs	Mean	St. Dev	Min	Max
Estimation cost	222	239,115.15	127,973.26	4,122	500,000
Estimation saving	222	3,390.80	2,658.17	0	10,000
Estimation payback	222	9.50	6.48	1	25

Before proceeding with the econometric analysis, it is necessary to assess respondents' level of awareness through a market analysis. To establish a benchmark for the cost of installing a solar power plant, we analyzed data from Ukrainian companies that install solar panels across various regions of Ukraine. As of 2024, prices have stabilized following the full-scale invasion.

According to a licensed Ukrainian installer Generacia Energy, the average price per 1 kW of installed capacity is approximately $800–$1,000. The company notes that an average household requires about 5 kW of capacity, bringing the total cost of the system to approximately $4,000 on average across Ukraine (excluding installation), which at the exchange rate as of the end of 2024 would be about 170,000–180,000 UAH. Meanwhile, the Ukrainian company Atmosfera has set a price of 220,000–235,000 UAH for a 5 kW solar power plant, including installation, which is equivalent to $5,500 (at the exchange rate as of the end of 2024). Alteco also offers the installation of a 5 kW solar power plant for $5,500–$5,765 (230,000–242,400 UAH).

Based on calculations for the solar panel market in Ukraine, the average cost of installing a 5kW solar panel system range from UAH 180,000 to 220,000. UAH 200,000, which is corresponded to Ukrainian market. UAH 200,000 is the upper limit of the price range for a basic grid-connected system without batteries. More expensive options, starting at UAH 210,000 – UAH 230,000, include additional features such as installation in another city.

Moreover, this cost was selected for the analysis because it falls within the calculated range and represents the average cost of solar panel installation. In addition to the cost, the payback period was calculated based on the sources provided above. At the same time, using the sources listed above, the payback period can be determined. Considering the characteristics, such as the generation volume in kW, the average consumption level, and current electricity rates, the average payback period is approximately 6–7 years. These perceptions create a barrier to purchase solar panels. Additionally, in the analysis, we calculated how consumers are sensitive to overestimation and underestimation. To achieve this, we provided following table 5 and table 6 below.

Table 5. Consumers sensitivity to cost errors

Statistic	Min	Median	Mean	Max
Low error cost	-175.88	56.61	56.95	320.00
Middle error cost	-195.88	36.61	36.95	300.00
High error cost	-245.88	-13.39	-13.05	250.00

The two benchmarks of UAH 180,000 and UAH 200,000 indicate that people overestimate the value by an average of UAH +57,000 and UAH +37,000 UAH, respectively. However, when the price reaches the higher range of 250,000, then the median becomes negative. This indicates that people systematically

overestimate the cost of solar panels. These results showed that people overestimated prices.

The sensitivity analysis for the payback period yields slightly different results. With a result of 4 years — considered the minimum number of years required for payback. The analysis shows that respondents overestimated the payback period (mean: +5.4 years). With a 7-year payback period, the mean indicates 2.4 years. This suggests that respondents generally chose a payback period closer to 9 years, which confirms the 9-year anchor. See the table 6 below.

Table 6. Consumers sensitivity to payback errors

Statistic	Min	Median	Mean	Max
Low error payback	-3.000	3.000	5.398	21.000
Middle error payback	-6.000	0.000	2.398	18.000
High error payback	-8.000	-2.000	0.398	16.000

Sensitivity analysis for both errors displays that respondents consistently overestimate the cost and the payback period of installing solar panels compared to actual market prices. In other words, people think the panels are more expensive than they are. The detailed distribution of respondents' misperceptions is represented by Figure 4 below.

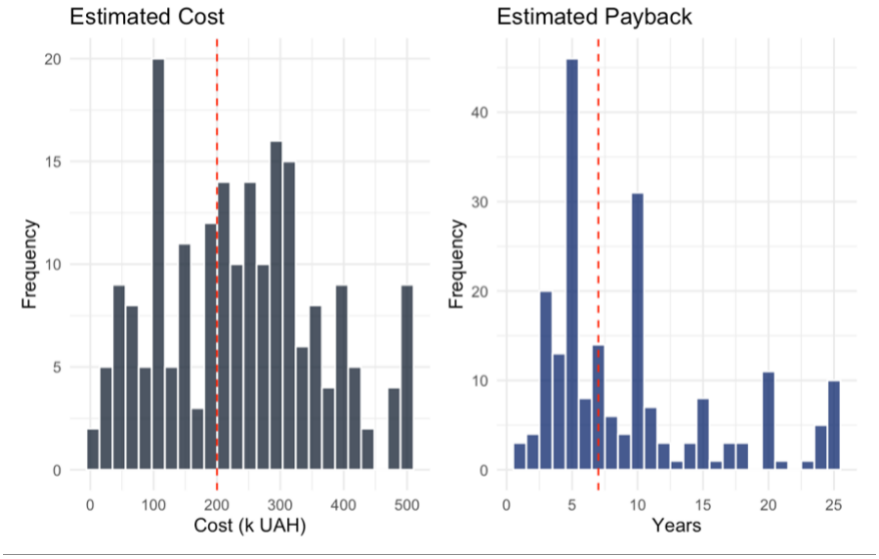


Figure 4. Respondents' economic perceptions: cost and payback period

The average price per 5 kW and the average payback period calculations allow us to assess the extent of the distortion in people's perceptions. In the analysis, any deviation from the stated price or payback period is presented as an error. This was done to show that smaller or larger errors have a stronger or weaker impact on webinar registration. All errors in cost or payback period were measured as the difference between the respondent's estimate and the true value of 200,000 UAH or 6 years for a return period.

According to calculations, approximately 64% of survey respondents overestimate the cost of solar panel installation. Moreover, almost 48% of respondents believe that the payback period will be longer, given that the actual payback period is 6 years. Thus, the survey shows that respondents tend to overestimate the price and payback period. The fact that such a large proportion of respondents hold misconceptions provides a basis for testing the main hypotheses: whether informational interventions can influence people's willingness to sign up for a webinar on solar panels.

In previous part, we confirmed that the experimental manipulation was correctly perceived by the respondents. Thus, in this subsection, the primary outcome is going to be analyzed. 45.16% of respondents in the control group who read a text about solar energy left their contact information for the webinar registration. 51.1% of respondents who received information about the cost also have confirmed their participation in the webinar. While text #3 about payback period has a worse impact than text about cost, and only 39% left their contact for a consultation.

In contrast, Text #4 was the most overwhelming version for respondents. According to the results, compared to the control group, the likelihood of registering for the webinar drops from 45.2% to 33.6%, a decrease of 11.6%. This result may indicate that the respondent experienced information overload due to the large number of calculations regarding price and payback period, which reduced their interest in signing up for the webinar (Figure 5).

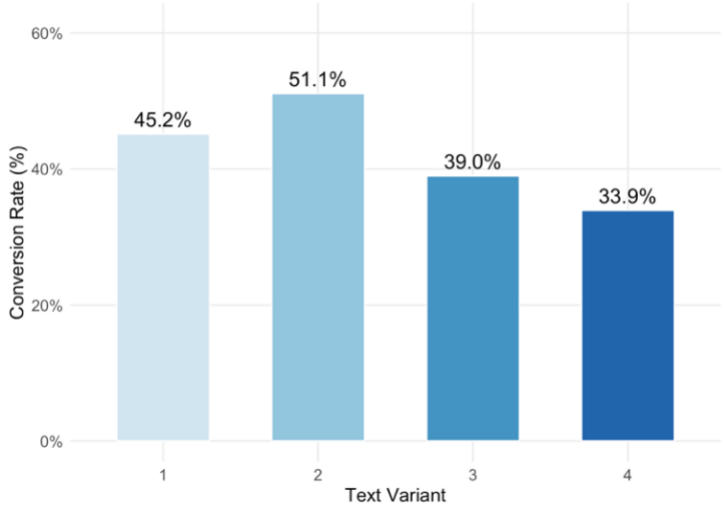


Figure 5. Respondents' willingness to sign up for a webinar

Chapter 5

ESTIMATION RESULTS

Based on the methodology and data described in the previous chapters, we provided a model and estimated the results that will be described in this chapter. Table 7 presents the estimation results for both the Linear Probability Model (LPM) and Probit Average Marginal Effects (AME).

5.1 Main model results

Given that linear models have heteroscedasticity, the studentized Breusch-Pagan test was done to check heteroscedasticity. The test shows that p-value = 0.01809 < 0.05, thus, the null hypothesis of homoscedasticity is rejected. To solve this issue, we additionally checked robust standard errors. The robust standard errors are presented in Table 7 as well.

None of the information provided has a statistically significant impact on registration. Based on a small sample, most results are insignificant. LPM results displays that all treatments are not statistically significant. In linear probability model, text #2, text #3 and text #4 do not show any results for increasing or decreasing probabilities for a webinar sign up. However, probit model showed that results for text #2 and text #3 did not increase the likelihood of me signing up for the webinar, but text #4 provides significant results at 10% level. While using a probit model, the results show robustness – Text #3 and Text #4 are consistent in sign across both models and Text #4 shows a significant result in Probit model only: -17 percentage points of decreasing in webinar registration.

In contrast, additional control variables have a strong impact on the binary outcome. All variables are checked by robustness based on the probit model and

significant in LPM and Probit models. Those results show that willingness to register for a webinar is mostly driven by individuals characteristics as age, previous knowledge and experience about solar panels adoption and how people are prone to taking risks during wartime. Age is a significant variable, which means that the older a person is, the more likely they are to sign up for a webinar by +0.9 percentage points. For respondents, prior experience was a key factor in deciding to register for the webinar – having prior experience increased webinar registration by 8.2 percentage points. The amount paid for electricity also influences interest in registration: people who pay between UAH 1,500 and UAH 2,000 per month are more likely to register for the webinar.

The results for the interactions remain are insignificant except interaction Text #4 × Error in cost. Generally, this indicates that the respondents' error does not work in conjunction with the text, thus the null results are received. However, Text #4, which contains information about both price and payback period, combined with human error (both underestimation and overestimation) has a significant effect on an edge of -1.6 percentage points. There were 6 interactions in total, but only 1 interaction is significant, so we can consider these results as fragile to interpret.

The result suggests that people who had misperceptions about cost estimations of solar panels and received Text #4 will be less likely to register for the webinar. Full model with electricity costs variable is in the Appendix D. Results are presented in the Table 7 below.

Table 7. Main results for LPM and Probit AME specifications

	Model Specification	
Variable	(1) LPM	(2) Probit AME
Text #2	0.016	-0.021
	(0.118)	(0.108)
Text #3	-0.041	-0.109
	(0.108)	(0.098)
Text #4	-0.078	-0.170*
	(0.106)	(0.092)
Error in cost estimation	0.006	-0.001
	(0.006)	(0.003)
Error in payback period	-0.000	-0.007
	(0.012)	(0.006)
Female	0.049	0.053
	(0.070)	(0.069)
Age	0.009**	0.010**
	(0.004)	(0.004)
Prior experience	0.082**	0.091**
	(0.040)	(0.040)
Outage worry	0.019	0.021
	(0.030)	(0.030)
Patience	0.011	0.010
	(0.020)	(0.019)
Risk tolerance	0.032	0.037*
	(0.021)	(0.020)
Text #2 × Error in cost	-0.005	-
	(0.009)	
Text #3 × Error in cost	-0.006	-
	(0.008)	
Text #4 × Error in cost	-0.016*	-
	(0.008)	
Text #2 × Error in payback	-0.002	-
	(0.018)	
Text #3 × Error in payback	-0.015	-
	(0.014)	
Text #4 × Error in payback	-0.010	-
	(0.015)	
Observations	206	206
R-squared	0.184	-
Adjusted R-squared	0.075	-

Note: Robust errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Electricity cost and city type dummies included but not reported.

Additionally, during proceeding LPM and Probit model, the Probit model showed that variables that are included in interactions do not resemble those of LPM. Given the randomization, the results of the two models should be close to each other. Due to this case, the interaction terms, which are used in a specification model are not calculated by marginal effects, and variables that are included into interactions may show overestimated results. Interaction terms cannot be calculated in marginal effects because they are not independent variables, they are defined as a compound index. We can extract marginal effects for interactions separately. After calculating marginal effects for the probit model, all interactions in LPM and Probit models are consistent in sign and magnitude. Given results can be interpreted as robust to model specification, and the results are provided in Table 8 below.

Table 8. Calculated marginal effects results for interactions

Variable	(1) LPM	(2) AME
Text #2 × Error in cost	-0.005	-0.005
	(0.009)	(0.009)
Text #3 × Error in cost	-0.006	-0.006
	(0.008)	(0.008)
Text #4 × Error in cost	-0.016*	-0.018*
	(0.008)	(0.008)
Text #2 × Error in payback	-0.002	-0.003
	(0.018)	(0.017)
Text #3 × Error in payback	-0.015	-0.016
	(0.014)	(0.014)
Text #4 × Error in payback	-0.010	-0.013
	(0.015)	(0.016)
Observations	206	206
R-squared	0.184	-
Adjusted R-squared	0.075	-

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

Interactions between Text #2, Text #3 and errors has no significant effect on willingness to sign up for a webinar, in this part the superadditivity is checked by using a Wald test to find out if the effect of Text #4 is stronger and exceeds the sum of Text #2 and Text #3 effects together. The p-value is more than 0.05 and equals 0.733. This means that we failed to reject H0. The test indicates that Text 4 has no additional effect that could significantly influence a person's decision to register for the webinar. This suggests that the effect of Text 4 is no different from the combined effect of Text #2 and Text #3

5.2 Heterogeneous effects analysis

From previous analysis can be seen that the separate effect from texts and interactions between interventions and errors are minimal. In this part, we checked how exactly the assessment (overestimation or underestimation) of the error after reading the text affects a person's willingness to register for the webinar. For the analysis, price and payback errors were divided into two groups: >0 and ≤ 0. Subsequently, we built regressions with fewer control variables due to the small sample size. The LPM model was used for the regression results, and the results are presented in Table 9.

People, who overestimate the cost for solar panels and have previous knowledge about solar panels will more likely register for a webinar, but women mostly rejected this opportunity. In contrast, those respondents who underestimated a cost, prior experience remains as the strongest predictor of interest in a webinar. When considering the female gender, the variable has both positive and negative values in each of the subgroups. However, we can assume that these estimates are inaccurate, since the CI turned out to be quite wide during the verification process. Therefore, we have reason to believe that the results may be subject to

statistical uncertainty. It is hard to estimate the effect due to the small sub-group (Appendices E and F).

We would like to note that the model differs from the LPM, as the sample sizes for each subgroup have decreased. Given the number of respondents in each subgroup, it is important to maintain stability across all four groups. Thus, variable outage worry was excluded. Additionally, the variable "housing status" was added to the subgroup models, as it may influence respondents' reactions.

The information provided about the payback period did not influence people who overestimated the timeframe. The study's findings show that the text content has no effect on people's willingness to register for a webinar, but additional demographic factors such as age, prior experience, or ownership status do influence whether a person registers for the webinar. The results are presented in the Table 9 (Appendix G for a full model with housing status variable).

Table 9. Over- and underestimation among four treatment groups

	Registration for a webinar (cost errors)		Registration for a webinar (payback errors)	
	$err > 0$	$err \leq 0$	$err > 0$	$err \leq 0$
Text #2	-0.193	-0.189	0.022	-0.020
	(0.194)	(0.395)	(0.257)	(0.30)
Text #3	-0.213	0.051	-0.366	0.170
	(0.163)	(0.297)	(0.233)	(0.228)
Text #4	-0.158	-0.520	-0.017	-0.153
	(0.179)	(0.368)	(0.233)	(0.250)
Error in cost estimation	0.008	-0.002	-	-
	(0.009)	(0.019)		
Error in payback estimation	-	-	-0.010	-0.035
			(0.018)	(0.05)
Age	0.006	-0.000	0.000	0.006
	(0.005)	(0.006)	(0.005)	(0.005)
Prior experience	0.154***	0.113	0.077	0.148**
	(0.041)	(0.058)	(0.056)	(0.05)
Female	-0.213*	0.244	-0.002	0.035
	(0.086)	(0.123)	(0.104)	(0.101)
Text #2 × Error in cost	0.011	-0.020	-	-
	(0.013)	(0.030)		
Text #3 × Error in cost	-0.004	0.007	-	-
	(0.013)	(0.026)		
Text #4 × Error in cost	-0.011	-0.052	-	-
	(0.011)	(0.034)		
Text #2 × Error in payback	-	-	0.006	0.024
			(0.029)	(0.097)
Text #3 × Error in payback	-	-	0.015	0.103
			(0.024)	(0.097)
Text #4 × Error in payback	-	-	-0.020	0.009
			(0.022)	(0.088)
Observations	132	74	98	108
R-squared	0.272	0.221	0.172	0.157
Adjusted R-squared	0.185	0.036	0.033	0.030

Note: Robust errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Housing status dummies included but not reported.

The graph (see the figure 6 below) represents the probability of signing up in case of underestimation and overestimation. The probability of registering for the webinar decreases among the experimental group that received message #2, whose participants underestimated the cost of solar panels by 1.5 percentage

points compared to the control group. The other two groups, compared to the control group, show an even greater decrease in the probability of registering for the webinar after receiving the information. The results after receiving information about the payback period (experimental group #3) showed that the probability decreases by 16.7 percentage points. Experimental group #4 shows the most negative result: after receiving all information about the price and payback period, the probability of registration decreases by 23.4 percentage points. In other words, those who received information about the price and payback period will not register for the webinar, and the probability will be higher in the control group.

A different situation is observed in the group that overestimated the cost and payback period before reading the text. After reading the text, the control group remained unchanged. There was no huge difference between those who overestimated and those who underestimated the cost and payback period of solar panels. In general, the probability is prone to increase after reading treatment texts. Basically, those people, who firstly overestimated solar panels cost are more likely to sign up for a webinar, and the probability is increased by 14.4 percentage points. Payback treatment text increased probability by 2.9 percentage points, while treatment group #4 has a stronger impact (+7.9 percentage points) than treatment group #3 (payback group).

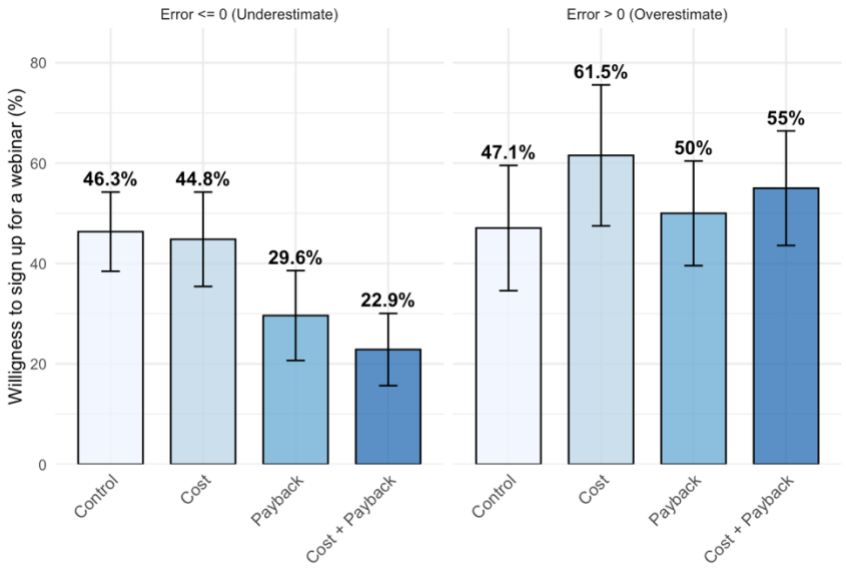


Figure 6. Comparison of respondents by cost and payback period misestimation (underestimation vs. overestimation)

Based on analysis, heterogeneous effect is presented and this effect depends on the initial misperception. The results suggest that if a person overestimated a cost or payback period, after reading an assigned text due to given treatment group, the probability is going to be increased compared to the control group. In contrast, another subgroup, who underestimated the cost and payback period showed slightly worse results compared to the overestimation subgroup. Thus, people in underestimation subgroup displays negative patterns. As was mentioned before, both control groups in subsections are almost equal. This reflects that absence of information and misperceptions about both information are working in the same direction. While cost group is almost on the same level as control group, but the results is slightly worse, which shows us a 1.5 percentage point decrease in probability to sign up. The group that underestimated the payback period performed worse than the control group. Based on these results, the likelihood of registering for the webinar dropped by 16.7 percentage points

in comparison with a control group. Both information (cost + payback) provided a decrease by 23.4 percentage points.

5.3 Results discussion

A belief accuracy regarding solar costs and payback periods may be a key solution to stimulate investments in alternative energy. The logic behind showing if households receive accurate information about installation costs and payback periods then it can encourage investment in renewable energy. In other words, the primary focus is on the lack of information and people's preconceptions. Nevertheless, if individuals are provided with how things really are, then information symmetry should reduce uncertainty among Ukrainians and increase the percentage of adoption of decentralized self-generation through rooftop solar PV. Even so, installing solar panels is seen more as of survival amid the war and the energy crisis, so most people do not accept solar panels as a long-term investment.

When respondents saw the real cost and payback period information, this is mostly represented as information overload, which is driving people further apart, rather than encourage them to learn more about alternative energy, especially about solar panels. The results obtained in Sections 5.1 and 5.2 are consistent with the literature: Wolske et al. (2018) found that complex information is ineffective, and one possible explanation is people's reluctance to invest in solar panels during wartime. Also, returning to the results of Alt et al. (2024), Text #4 did indeed yield a stronger result than Texts #2 and #3, but the effect was diminishing. This indicates a decrease in the effectiveness of the interventions, suggesting that after reading Text #4, which contained two interventions simultaneously, the effect is smaller, while effects for Text #2 and Text #3 represented by null results. Additionally, people lack confidence in their

future actions, as confirmed by the data: people from different regions rated their willingness to take risks on a scale of 1 to 10, indicating that, people are currently unwilling to take risks or invest in the future due to the war. In this case, useful information regarding the exact cost and payback period does not influence the decision.

A closer look at the graphs reveals that respondents who struggle most with power outages are not willing to take risks. Figure 7 shows that some regions are highly concerned about power outages, yet their level of preparedness for such risks is minimal. Furthermore, much of the information is perceived as complex, leading people to postpone decisions about adopting alternative energy sources.

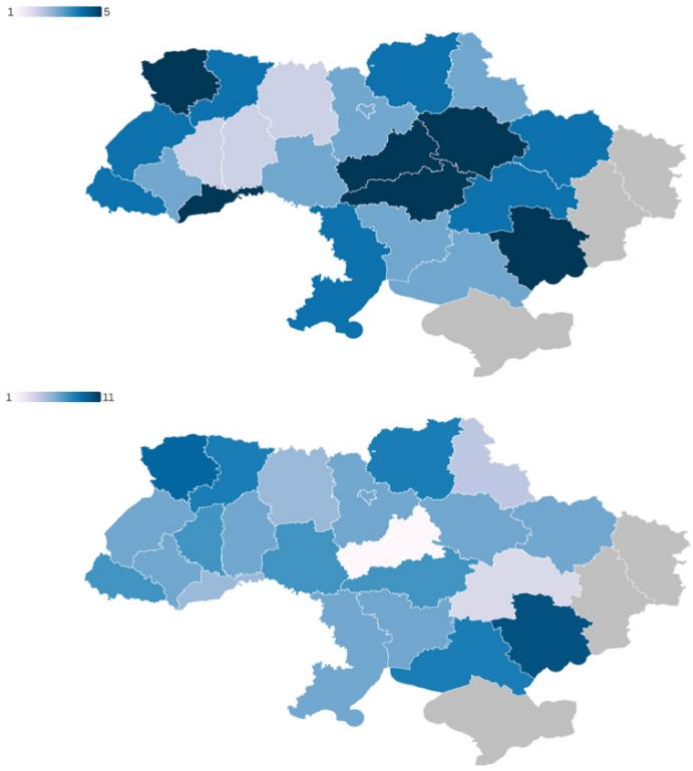


Figure 7. Upper graph: levels of concern about power outages among Ukrainian region

Chapter 6

CONCLUSIONS

This study examined how accurate information about the cost and payback period of solar panels affects the likelihood of Ukrainian respondents registering for a webinar. To investigate this question, we conducted an experiment involving 222 respondents to test three hypotheses regarding the effectiveness of texts providing different information about price and payback period. All respondents were divided into four groups, each assigned to a different treatment category: control group, cost-only group, payback-only group, and both-information group.

6.1 Conclusions

Our first hypothesis tested whether each treatment — focusing on cost, payback, or providing both types of information – would increase the probability of registration. To test this hypothesis, we used two models: LPM and Probit. Text #2, Text #3, and Text #4 showed insignificant results in the LPM. The LPM showed that the probability of registering for the webinar after reading Text #2 increased by 1.6 percentage points, Text #3 decreased by 4.1 percentage points, and Text #4 decreased by 7.8 percentage points. This indicates that none of the texts were effective and that the treatment effect on probability is insignificant.

Marginal effects indicated that the effect of Text #4 is significant and suggests that the probability of respondents registering for the webinar after reading Text #4 decreases by 17 percentage points. This can be interpreted as people are overwhelmed with too much information about solar panels all at once. For many, renewable energy already sounds too complicated and unfamiliar, and

providing additional information during the war – specifically about cost and payback period – negatively affects the likelihood of signing up for the webinar.

The second hypothesis tests whether the Text #4 is stronger than the effect of the two separate texts, Text #2 and Text #3. To do this, we used the Wald Test, and the results showed that Text #4 does not produce a stronger effect than the combined effect of Text #2 and Text #3. There is no statistically significant evidence of superadditivity in the data. We can analyze this again as information overload. One possible explanation is that people are unable to quickly and effectively process all the information received from Text #4. Additionally, each person has their own motivations, and the two different texts, Text #2 and Text #3, have different effects on different people. Since there are people for whom the price of alternative energy is more important, and there are others for whom payback is important, both effects do not work simultaneously in Text #4, as they do not reinforce each other due to different types of motivations.

Our third hypothesis tests for the presence of heterogeneous effects. The final hypothesis in this study focused on how information would influence people who had overestimated the cost. The estimation results were insignificant and showed the unconfirmed predicted probabilities of respondents who overestimated the cost of solar panels signing up for the webinar as 14.4% compared to the control group. The other texts, Text #2 and Text #3, showed smaller percentage changes, they were: 2.9% and 7.9%, respectively. However, these estimates do not differ from zero at any standard significance level and cannot be interpreted as a real effect. We can note that the treatment had an effect on those who overestimated the cost of solar panels. In other words, the information in Text #2, which the respondents read, allowed people to reconsider their initial expectations, upon learning that the actual price was lower than expected, the respondents became more interested in alternative energy sources that could be installed in their homes. The empirical study displays that there is no

confirmation that treatments correct misperceptions and encourage respondents to sign-up for a webinar. We do not find statistically significant treatments effect in the given study.

However, it is worth noting that information is not the only factor influencing a person's decision. Estimation results showed that control variables as age, prior experience and gender are significant, but estimated confidence intervals are wide and may be reported as weak or marginally significant. Additionally, it should be noted right away that these groups are quite small for analysis. Nevertheless, this effect should still be present, and with a larger sample size, the significance may remain though the values will be more realistic. Additionally, an individual's risk tolerance also influences their decision-making. This situation is evident in the illustrated map, where people who suffer the most from power outages are not willing to take risks or assume responsibility for installing solar panels.

6.2 Contribution and limitations

This study focuses on an experiment on renewable energy adoption and information provision. This work is valuable to the literature, because it is a first wartime belief-correction experiment in the context of wartime conditions in Ukraine.

Given experiment showed us none of the treatments were statistically significant across any treatment groups or subgroups. and the results are null. Thus, correcting information did not significant affect the webinar sign-up. These null results indicate that correcting misperceptions about cost and payback is insufficient to change behavioral intentions under wartime conditions. We can also consider that these results are essential because obstacles to installing solar panels may not be based only on misconceptions.

The conducted experiment could serve as a basis for public communication campaigns in Ukraine, including a website with a step-by-step guide on how solar panels work, their potential benefits, and the financial programs available for installation. Moreover, the policy may target not only information campaigns but also developing additional programs with a developed scheme of "green" tariffs, because information interventions alone are insufficient.

Additionally, it is a need to be acknowledged with limitations. The total sample size is 222 respondents, which affects the results and may reduce the statistical power of the analysis. This also applies to subgroups in the heterogeneous analysis. Since the small sample was further divided into small subgroups, this affects the results within the subgroups, and they turned out to be quite large. Therefore, these results should not be considered definitive but rather interpreted as indicating the presence of an effect within the subgroups. Additionally, this analysis was conducted during wartime in a period of uncertainty, so the results may differ significantly if the analysis were conducted in another country or in Ukraine during peacetime.

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APPENDIX A.

Section 1: Screening and criteria selection

Q1.1: What is your age?

If the age < 18, end survey

Q1.2. What type of housing do you currently live in?

- Detached house
- Semi-detached house / Townhouse
- Apartment
- Other: _____

Q1.3. What is your ownership status?

- Owner
- Co-owner
- Renter
- Living with family (not owner)
- Other: _____

Q1.4. Are you involved in making decisions about home improvements and energy-related investments in your household?

- Yes, I make these decisions
- Yes, I share these decisions with others
- No, someone else makes these decisions → **[screen out]**

Section 2: Demographics

Q2.1 What is your gender?

- Male
- Female
- Prefer not to say)

Q2.2 In which region of Ukraine do you currently reside?

{drop down list}

Q2.3. Do you live in:

- A city (over 100,000)
- A town (10,000 - 100,000)
- A rural area or a village

Q2.4. What is your highest completed education?

- Secondary or less
- Vocational/college
- Bachelor's degree
- Master's
- Doctoral

Q2.5 Which of the following best describes your household's current financial situation?

- We struggle to afford basic necessities (food, utilities)
- We can afford necessities but little else
- We are comfortable but must budget carefully for larger purchases
- We can afford most things we need without difficulty
- We can afford expensive purchases (car, renovation) without difficulty

Section 3: Expenses

Q3.1 What are your average monthly electricity expenses? (UAH, open or ranges)

Less than 500 UAH

- 500 - 1,000 UAH
- 1,000 - 1,500 UAH
- 1,500 - 2,000 UAH
- 2,000 - 3,000 UAH
- More than 3,000 UAH
- I don't know

Q3.2. How often did you experience electricity blackouts in your area in the past 3 months?

Never

- Rarely (a few times)
- Sometimes (monthly)
- Often (weekly)
- Very often (almost daily during peak outages)

Q3.3. How worried are you about electricity outages in the next few months?

- 1 (Not worried at all)
- 2
- 3
- 4
- 5 (Extremely worried)

Q3.4. In your opinion, how much does it typically cost to install a rooftop solar panel system (approximately 5 kW) for a household?

[Slider: 0 - 500,000 UAH]

Q3.5. How confident are you in this estimate?

- Not at all confident
- Slightly confident
- Moderately confident
- Very confident
- Extremely confident

Q3.6. In your opinion, how much can a solar panel system save (or earn) per month on electricity?

[Slider: 0–10,000 UAH]

Q3.7. How confident are you in this estimate?

- Not at all confident
- Slightly confident
- Moderately confident

- Very confident
- Extremely confident

Q3.8. In your opinion, how many years does it typically take for a solar panel system to pay for itself through electricity savings?

[Slider: 0 - 25 years]

Q3.9. How confident are you in this estimate?

- Not at all confident
- Slightly confident
- Moderately confident
- Very confident
- Extremely confident

Section 4: Attention check

Q4.1. The next question checks whether you are reading carefully. In surveys like ours, sometimes participants click through quickly without reading. This creates random answers that compromise research quality. To show you are paying attention, please select "Green" as your answer below.

What is your favorite color?

- Blue
- Green
- Red
- Yellow
- Other

Section 5: Experience and stages of consideration for installing solar panels

Experience module

Q5.1 How would you rate your knowledge about solar panels

- Very poor

- Poor
- Average
- Good
- Very good

Q5.2. Have you previously considered installing solar panels?

- Never thought about it
- Have thought about it but took no action
- Looked for information
- Consulted with a provider / received a quote
- Made concrete plans to install
- Already have solar panels → [screen out]

Q5.3. How interested are you in installing solar panels at your home?

1 ○—○—○—○—○ 5 (Not at all — Very interested)

Q5.4. Do you personally know anyone who has installed solar panels?

- Yes, close friend or family member
- Yes, acquaintance or neighbor
- No

Time preferences, risk assessment and present bias module

In the next questions, please choose the option you prefer.

Q5.5. How willing are you to give up something that is beneficial for you today in order to benefit more from that in the future?

0 ○—○—○—○—○—○—○—○—○—○—○ 10

(0 = Completely unwilling, 10 = Very willing)

Q5.6. How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?

0 ○—○—○—○—○—○—○—○—○—○—○ 10

(0 = Not at all prepared to take risks, 10 = Fully prepared to take risks)

Q5.7. Imagine you could receive 1,000 UAH today OR a larger amount in 12 months. What is the minimum amount in 12 months that would make you willing to wait?

- 1,000 UAH
- 1,100 UAH
- 1,250 UAH
- 1,500 UAH
- 2,000 UAH
- More than 2,000 UAH

Q5.8. Which option would you choose?

- 900 UAH today
- 1,050 UAH in 1 month

Q5.9. Which option would you choose?

- 900 UAH in 6 months
- 1,050 UAH in 7 months

Section 6. Information scenario (randomized)

TREATMENT 0: CONTROL

How do solar panels work?

Solar panels convert sunlight into electricity through a process called the photovoltaic effect. When sunlight hits the solar cells, it causes electrons to move, creating an electrical current.

A typical residential solar system consists of solar panels (usually mounted on the roof, facing south for maximum sunlight exposure), an inverter (which converts the direct current produced by panels into alternating current used by home appliances), and a meter to track electricity produced and consumed.

Solar panels work during daylight hours. Energy production varies by season — more in summer, less in winter. Most residential rooftop systems in Ukraine range from 5 to 10 kW capacity, depending on household size and energy needs. For

apartments, smaller balcony solar systems (600–800W) are also available and can be installed without professional help.

Solar panels require minimal maintenance: occasional cleaning and periodic inverter checks. Most systems last 25–30 years

Source: General information on residential solar technology

TREATMENT A: Cost Information Only

What does it actually cost to install solar panels?

Many Ukrainians believe that installing solar panels costs 400,000 UAH or more. However, according to 2024 market data from Ukrainian solar providers, the actual cost is significantly lower.

A standard 5 kW rooftop solar system — sufficient for a typical household — costs approximately 180,000–220,000 UAH (around $4,500–5,500 USD). This price includes solar panels, inverter, mounting equipment, and professional installation. Larger homes may require a 10 kW system, which costs approximately 350,000–450,000 UAH.

For apartments or smaller needs, balcony solar kits (600–800W) cost about 20,000–40,000 UAH and require no professional installation.

Source: Average prices from licensed Ukrainian solar installers, 2024

TREATMENT B: Payback Information Only

How long does it take for solar panels to pay for themselves?

Many Ukrainians believe that solar panels take 15 years or longer to pay off the initial investment. However, based on current electricity tariffs and the green tariff program, the actual payback period is much shorter.

A typical 5 kW household system produces approximately 5,000–6,000 kWh of electricity per year. At current tariffs of around 6 UAH/kWh, this translates to over 30,000 UAH in annual savings (or income, if you sell surplus to the grid).

The payback period is approximately 6–7 years. After payback, the system provides 15–20 additional years of free electricity. Solar panels typically last 25–30 years with minimal maintenance.

For balcony systems, payback is typically 4–6 years due to lower upfront cost but lower capacity needs to be taken into account.

Source: Calculations based on State Energy Efficiency Agency data and current green tariff rates

TREATMENT C: Both Cost and Payback

What does it actually cost to install solar panels, and how quickly do they pay off? Many Ukrainians overestimate both the cost and the time needed to see returns from solar panels. Here are the facts.

Many people believe solar installation costs 400,000 UAH or more. According to 2024 market data, a standard 5 kW rooftop system actually costs approximately 180,000–220,000 UAH (~$4,500–5,500 USD), including panels, inverter, and installation. Larger homes may need a 10 kW system (350,000–450,000 UAH). For apartments, balcony solar kits cost just 20,000–40,000 UAH.

Many people also believe solar takes 15+ years to pay off. Based on current electricity tariffs (≈6 UAH/kWh) and green tariff rates, a typical rooftop system pays for itself in approximately 6–7 years. Balcony kits pay off in 4–6 years. A 5 kW system produces around 5,000–6,000 kWh annually, saving or earning over 30,000 UAH per year.

After the payback period, solar panels provide 15–20 additional years of essentially free electricity. Most systems last 25–30 years.

Source: Ukrainian solar provider market data and State Energy Efficiency Agency, 2024

BLOCK 7: Manipulation Check

Q7.1. What information were you just provided with?

- How solar panels work
- Cost of solar panels
- Payback period of solar panels
- Both cost and payback period

BLOCK 8: Outcomes

Q8.1. Would you be willing to sign up for a free online information session about solar energy options for your home?

- Yes, I would sign up → Q8.2
- No, I would not sign up → skip to Q8.3

Q8.2. (if Q8.1 = Yes) Please provide your email or phone: _____

Q8.3. How interested are you in installing solar panels at your home?

- 1 – Not at all interested
- 2
- 3
- 4
- 5 – Very interested

Q8.4. What is the maximum amount of money you would be willing to pay upfront to install solar panels?

- Less than 50,000 UAH
- 50,000–100,000 UAH
- 100,000–150,000 UAH
- 150,000–200,000 UAH
- 200,000–250,000 UAH
- More than 250,000 UAH
- Would not install regardless of price

BLOCK 9: Post manipulation

Q9.1. How affordable do you think solar panels are for a typical Ukrainian household?

- 1 – Not at all affordable
- 2
- 3
- 4
- 5 – Very affordable

Q9.2. How worthwhile do you think installing solar panels would be as a long-term investment?

- 1 – Not at all worthwhile
- 2
- 3
- 4
- 5 – Very worthwhile

Q9.3. How risky do you think it is to invest in solar panels in Ukraine right now?

- 1 – Not at all risky
- 2
- 3
- 4
- 5 – Very risky

BLOCK 10: Trust & Data Quality

Q10.1. How credible do you find the information provided about solar panels?

- 1 – Not at all credible
- 2
- 3
- 4
- 5 – Very credible

Q10.2. [Open-ended — for data quality/bot detection]

Do you have any comments or feedback about this survey?

[Text box]

APPENDIX B

Table 10. Balance table check

Variable	Level	Group 1 (Control) (n=58)	Group 2 (Cost) (n=42)	Group 3 (Payback) (n=51)	Group 4 (Combined) (n=55)	p-value
Age (SD)	—	41.40 (8.36)	41.38 (9.53)	43.06 (10.45)	44.96 (9.55)	0.166
Gender, n (%)	Female	30 (51.7%)	21 (50.0%)	30 (58.8%)	27 (49.1%)	0.755
	Male	28 (48.3%)	21 (50.0%)	21 (41.2%)	28 (50.9%)	
Education, n (%)	1	0 (0.0%)	0 (0.0%)	0 (0.0%)	1 (1.8%)	0.614
	2	0 (0.0%)	0 (0.0%)	0 (0.0%)	1 (1.8%)	
	3	4 (6.9%)	2 (4.8%)	3 (5.9%)	3 (5.5%)	
	4	22 (37.9%)	14 (33.3%)	26 (51.0%)	16 (29.1%)	
	5	13 (22.4%)	10 (23.8%)	7 (13.7%)	14 (25.5%)	
	6	19 (32.8%)	15 (35.7%)	15 (29.4%)	20 (36.4%)	
	7	0 (0.0%)	1 (2.4%)	0 (0.0%)	0 (0.0%)	
Income, n (%)	1	6 (10.3%)	2 (4.8%)	2 (3.9%)	5 (9.1%)	0.670
	2	17 (29.3%)	19 (45.2%)	19 (37.3%)	20 (36.4%)	
	3	33 (56.9%)	20 (47.6%)	27 (52.9%)	26 (47.3%)	
	4	2 (3.4%)	0 (0.0%)	3 (5.9%)	3 (5.5%)	
	5	0 (0.0%)	1 (2.4%)	0 (0.0%)	1 (1.8%)	
City Type, n (%)	1	17 (29.3%)	16 (38.1%)	28 (54.9%)	25 (45.5%)	0.037*
	2	20 (34.5%)	19 (45.2%)	16 (31.4%)	19 (34.5%)	
	3	21 (36.2%)	7 (16.7%)	7 (13.7%)	11 (20.0%)	
Region, n (%)	1	5 (8.6%)	6 (14.3%)	7 (13.7%)	7 (12.7%)	0.910
	2	12 (20.7%)	8 (19.0%)	8 (15.7%)	10 (18.2%)	
	3	14 (24.1%)	9 (21.4%)	11 (21.6%)	10 (18.2%)	
	4	20 (34.5%)	12 (28.6%)	13 (25.5%)	16 (29.1%)	
	5	5 (8.6%)	6 (14.3%)	9 (17.6%)	6 (10.9%)	
	6	2 (3.4%)	1 (2.4%)	3 (5.9%)	6 (10.9%)	
Housing Type, n (%)	1	34 (58.6%)	26 (61.9%)	21 (41.2%)	29 (52.7%)	0.275

Table 10. Balance table check — Continued

	2	2 (3.4%)	0 (0.0%)	0 (0.0%)	2 (3.6%)	
	3	21 (36.2%)	16 (38.1%)	30 (58.8%)	23 (41.8%)	
	4	1 (1.7%)	0 (0.0%)	0 (0.0%)	1 (1.8%)	
Electricity Costs, n (%)	1	6 (10.3%)	6 (14.3%)	7 (13.7%)	9 (16.4%)	0.460
	2	21 (36.2%)	9 (21.4%)	18 (35.3%)	19 (34.5%)	
	3	10 (17.2%)	9 (21.4%)	12 (23.5%)	13 (23.6%)	
	4	13 (22.4%)	12 (28.6%)	5 (9.8%)	4 (7.3%)	
	5	6 (10.3%)	3 (7.1%)	4 (7.8%)	6 (10.9%)	
	6	2 (3.4%)	3 (7.1%)	5 (9.8%)	4 (7.3%)	
Prior Experience, M (SD)	—	2.41 (0.88)	2.52 (1.09)	2.47 (0.92)	2.45 (0.98)	0.955
Knowledge, n (%)	1	9 (15.5%)	5 (11.9%)	6 (11.8%)	9 (16.4%)	0.510
	2	29 (50.0%)	16 (38.1%)	23 (45.1%)	25 (45.5%)	
	3	18 (31.0%)	19 (45.2%)	21 (41.2%)	18 (32.7%)	
	4	1 (1.7%)	0 (0.0%)	1 (2.0%)	3 (5.5%)	
	5	1 (1.7%)	2 (4.8%)	0 (0.0%)	0 (0.0%)	

APPENDIX C

Table 11. Baseline vs Filtered sample robustness check

	Model Specification	
Variable	(1) LPM	(2) LPM (Filtered)
Text #2	0.016	-0.013
	(0.118)	(0.148)
Text #3	-0.041	-0.091
	(0.108)	(0.134)
Text #4	-0.078	-0.104
	(0.106)	(0.124)
Error in cost estimation	0.006	0.004
	(0.006)	(0.007)
Error in payback period	-0.000	-0.0001
	(0.012)	(0.013)
Female	0.049	0.073
	(0.070)	(0.086)
Age	0.009**	0.009*
	(0.004)	(0.005)
Prior experience	0.082**	0.069
	(0.040)	(0.048)
Outage worry	0.019	0.009
	(0.030)	(0.036)
Patience	0.011	0.012
	(0.020)	(0.023)
Risk tolerance	0.032	0.051**
	(0.021)	(0.025)
Electricity costs (500 – 1,000 UAH)	0.054	0.050
	(0.119)	(0.149)
Electricity costs (1,000 – 1,500 UAH)	0.152	0.131
	(0.122)	(0.157)
Electricity costs (1,500 – 2,000 UAH)	0.222*	0.206
	(0.127)	(0.158)
Electricity costs (2,000 – 3,000 UAH)	0.145	0.071
	(0.161)	(0.206)
Electricity costs (> 3,000 UAH)	0.167	0.226
	(0.171)	(0.210)
City type (a town: 10,000 - 100,000)	-0.043	-0.074
	(0.085)	(0.098)
City type (rural area or a village)	0.056	0.026
	(0.094)	(0.114)
Text #2 × Error in cost	-0.005	-0.001
	(0.009)	(0.011)
Text #3 × Error in cost	-0.006	-0.002
	(0.008)	(0.010)

Table 11. Baseline vs Filtered sample robustness check— Continued

Text #4 × Error in cost	-0.016*	-0.013
	(0.008)	(0.010)
Text #2 × Error in payback	-0.002	-0.008
	(0.018)	(0.020)
Text #3 × Error in payback	-0.015	-0.010
	(0.014)	(0.016)
Text #4 × Error in payback	-0.010	-0.012
	(0.015)	(0.018)
Observations	206	154
R-squared	0.184	0.182
Adjusted R-squared	0.075	0.030

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

APPENDIX D

Table 12. Main results from the full model: LPM and Probit AME specifications with the electricity cost variable

	Model Specification	
Variable	(1) LPM	(2) Probit AME
Text #2	0.016	-0.021
	(0.118)	(0.108)
Text #3	-0.041	-0.109
	(0.108)	(0.098)
Text #4	-0.078	-0.170*
	(0.106)	(0.092)
Error in cost estimation	0.006	-0.001
	(0.006)	(0.003)
Error in payback period	-0.000	-0.007
	(0.012)	(0.006)
Female	0.049	0.053
	(0.070)	(0.069)
Age	0.009**	0.010**
	(0.004)	(0.004)
Prior experience	0.082**	0.091**
	(0.040)	(0.040)
Outage worry	0.019	0.021
	(0.030)	(0.030)
Patience	0.011	0.010
	(0.020)	(0.019)
Risk tolerance	0.032	0.037*
	(0.021)	(0.020)
Electricity costs (500 – 1,000 UAH)	0.053	0.063
	(0.112)	(0.122)
Electricity costs (1,000 – 1,500 UAH)	0.152	0.176
	(0.122)	(0.125)
Electricity costs (1,500 – 2,000 UAH)	0.222*	0.243*
	(0.127)	(0.130)
Electricity costs (2,000 – 3,000 UAH)	0.145	0.148
	(0.161)	(0.157)
Electricity costs (> 3,000 UAH)	0.167	0.143
	(0.171)	(0.175)
City type (a town: 10,000 - 100,000)	-0.043	-0.037
	(0.085)	(0.084)
City type (rural area or a village)	0.056	0.068
	(0.094)	(0.090)
Text #2 × Error in cost	-0.005	-
	(0.009)	

Table 12. Main results from the full model: LPM and Probit AME specifications with the electricity cost variable — Continued

Variable	(1) LPM	(2) Probit AME
Text #3 × Error in cost	-0.006	-
	(0.008)	
Text #4 × Error in cost	-0.016*	-
	(0.008)	
Text #2 × Error in payback	-0.002	-
	(0.018)	
Text #3 × Error in payback	-0.015	-
	(0.014)	
Text #4 × Error in payback	-0.010	-
	(0.015)	
Observations	206	206
R-squared	0.184	-
Adjusted R-squared	0.075	-

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

APPENDIX E

Table 13. CI for cost underestimation and overestimation

	CI for underestimators (cost)		CI for overestimators (cost)	
	2.5%	97.5%	2.5%	97.5%
Text #2	-1.003	0.624	-0.558	0.172
Text #3	-0.573	0.675	-0.568	0.142
Text #4	-1.372	0.332	-0.487	0.172
Error in cost estimation	-0.041	0.038	-0.009	0.025
Age	-0.013	0.013	-0.003	0.015
Prior experience	-0.009	0.236	0.066	0.242
Female	-0.004	0.491	-0.378	-0.048
Housing status (Co-owner)	0.045	0.732	-0.290	0.149
Housing status (Renter)	-0.196	0.649	-0.738	-0.061
Housing status (Living with a family)	-0.182	0.532	-0.312	0.105
Housing status (Other)	-0.504	1.596	-1.441	0.323
Text #2 × Error in cost	-0.087	0.048	-0.016	0.038
Text #3 × Error in cost	-0.049	0.063	-0.030	0.021
Text #4 × Error in cost	-0.130	0.026	-0.034	0.012
Observations	74		132	

APPENDIX F

Table 14. CI for payback underestimation and overestimation

	CI for underestimators (payback period)		CI for overestimators (payback period)	
	2.5%	97.5%	2.5%	97.5%
Text #2	-0.589	0.549	-0.445	0.490
Text #3	-0.334	0.673	-0.865	0.133
Text #4	-0.641	0.336	-0.467	0.432
Error in payback estimation	-0.157	0.087	-0.043	0.022
Age	-0.006	0.017	-0.010	0.011
Prior experience	0.043	0.253	-0.034	0.187
Female	-0.168	0.238	-0.208	0.204
Housing status (Co-owner)	-0.002	0.612	-0.336	0.195
Housing status (Renter)	-0.329	0.298	-1.152	0.319
Housing status (Living with a family)	-0.114	0.456	-0.427	0.103
Housing status (Other)	-1.474	0.591	-0.256	1.816
Text #2 × Error in payback	-0.170	0.218	-0.046	0.058
Text #3 × Error in payback	-0.099	0.306	-0.034	0.064
Text #4 × Error in payback	-0.169	0.187	-0.067	0.027
Observations	108		98	

APPENDIX G

Table 15. Full model: distribution of over- and underestimation among four treatment groups with housing status variable

	Registration for a webinar (cost errors)		Registration for a webinar (payback errors)	
	$err > 0$	$err \leq 0$	$err > 0$	$err \leq 0$
Text #2	-0.193	-0.189	0.022	-0.020
	(0.194)	(0.395)	(0.257)	(0.30)
Text #3	-0.213	0.051	-0.366	0.170
	(0.163)	(0.297)	(0.233)	(0.228)
Text #4	-0.158	-0.520	-0.017	-0.153
	(0.179)	(0.368)	(0.233)	(0.250)
Error in cost estimation	0.008	-0.002	-	-
	(0.009)	(0.019)		
Error in payback estimation	-	-	-0.010	-0.035
			(0.018)	(0.05)
Age	0.006	-0.000	0.000	0.006
	(0.005)	(0.006)	(0.005)	(0.005)
Prior experience	0.154***	0.113	0.077	0.148**
	(0.041)	(0.058)	(0.056)	(0.05)
Female	-0.213*	0.244	-0.002	0.035
	(0.086)	(0.123)	(0.104)	(0.101)
Housing status (Co-owner)	-0.070	0.388*	-0.070	0.305*
	(0.114)	(0.178)	(0.142)	(0.141)
Housing status (Renter)	-0.400***	0.226	-0.416*	-0.015
	(0.092)	(0.187)	(0.166)	(0.147)
Housing status (Living with a family)	-0.103	0.175	-0.162	0.171
	(0.096)	(0.180)	(0.128)	(0.152)
Housing status (Other)	-0.559***	0.546**	0.780***	-0.442**
	(0.105)	(0.181)	(0.177)	(0.135)
Text #2 × Error in cost	0.011	-0.020	-	-
	(0.013)	(0.030)		
Text #3 × Error in cost	-0.004	0.007	-	-
	(0.013)	(0.026)		
Text #4 × Error in cost	-0.011	-0.052	-	-
	(0.011)	(0.034)		
Text #2 × Error in payback	-	-	0.006	0.024
			(0.029)	(0.097)
Text #3 × Error in payback	-	-	0.015	0.103
			(0.024)	(0.097)
Text #4 × Error in payback	-	-	-0.020	0.009
			(0.022)	(0.088)
Observations	132	74	98	108
R-squared	0.272	0.221	0.172	0.157

Table 15. Full model: distribution of over- and underestimation among four treatment groups with housing status variable — Continued

	Registration for a webinar (cost errors)		Registration for a webinar (payback errors)	
	$err > 0$	$err \leq 0$		$err > 0$
Adjusted R-squared	0.185	0.036	0.033	0.030

Note: Robust errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Housing status dummies included and reported.