PRESENT BIAS AND INFORMATIONAL FRAMING IN RESIDENTIAL SOLAR ENGAGEMENT: EXPERIMENTAL EVIDENCE FROM UKRAINE

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Kyiv School of Economics

Abstract

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In this thesis, we provide the first exploratory experimental evidence on behavioral barriers to household solar engagement in Ukraine. Motivated by wartime energy insecurity caused by damage to the centralized energy infrastructure and persistent risks of blackouts, the study examines whether present bias and informational framing of financial benefits are associated with households' willingness to engage with solar energy. We use primary data from a randomized online survey experiment conducted in March 2026 in collaboration with InfoSapiens (N=213). In the experiment, all respondents were randomly assigned to one of three informational conditions that emphasized neutral, immediate, and delayed framings of financial benefits from the installation of solar panels, while the individual time preferences were measured by using a two-question intertemporal choice task. Results show no statistically significant effect of informational framing on signup behavior, and estimated effects of present bias remain weak and statistically imprecise. At the same time, pre-treatment attitudes appear to be meaningful predictors of engagement. This suggests that decisions on residential solar engagement are shaped by broader structural and attitudinal factors rather than pure behavioral preferences.

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LIST OF ABBREVIATIONS

PV. Photovoltaic.

EBRD. European Bank of Reconstruction and Development.

ESSF. Energy Security Support Facility.

WTP. Willingness to Pay.

LPM. Linear Probability Model.

CDF. Cumulative Distribution Function.

MPL. Multiple Price List.

AME. Average Marginal Effects.

ITT. Intention-to-Treat.

We suffer more in imagination than in reality.

Seneca, *Letters to Lucilius*

Chapter 1

INTRODUCTION

Sustainable energy transition has become a central challenge for modern economies, and solar power is among the most promising solutions. Global solar capacity increased by 600 GW in 2024, accounting for 81% of new renewable additions (SolarPower Europe 2025). In the European context, Ukraine has favorable natural conditions for solar-PV adoption, especially in its southern and central regions, where solar irradiation levels can easily compete with EU member states which already have well-developed solar markets.

The country already has several useful policy tools that can make it easier to adopt solar technology. Some examples include the green tariff, recently replaced by net billing, as well as interest-free loans and tax exemptions (Ministry of Energy of Ukraine 2022, 2023, 2024). In addition, there is support from international financial institutions offering attractive financing for the adoption of solar energy solutions in Ukraine. For instance, the European Bank of Reconstruction and Development launched the Energy Security Support Facility in 2024, which aims to finance renewable energy solutions for households, municipalities, and small enterprises. Taken together, these policies demonstrate that there is an increasing institutional and financial support for household-level solar adoption in Ukraine.

Still, despite high technical potential, rising public interest, and growing international financial support, households are not actively adopting solar energy. By 2023, Ukraine has approximately 53,000 household prosumers, while recent estimates suggest rooftop photovoltaic potential of nearly 238.8 GW, corresponding to around 290 TWh of annual electricity generation – almost twice Ukraine's pre-war electricity production (Solar Energy Association of Ukraine

2023; Winkler et al. 2024). This gap indicates that, even if investing in solar panels is economically justified in the long run, many households avoid installing them.

In the existing international literature, we see clear evidence that behavioral factors play an important role in decision-making related to renewable energy. One determinant often mentioned by researchers is present bias. Present bias is the tendency to overweight immediate payoffs relative to future ones (Frederick, Loewenstein and O'Donoghue 2002). This phenomenon may be particularly important in the Ukrainian wartime context where economic uncertainty and psychological stress can increase time discounting and intensify preferences for immediate rewards (Haushofer and Fehr 2014; Lochstoer et al. 2025).

At the same time, existing Ukrainian studies mainly focus on technical potential and financial feasibility of renewable energy decisions. While these studies provide insightful macro-level information about the development of solar energy in Ukraine, they do not explicitly control for micro-level behavioral factors that influence individual household decisions.

The present study aims to fill this gap by providing exploratory experimental evidence on the role of present bias in shaping individuals' willingness to engage with solar energy in Ukraine – especially in the context of ongoing war and economic uncertainty. Rather than focusing on actual installation decisions, we examine a preceding behavioral step – households' willingness to sign up for a free informational session on solar energy. This decision involves immediate costs in terms of time and effort in exchange for potential future benefits from improved information.

Therefore, the main research question of this study is: **How does present bias affect Ukrainian households' willingness to sign up for a free informational session about solar energy?** In addition, we examine whether emphasizing

short-term versus long-term financial benefits interacts with present bias in shaping signup behavior.

Based on the theoretical framework of present-biased preferences and existing empirical evidence, we test the following two hypotheses. First, individuals who exhibit stronger present bias are less willing to sign up for a free informational session about solar energy because they tend to place relatively greater weight on the immediate time and effort costs of attendance than on the potential future informational benefits. Second, framing the informational treatment around immediate benefits increases signup intentions compared to framing around future benefits, and the effect is stronger among present-biased individuals. Beyond these pre-specified hypotheses, we also conduct exploratory heterogeneity analysis across demographic and household characteristics in order to examine whether treatment responses differ across subgroups.

To test these hypotheses, we conducted a randomized online survey experiment (N=213) in March 2026 in collaboration with Ukrainian survey agency InfoSapiens. Present bias is measured using a standard two-question intertemporal choice task that compares preferences over immediate and delayed monetary rewards. Based on these responses, individuals are classified as present-biased if they exhibit time-inconsistent preferences. After eliciting time preferences and collecting baseline characteristics, respondents are randomly assigned to one of three information scenarios which vary the framing of solar panel benefits. This experimental design allows us to examine how present bias and benefit framing jointly influence individuals' willingness to engage with solar energy-related information.

Results show that informational treatments alone may not be sufficient to significantly influence individuals' behavior toward solar energy. Neither immediate nor delayed framing produces a statistically significant effect on signup

rates. Given the limited sample size, in particular for interaction analyses, the study is underpowered to detect small behavioral effects. Therefore, we interpret the findings of the present thesis as exploratory evidence to motivate further research.

At the same time, several attitudinal and structural characteristics appear to be associated with engagement outcomes. In particular, pre-treatment interest in solar energy is positively associated with signup behavior, while higher risk aversion is linked to lower willingness to engage. These findings are consistent with the broader literature on the attitude-behavior gap in environmentally sustainable behavior that positive attitudes do not necessarily translate into concrete action (Kollmuss and Agyeman 2002). Although respondents recognize the long-term value of solar energy, their concerns about affordability, risk, and installation constraints remain to be the important considerations.

From a policy perspective, the findings imply that informational campaigns alone are unlikely to be effective in increasing households' engagement with solar energy. More effective approaches may combine behavioral communication strategies with the interventions aimed to reduce structural barriers such as improving access to financing and lowering perceived investment risk.

The remainder of this thesis is organized as follows. *Chapter 2* reviews the relevant theoretical and empirical literature on present bias, time preferences, and renewable energy adoption. *Chapter 3* presents the empirical methodology and experimental design of a randomized online survey. *Chapter 4* describes the data and key variables. Empirical results are discussed in *Chapter 5*. Finally, *Chapter 6* concludes with key findings and further policy recommendations.

Chapter 2

LITERATURE REVIEW

2.1. Theory and evidence on present bias and intertemporal decisions

The existing empirical literature shows that present bias may significantly affect individuals' economic behavior. In particular, it can influence environmentally sustainable choices where immediate costs are certain, but benefits are realized only in the future. Several studies provide evidence that time preferences influence energy-related decisions. Allcott and Taubinsky (2015) show that consumers systematically undervalue future energy savings when they make purchasing decisions for energy-efficient technologies. In particular, the authors find that providing consumers with information about long-term electricity savings increased the market share of energy-efficient CFL bulbs by approximately 12 percentage points at market prices and raised willingness to pay by about $2.30 on average. Similarly, Schleich et al. (2019) provide large-scale empirical evidence that present-biased and more impatient households are significantly less likely to invest in energy-efficient technologies. Together, these findings directly impact the present study by suggesting that intertemporal preferences may represent an important behavioral barrier to household energy adoption alongside financial and informational constraints.

At the same time, when individuals are presented with information that changes the perception of future benefits, this may partly offset present-biased decision-making. Duflo, Kremer, and Robinson (2011) show that small, time-limited "early-bird" incentives offered at the right time can successfully overcome procrastination and increase participation in programs that include delayed benefits. The results of the study emphasize that the timing of incentives may be even more important than their size. In other words, if part of future benefits is

released to individuals immediately, it may effectively counteract present-biased preferences and encourage individuals to take action. This insight motivates the present study's experimental design, which tests whether emphasizing immediate financial savings rather than cumulative long-term benefits increases willingness to engage with solar-related information, in particular among those individuals who exhibit present bias.

More broadly, evidence from residential solar adoption suggests that households make decisions based not only on financial payoffs but also on information spillovers and behavioral frictions. For example, home-energy reports that provide social comparisons can reduce electricity consumption, but treatment effects tend to decline over time (Allcott and Rogers 2014). Likewise, peer effects and local social interactions significantly influence residential photovoltaic adoption (Bollinger and Gillingham 2012). This implies that behavioral and contextual factors can influence individuals' decisions toward solar technologies beyond purely economic incentives. Together with evidence on present bias and energy-efficient investments, these findings suggest that behavioral factors matter for energy-related decisions; however, they are unlikely to operate independently from economic incentives, information constraints, and household characteristics.

From a methodological perspective, there are several works which emphasize that it is very important to identify time preferences properly. Structural models of intertemporal choice often distinguish between exponential discounting and present bias and may additionally account for risk preferences and utility curvature (Laibson 1997; O'Donoghue and Rabin 1999; Andersen et al. 2008). However, when implementing such structural estimation, extensive experimental data and more complex elicitation procedures are typically required. By contrast, simplified survey-based measures, such as short intertemporal choice tasks,

provide a more feasible but less precise proxy for identifying present-biased preferences.

2.2. Empirical evidence on time preferences and energy-related decisions

Empirical evidence suggests that time preferences are an important determinant of energy-related decisions, especially when investments involve immediate costs and delayed returns. Fuerst and Singh (2019) show that individuals with observed present bias are less willing to invest in energy-efficient appliances in India, even though such investments are financially attractive. Authors introduce their analysis in the framework of the hyperbolic discounting concept, which states that individuals have a declining rate of time preference (Frederick, Loewenstein and O'Donoghue 2002). Consistent with this, Werthschulte and Loschel (2021) find that present-biased households consume 9-10% more electricity than time-consistent households, even after controlling for appliance efficiency.

Moreover, there are many studies related to heterogeneous preference dimensions. They further emphasize the relevance of time preferences in sustainable behavior. In one of such studies, Fischbacher, Schudy and Teyssier (2013) show that more future-oriented homeowners undertake deeper energy-saving renovations and achieve lower energy consumption. They also explore large heterogeneity in discount factors across individuals, and this highlights the importance of measuring time preferences explicitly in energy-related research. Following this, Meissner et al. (2022) report robust correlations between demographic characteristics and time preferences in a large-scale European survey. In this research, the authors show evidence that younger individuals have stronger present-biased preferences and higher discount rates. These findings are important for understanding variations in sustainable adoption decisions across different demographic groups.

2.3. Renewable energy adoption in Ukraine under wartime uncertainty

In the Ukrainian context, a growing body of literature shows both the structural potential for renewable energy and the social demand for cleaner and more secure energy sources. Before the war, there were 62 industrial solar plants and about 45,000 household prosumers (owners of residential solar plants) in the country. By 2023, the number of household prosumers had increased to nearly 53,000 (Solar Energy Association of Ukraine 2023). However, Ukraine's centralized energy infrastructure was constantly attacked during the war. As a result, we now have widespread blackouts and damage to large power plants and heat plants (IEA 2025; Energy Community 2024). For example, 18 combined heat and power plants and over 800 boiler houses were destroyed or damaged over the course of the years 2022-2024 (IEA 2025).

At the same time, Ukraine possesses substantial solar potential. Recent studies show that the country has rooftop photovoltaic potential of 238.8 GW, corresponding to approximately 290 TWh of annual electricity generation excluding north-facing roofs (Winkler et al. 2024). This amount is almost twice Ukraine's total pre-war electricity production of around 158 TWh. This suggests that solar could play a key role in building a more resilient and decentralized energy system.

Similarly, Kuzior et al. (2021) demonstrate that Ukraine is "geographically and territorially attractive for green energy development and investment" and report a rapid increase in household solar installations over the past decade which clearly indicates growing public demand for renewable energy and energy security. Trypolska and Rosner (2022) examine how Austria's successful experience with household solar could be transferred to post-war Ukraine and emphasize the role of well-designed support schemes and prosumer-oriented policies. A few studies assess the economic and technical feasibility of rooftop photovoltaics –

particularly Iwaszczuk et al. (2023) conclude that all regions of Ukraine are suitable for solar development and expect significant PV expansion during post-war reconstruction, while Low Carbon Ukraine (2023) demonstrate that 5kW rooftop systems in Kyiv can be financially attractive for both average and high-consumption households, depending on tariff structures and prosumer provisions.

Another recent Ukrainian research provides strong evidence that household solar energy adoption has expanded significantly over the course of the last decade, but this expansion was uneven across regions so that there is substantial regional heterogeneity in Ukraine. Kurbatova et al. (2025) analyze the development of household solar electricity generations across regions during 2016-2022. According to the results of their research, there is no convergence across Ukrainian regions so that areas with initially higher or lower levels of household solar adoption did not systematically align with each other over time. Moreover, these regional disparities have even deepened after the onset of full-scale invasion in 2022. The authors conclude that Ukraine's household solar energy sector follows divergent and spatially fragmented development paths and is influenced not only by economic and institutional differences, but also by external shocks such as war and infrastructure damage. At the same time, the study shows that households have become an important actor in a country's energy transition as residential solar generation grew more than 360-fold on average during the research period.

Beyond this, there is evidence that wartime shocks in Ukraine can increase time discounting and exacerbate present bias in intertemporal choices (Yudenko 2023). Behavioral factors such as time preferences may critically impact the households' responses to long-term investment opportunities.

Recent behavioral and financial economics research further suggest that present bias may intensify under conditions of stress and uncertainty. Lochstoer, Lundeby and Tancheva (2025) argue that adverse economic and traumatic conditions can amplify present-biased behavior by impairing individuals' planning and self-control capacities. Authors use survey evidence on consumption expectations in their study and show that individuals systematically overconsume relative to their own expectations and this inaccurate forecasting becomes much stronger during periods of economic stress. Their findings support the broader argument that stressful environments may increase short-term decision-making and reduce willingness to engage in investments with delayed benefits. This insight is particularly relevant in wartime Ukraine, where households face persistent uncertainty and financial pressure.

Together these studies indicate that, while Ukraine has high technical and social potential for household-level renewables, its adoption is highly dependent not only on economic conditions and policy design, but also on underlying behavioral preferences that are aimed to be addressed in this paper. For example, Kurbatova et al. (2025) acknowledge that their study does not account for behavioral factors that should also influence households' decisions on solar energy adoption. Therefore, in the current thesis, we aim to fill this gap by examining how present bias and informational framing jointly influence Ukrainian households' willingness to engage with solar adoption in conditions of war and uncertainty.

Chapter 3

METHODOLOGY

3.1. Theoretical framework of the research

The theoretical framework of this study is based on the quasi-hyperbolic discounting model developed by Laibson (1997) and formalized by O'Donoghue and Rabin (1999). In this framework, individuals value present consumption disproportionately more than future consumption, which leads to a deviation from the standard exponential discounting model. The individual's intertemporal utility at time t is expressed as

$$U_t = u(c_t) + \beta \sum_{\tau=1}^{\infty} \delta^{\tau} u(c_{t+\tau}), \quad (1)$$

where $u(c_t)$ is the instantaneous utility of consumption in period t, $0 < \delta < 1$ represents the standard long-term discount factor, and $0 < \beta \leq 1$ captures present bias. When $\beta = 1$, preferences are time-consistent, while $\beta < 1$ indicates present bias – so that individuals undervalue future benefits relative to immediate costs.

In the context of this research, respondents should make a decision whether to sign up for a free online informational session about solar energy and panel installation or not. This decision already requires a small immediate cost, such as time and effort ($h > 0$), and it promises a delayed potential benefit (improved knowledge and higher probability of installing solar panels) in the future ($\Delta V > 0$). Based on the $\beta - \delta$ model, an individual will decide to sign up if the discounted future benefit, weighted by $\beta\delta$, exceeds the immediate cost:

$$-h + \beta\delta\Delta V \geq 0 \tag{2}$$

When incentives are introduced at different times – an immediate (early-bird) incentive s_E or a delayed incentive s_D received after τ periods – the decision criterion becomes:

$$-h + s_I + \beta\delta\Delta V \geq 0 \quad (immediate\ benefit) \tag{3a}$$

$$-h + \beta\delta^{\tau} s_D + \beta\delta\Delta V \geq 0 \quad (delayed\ benefit) \tag{3b}$$

These expressions imply that individuals with stronger present bias (lower β) place lower weight on future benefits, making them less likely to sign up in the control condition and more responsive to immediate rewards. Consequently, the model predicts that (i) present bias reduces willingness to sign up, and (ii) an early-bird incentive increases participation more than a delayed incentive, especially among present-biased individuals. Similar behavioral frameworks were applied in empirical studies about intertemporal decision-making and energy behavior, where individuals must trade off immediate costs against delayed benefits (Allcott and Taubinsky 2015; Schleich et al. 2019).

3.2. Survey experiment design

Aligning with the theoretical framework described above, we conduct a randomized survey experiment in our study. In the first stage, each respondent completes a brief time-preference module consisting of two binary choices between smaller, immediate monetary rewards and larger, delayed ones (choice between 900 UAH today and 1,050 UAH in one month, and between 900 UAH

in six months and 1,050 UAH in seven months).[1] These intertemporal choices are hypothetical and non-incentivized (respondents do not receive actual monetary rewards based on their decisions). Respondents who choose the immediate reward in short-term trade-offs but prefer the delayed reward when both options are in the future are classified as present-biased. This simplified elicitation approach follows experimental designs used in studies of time-inconsistency and self-control, such as Ashraf, Karlan, and Yin (2006), who demonstrated how individuals employ commitment mechanisms to mitigate present bias. Still, compared to richer elicitation procedures that are broadly used in experimental economics (e.g., Andersen et al. 2008), the two-question design employed in this study provides a simplified and relatively coarse proxy for present bias. Because the measure relies on two hypothetical and non-incentivized intertemporal choices, it is likely to identify only stronger forms of present bias and fail to capture weaker or more nuanced time-inconsistent preferences. The relatively low prevalence of present-biased respondents in the sample (18%) may partly reflect measurement limitations of this simplified approach.

In addition, we include supplementary preference-related measures in the analysis, such as risk attitudes and general patience. However, the main empirical analysis relies primarily on the binary present-bias indicator which is derived from the intertemporal choice module. These additional measures are used descriptively and to provide broader context on respondents' behavioral characteristics.

In the second stage, respondents are randomly assigned to one of three informational conditions. The control group receives a neutral description of a rooftop solar system, its approximate cost, lifespan and average payback period. The immediate-benefit group reads the same description, but the financial benefits are framed as short-term monthly and yearly savings (for example, 1st-month and

[1] Questions Q5.4 and Q5.5 in the survey in Appendix 1

1st-year electricity bill savings). The delayed-benefit group also receives the same baseline information, but the benefits are framed as cumulative savings over the full lifetime of the system.

Although the informational treatments were designed to vary the temporal framing of financial benefits, they also differ in the salience and cumulative magnitude of the reported savings. Therefore, we interpret this experimental manipulation as emphasizing short-term versus long-term financial outcomes rather than as a pure framing intervention.

After reading the scenario, participants are asked to answer five comprehension questions designed to ensure that they correctly understand the provided information about solar panel costs, lifespan, and potential savings. To account for data quality and attentiveness, we construct a binary indicator identifying respondents who answered fewer than four out of five comprehension questions correctly. We chose the threshold of four correct answers out of five to balance data quality concerns with sample retention. In this way, we include in the main analysis those respondents who demonstrate a high level of treatment understanding while avoiding excessive sample loss.

Because we measure comprehension after exposure to the informational treatment, it should be interpreted as a post-treatment measure that may itself be influenced by treatment assignment. As a supplementary robustness check, we also estimate restricted-sample specifications that include only respondents who passed the comprehension checks.

The primary outcome variable is participants' willingness to sign up for a free online informational session about solar energy. Focusing on signup intentions allows us to capture a low-commitment yet behaviorally meaningful step toward solar adoption, as participation in such a session still requires time and effort and often serves as a prerequisite for more substantial investment decisions later.

In addition to focusing on the primary outcome measure, we also include the secondary outcome variable. Since willingness to sign up is a binary measure that may exhibit limited variation (e.g., a floor effect if few participants sign up), including the secondary outcome measure may broaden the analysis. The secondary variable we include is the stated interest in installing solar panels, and it is measured on a 5-point scale. Although we observe here a stated preference rather than a behavioral measure, it still clearly shows gradation in interest that the dummy signup variable cannot.

The overall structure of the survey experiment is summarized in Figure 1, and the full questionnaire is included in Appendix A.

Since the empirical analysis includes multiple outcome measures and interaction terms, we acknowledge the possibility of false positive findings due to multiple hypothesis testing. Therefore, we distinguish between the pre-specified primary outcome (signup for the informational session) and the secondary exploratory outcome. To assess the robustness of the focal behavioral results, we apply a Benjamini-Hochberg correction to the hypothesis-related coefficients (present bias and interaction terms across outcomes). After adjustment, none of the coefficients remain statistically significant. Consequently, secondary findings are interpreted as exploratory rather than confirmatory evidence.

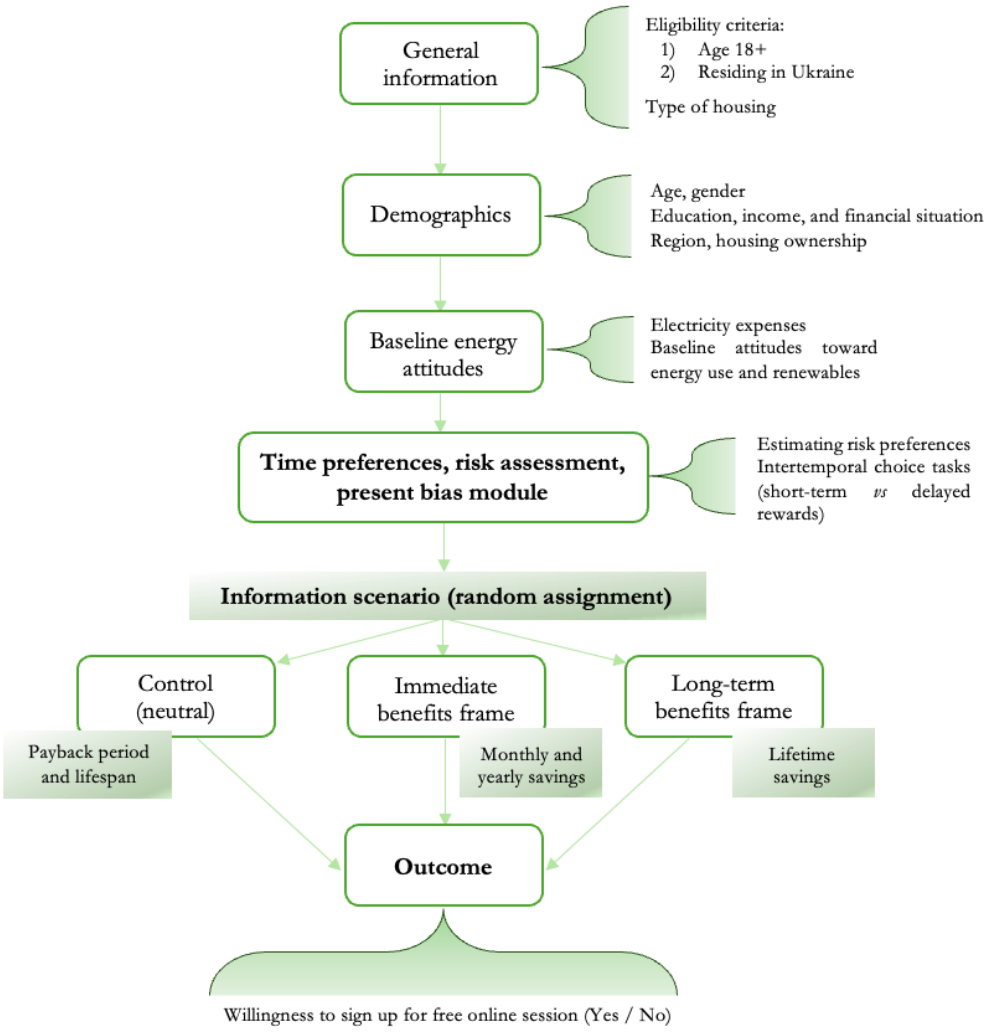


Figure 1. Structure of the survey experiment

Note: own presentation based on the survey design

3.3. Empirical model specification

The empirical analysis distinguishes between confirmatory and exploratory components. The two main hypotheses examining (i) the relationship between present bias and signup behavior and (ii) the moderating role of informational

framing are theory-driven and specified ex ante. Additional analyses which include heterogeneity tests, secondary outcome measure, and alternative model specifications, are exploratory and are interpreted as post-hoc robustness exercises rather than confirmatory causal tests.

Empirically, the relationships described above are tested using a binary outcome variable, $SignUp_i$, which equals 1 if respondent *i* indicates willingness to sign up for the free online informational session, and 0 otherwise. The estimation strategy follows Schleich et al. (2019) and related behavioral-energy studies. We employ a linear probability model to estimate the probability of signup as a function of behavioral and demographic variables:

$$SignUp_i = \alpha + \beta_1 Current_i + \beta_2 Delayed_i + \gamma PresentBias_i + \\ + \delta_1(Current_i \times PresentBias_i) + \delta_2(Delayed_i \times PresentBias_i) + \\ + X_i\theta + \epsilon_i \quad (4)$$

where $Current_i$ and $Delayed_i$ are binary treatment indicators for the experimental conditions (the control group is the omitted category), and $PresentBias_i$ is a binary variable derived from respondents' intertemporal choice tasks. The vector X_i includes demographic controls such as age, gender, education, income, household decision-making autonomy, ownership, type of dwelling, and attitudinal characteristics such as pre-treatment interest in solar energy, prior knowledge, risk attitudes, anxiety about electricity outages, as well as comprehension failure. Lastly, the interaction term $Current_i \times PresentBias_i$ shows an additional change in signup probability caused by the current-benefit framing among present-biased individuals, and $Delayed_i \times PresentBias_i$ represents signup probability among present-biased respondents who received the delayed-benefit framing.

Given the final sample size of 213 respondents, the study is primarily able to detect relatively large treatment effects in signup behavior. In particular, since there are only 18% of respondents who are classified as present-biased, the effective subgroup sizes for interaction terms are relatively small (approximately 13 respondents per treatment cell). Assuming a baseline signup probability of approximately 25% and a conventional statistical power threshold of 80%, we find that the corresponding minimum detectable effect is around 23 percentage points. As a result, smaller behavioral effects may remain undetected, and null findings should therefore be interpreted with caution.

The main model described in equation (4) is estimated using OLS regression with robust standard errors. A negative coefficient on $PresentBias_i$ ($\gamma < 0$) would support the first hypothesis that individuals with present bias are less willing to sign up for the informational session. A positive coefficient on the interaction term ($\delta > 0$) would provide evidence for the second hypothesis that present-biased households are more likely to sign up if some immediate benefits are shown to them. The expected signs on these and other key explanatory variables are shown in Table 1.

Since in the main specification of the model (4) the control group is omitted, the coefficients β_1 and β_2 capture effects for non-present-biased respondents. The treatment effect for immediate framing among present-biased individuals is $\beta_1 + \delta_1$, while the effect for delayed framing among people with present bias is $\beta_2 + \delta_2$.

To ensure that the random assignment of treatments was successful, we conduct balance tests across treatment groups for observable characteristics. In this way, we verify that respondents in different treatment arms are comparable in terms of their pre-treatment characteristics.

Instead of estimating the main OLS regression alone, we also test the standard logit and probit models as robustness checks. This is important for critically analyzing

our main model and results. In both models, we include the same explanatory variables as in the main specification. We provide specifications for both models in Appendix B.

Table 1. Explanatory variables and expected signs

Variable	Description	Expected effect
$Current_i$	Dummy: 1- respondent received immediate-benefits framing. The coefficient shows the effect among non-present-biased respondents ($PresentBias_i$=0).	+ (vs Control)
$Delayed_i$	Dummy: 1- respondent received delayed-benefits framing. The coefficient shows the effect among non-present-biased respondents ($PresentBias_i$=0).	Ambiguous (vs Control)
$PresentBias_i$	Dummy: 1- respondent is classified as present-biased from the intertemporal-choice module. The coefficient shows a difference in the control group.	-
$Current_i \times PresentBias_i$	Interaction term: additional effect of immediate framing among present-biased respondents.	+
$Delayed_i \times PresentBias_i$	Interaction term: additional effect of delayed framing among present-biased respondents.	-
X_i	Demographic controls: age, gender, education, income, region, housing type/ownership, household decision-making rule.	Ambiguous

Note: "-" means that the negative effect is expected, while "+" refers to the positive effect.

In addition to the baseline analysis, we also explore heterogeneity in behavioral responses across individuals. We examine whether the relationship between present bias and willingness to sign up varies across demographic characteristics,

including age, education, and household decision-making responsibility. These subgroup analyses are exploratory and are intended to provide descriptive insights rather than confirmatory hypothesis tests. The focus on age, education, and household decision-making responsibility in the heterogeneity analysis is motivated by the empirical literature linking these characteristics to intertemporal decision-making and energy-related behavior. Prior studies show that time preferences and present bias vary systematically across age groups, with younger individuals tending to exhibit stronger present bias (Frederick, Loewenstein, and O'Donoghue 2002; Meissner et al. 2022). Education has also been shown to influence patience and overall responsiveness to energy-related interventions, even after controlling for income (Schleich et al. 2019; Allcott and Taubinsky 2015). Furthermore, studies by Duflo, Kremer, and Robinson (2011) and Werthschulte and Loschel (2021) show that individuals who have primary decision-making responsibility in the household are more likely to act, particularly in contexts that involve intertemporal trade-offs. Therefore, the heterogeneity analysis provides us with further insights into how present-biased preferences interact with individual characteristics in solar energy decisions as well as identifies potential patterns for future research.

Chapter 4

DATA

In our research, we use primary data that was collected through a randomized online survey experiment conducted in collaboration with InfoSapiens, a professional survey agency based in Ukraine, in March 2026. InfoSapiens uses online panel-based sampling and recruits participants through established respondent pools. While the sampling procedure aims to achieve diversity across demographic dimensions such as age, gender, and region, online panels are not fully representative of the Ukrainian population. In particular, they may underrepresent older individuals, lower-income households, rural residents, and individuals who have limited internet access.

The total sample consists of 235 respondents. But, as we included an attention check in the experiment and some people didn't pass it, we excluded those observations from the main analysis. As a result, the final dataset includes 213 responses. This is worth mentioning that attention-check failure is balanced across treatment groups (Chi-squared test: $p = 0.825$; Fisher test: $p = 0.852$), which suggests that exclusion is unlikely to be systematically related to treatment assignment. Although the sample size is limited, in particular for interaction analyses, the study should be interpreted as providing exploratory evidence and a basis for broader future research on behavioral determinants of residential solar engagement.

In Table 2 we present summary statistics for the key variables and demographic characteristics as well as results of the balance tests across treatment groups. First, as can be seen from the balance tests, the differences in observable characteristics between treatment and control groups are generally modest, and joint F-tests do not detect statistically significant differences (p-values of 0.775 and 0.828,

respectively). At the same time, some individual covariates (detached-house residence, baseline interest in solar energy, prior solar knowledge, and household decision-making characteristics) show modest imbalances in means. Since these characteristics are associated with engagement outcomes, we control for them in the main regression specifications to reduce concerns about confounding.

Table 2. Descriptive statistics and balance across treatment groups

Individual characteristics	Sample Mean	Treatment – Control Difference	Immediate – Delayed Difference
	(1)	(2)	(3)
Age	44.51	0.05	-2.92
	(10.45)	(1.53)	(1.74)
Female	0.62	-0.03	-0.06
	(0.49)	(0.07)	(0.08)
Sole decision-maker	0.33	0.06	0.02
	(0.47)	(0.07)	(0.08)
Bachelor's or higher	0.51	-0.08	0.00
	(0.50)	(0.07)	(0.08)
Income > 40,000 UAH	0.12	-0.02	-0.03
	(0.32)	(0.05)	(0.05)
Own dwelling	0.69	0.07	0.02
	(0.47)	(0.07)	(0.08)
Detached house	0.51	0.13	-0.04
	(0.50)	(0.07)	(0.08)
Present-biased	0.18	-0.04	-0.06
	(0.38)	(0.06)	(0.06)
Interest in solar	3.49	-0.14	-0.05
	(1.26)	(0.18)	(0.21)
Anxiety about outages	4.06	-0.02	-0.13
	(1.08)	(0.16)	(0.18)
Knowledge on solar	2.70	-0.14	-0.22
	(1.15)	(0.17)	(0.20)
Risk attitude	3.18	0.01	0.09
	(1.11)	(0.16)	(0.19)
F-test p-value		0.775	0.828

Note: N=213. Column (1) reports sample means of individual characteristics, and standard deviations are given in parentheses. Column (2) shows differences in means between the combined treatment group (Immediate and Delayed) and the control group. Column (3) presents differences in means between Immediate and Delayed treatment groups. Standard errors are provided in parentheses in columns (2) and (3). All variables are measured prior to treatment.

The average respondent is 44 years old, and, overall, there is a relatively wide age distribution (standard deviation of 10.45 years). The sample is slightly skewed toward women who constitute 62% of respondents. This share is somewhat higher than the population benchmark and may partly reflect survey participation patterns during wartime when many men are mobilized. In terms of decision-making responsibility, approximately one-third of respondents (33%) report being the sole decision-maker. A relatively high share of the sample is well-educated, with 51% having at least a bachelor's degree. At the same time, only 12% report a monthly income above 40,000 UAH, which means that higher-income households are underrepresented in the experiment. Since adoption of residential solar panels requires substantial upfront investment costs, this may limit the external validity of the findings for the segment of households which are most likely to adopt solar technologies.

As for behavioral characteristics, 18% of respondents are classified as present-biased according to the two-question intertemporal choice module. This prevalence appears to be substantially lower than in previous studies which employ more detailed elicitation methods. For example, Meier and Sprenger (2010) and Augenblick, Niederle, and Sprenger (2015) document present-bias prevalence rates closer to 30-50% depending on the elicitation method and sample. One possible explanation is that the simplified two-question switching design which we employ in our study gives a relatively coarse measure of present bias and may therefore identify only stronger forms of time-inconsistent behavior. As a result, we interpret the estimated present-bias coefficients conservatively, since respondents who have weaker forms of present-bias may be classified together with time-consistent individuals, and this attenuates estimated behavioral effects toward zero.

It is also useful to examine pre-treatment attitudes toward solar energy. The results show that the average level of interest in solar energy is moderate at 3.49 on a five-point scale. Respondents are highly concerned about electricity outages, with an

average score of 4.06, while self-assessed knowledge about solar energy remains comparatively low at 2.70. Risk attitudes are moderate at 3.18 on the respective scale.

Figure 2 below presents the share of present-biased and non-present-biased respondents across treatment groups. We can observe that the distribution is relatively similar across all groups, with approximately 14-20% of individuals classified as present-biased in each case. This pattern is consistent with the randomized assignment procedure and suggests no observable imbalance in present-bias prevalence across treatment groups.

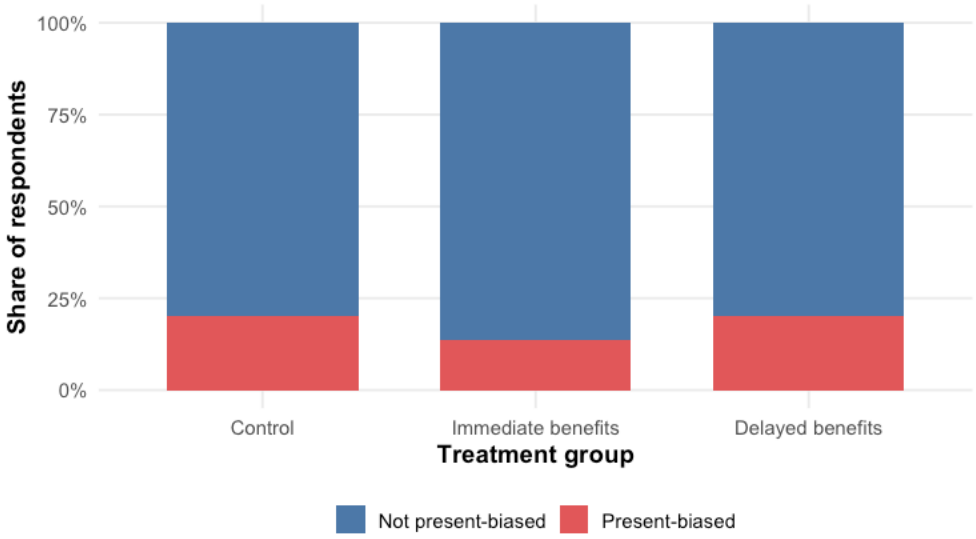


Figure 2. Distribution of respondents by treatment and present bias

Note: own presentation based on the survey data

Figure 3 below presents the geographic distribution of survey respondents across Ukrainian oblasts. The sample includes participants from most regions of the

country. However, it is not representative since respondents are concentrated primarily in several central, western, and southern regions, while eastern frontline regions are comparatively underrepresented and some oblasts include only a small number of observations. This limits the external validity of wartime-related interpretations, because the sample does not fully capture those households who are most directly exposed to energy insecurity.

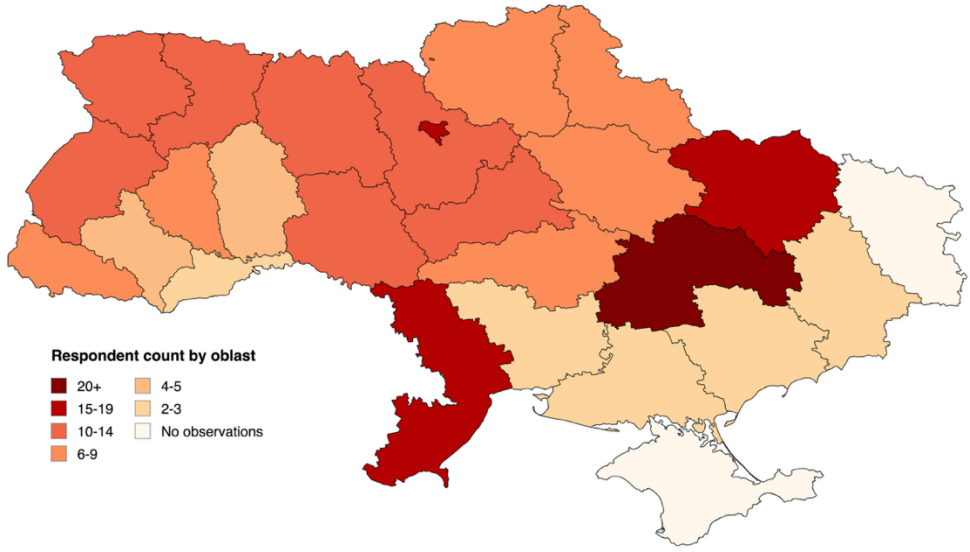


Figure 3. Geographic distribution of survey respondents
Note: own presentation based on the survey data

In Table 3 we can also observe the post-treatment characteristics such as interest in solar energy, perceived affordability, long-term value, and risk as well as the signup rate – our main dependent variable of interest. Signup rate is 24% across the respondents, and the average interest in solar energy after introducing the treatment text is 3.49 on a five-point scale. Additionally, the average perceived

affordability of installing solar panels across the respondents is quite low (2.31/5) which is logical since high-income households are underrepresented in the survey. At the same time, respondents believe that investing in solar energy is worthwhile but risky given the average perceived long-term value of 3.65 and the average perceived risk of 3.29 on a respective scale.

Table 3. Descriptive statistics of outcome variables

Individual characteristics	Mean (SD)
Signup rate	0.24 (0.43)
Post-treatment interest in solar energy	3.49 (1.11)
Post-treatment perceived affordability	2.31 (0.99)
Post-treatment perceived long-term value	3.65 (1.10)
Post-treatment perceived risk	3.29 (1.20)

Note: N=213. Table shows means for the main outcome variable Signup as well as for the post-treatment respondents' attitudes toward solar energy. Standard deviations are reported in the parentheses.

Overall, despite the limitations related to sample size and representativeness, the data provides useful exploratory evidence on the role of informational interventions and behavioral factors in solar energy adoption among Ukrainian households.

Chapter 5

ESTIMATION RESULTS

In this chapter, we present the empirical findings of the survey experiment. We begin with descriptive evidence on signup behavior across treatment groups and then report the main regression estimates and robustness checks.

In Figure 4 we can observe descriptive signup rates across treatment groups that distinguish between present-biased and time-consistent respondents. There are several patterns that emerge from the raw data, although, given the small underlying subgroup sizes (approximately 13 present-biased respondents per treatment cell), they are interpreted cautiously and suggest descriptive context rather than systematic behavioral differences.

First, in the control group, individuals who exhibit present bias have substantially lower signup rates when comparing to non-present-biased respondents (approximately 14% versus 25%). Second, in the immediate-benefits treatment group, we observe a reversed pattern: present-biased individuals show higher signup rates (approximately 30%) compared to non-present-biased respondents (approximately 23%). Finally, in the delayed-benefits treatment group, signup rates are relatively similar across the two groups, but present-biased individuals are still less engaged.

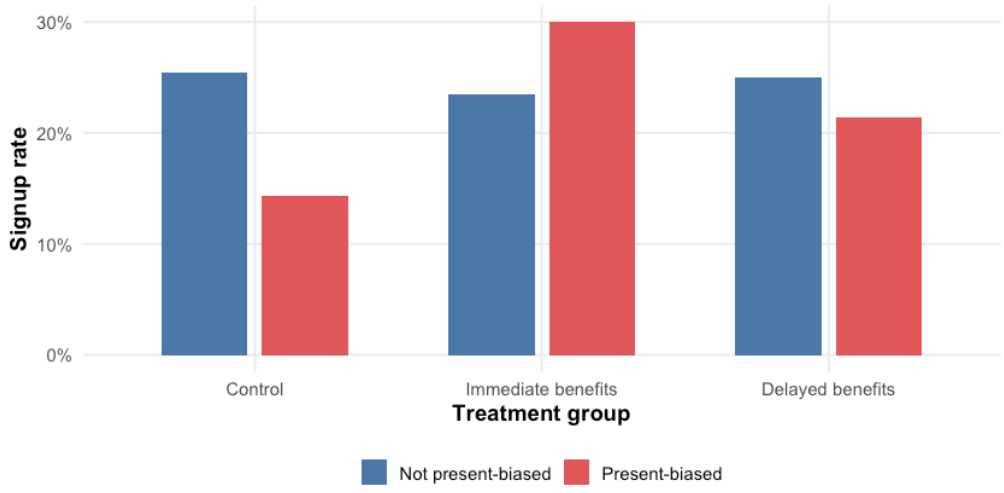


Figure 4. Signup rates by treatment group and present bias
Note: own presentation based on the survey data

Figure 5 below presents the distribution of perceived investment risk in solar energy when comparing present-biased and non-present-biased respondents. Both groups show moderate to relatively high levels of perceived risk. Although the figure suggests some visual differences in the distribution of responses, a Wilcoxon rank-sum test indicates that the difference between the two groups is not statistically significant ($p = 0.500$). Therefore, perceived investment risk appears relatively similar across present-biased and non-present-biased respondents in this sample.

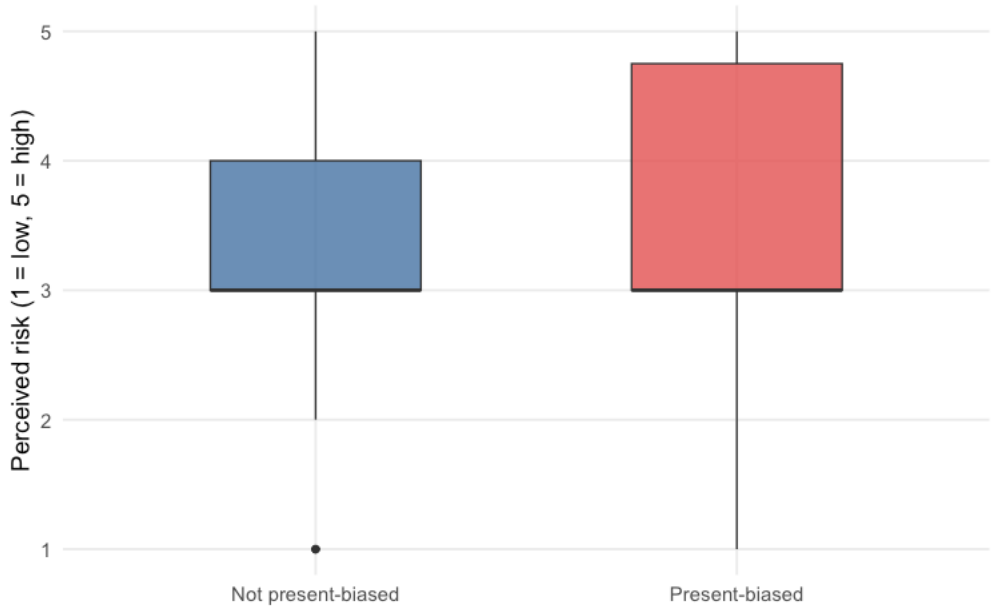


Figure 5. Perceived investment risk by present bias
Note: own presentation based on the survey data

To estimate the main model described in equation (4) and to ensure data quality as well as respondents' understanding of the treatment texts, we included five comprehension questions after the information treatment for each group. Instead of excluding respondents who failed these questions, we construct a dummy variable that indicates whether a respondent failed the comprehension check and include it as a control in the regression. This approach allows us to retain the full sample and avoid substantial loss of observations. When excluding such respondents we have a reduced sample of 138 observations which can significantly limit statistical power, in particular when detecting small treatment effects.

Results of estimation of the main regression model are provided in Table 4 below. It is estimated on the full sample while controlling for comprehension failure.

Table 4. Main regression results

	Signup	
	Baseline model	With binary controls
	(1)	(2)
Immediate benefits	-0.020	-0.003
	(0.080)	(0.075)
Delayed benefits	-0.005	-0.014
	(0.084)	(0.084)
Present-biased	-0.112	-0.104
	(0.112)	(0.109)
Immediate x Present-biased	0.177	0.175
	(0.192)	(0.183)
Delayed x Present-biased	0.076	0.051
	(0.168)	(0.154)
Age		0.001
		(0.003)
Female		0.048
		(0.062)
Sole decision-maker		0.093
		(0.061)
Bachelor and higher		-0.054
		(0.060)
Income > 40,000 UAH		0.067
		(0.082)
Own dwelling		0.063
		(0.059)
Detached house		0.041
		(0.059)
Prior interest in solar energy		**0.075*** **
		(0.027)
Knowledge about solar energy		0.050
		(0.032)
Risk attitude		**-0.068*** **
		(0.024)
Anxiety about outages		0.034
		(0.025)
Comprehension failure		-0.026
		(0.062)
Constant	0.255***	-0.201
	(0.060)	(0.167)
Observations	213	213
R2	0.005	0.177
Adjusted R2	-0.019	0.106

Note: The dependent variable is signup for a free informational session on solar energy (1=signup). Column (1) reports the baseline specification without controls. Column (2) includes demographic, housing, attitudinal, and comprehension controls. Robust standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

The first insight is that the treatment condition has no statistically significant effect on signup behavior. In particular, the coefficients on both treatment variables – immediate benefits and delayed benefits – are small and statistically insignificant. This suggests that the framing of benefits does not meaningfully affect individuals' willingness to sign up for the informational session on solar energy. The coefficients of -0.112 and -0.104 on present bias depending on specification suggests that present-biased individuals are approximately 10-11 percentage points less likely to sign up, though this effect is not statistically distinguishable from zero ($p > 0.10$), so we cannot observe any robust evidence that present bias alone influences signup behavior. Furthermore, most demographic and socioeconomic characteristics do not have statistically significant effects.

Although the interaction coefficients are not statistically significant at conventional levels, the estimated effects are directionally consistent with the theoretical predictions. In the control condition, present-biased respondents are less likely to sign up for the informational session than non-present-biased respondents. However, in the immediate-benefit framing, we observe higher signup probability among respondents who exhibit present bias relative to the control condition. The implied marginal effect for present-biased individuals is approximately +17.5 percentage points under immediate framing and +5.1 percentage points under delayed framing. This suggests that if we emphasize immediate benefits, we may partially offset lower baseline engagement among present-biased individuals. Still, because the number of respondents classified as present-biased in each treatment cell is relatively small (approximately 13 observations), the interaction estimates are imprecise.

At the same time, pre-treatment behavioral characteristics appear to be important predictors of engagement. In particular, baseline interest in solar energy is positively associated with signup behavior, while higher risk aversion

results in lower willingness to engage. Overall, when we include behavioral controls into the model, they improve model fit, which suggests that baseline preferences and attitudes explain an important share of variation in engagement decisions.

An important difference emerges when comparing the full sample with the restricted sample that excludes respondents who failed the comprehension check. In particular, estimation results of the restricted sample (N=138), reported in Table 5, show that present bias appears to be a statistically significant and economically meaningful predictor of behavior. It shows that, depending on the model specification, present-biased respondents are approximately 27-28 percentage points less likely to sign up for the informational session compared to their non-present-biased counterparts ($p<0.01$). Pre-treatment interest in solar energy, prior knowledge, and lower risk aversion also emerge as important predictors of engagement, consistent with the findings of the main model. Furthermore, household decision-making autonomy appears to be an important structural determinant of signup behavior. In particular, respondents who make household decisions independently are approximately 14.4 percentage points more likely to engage.

In contrast, the corresponding estimates in the full sample are substantially smaller and statistically insignificant once we include respondents who failed the comprehension checks. One possible explanation of this discrepancy is measurement quality. Respondents who fail comprehension checks may not fully understand the treatment information or survey questions. In this way they introduce noise into the data. Including such observations in the full sample attenuates estimated effects and biases coefficients toward zero.

Table 5. Restricted sample regression results

	Signup	
	Baseline model	With binary controls
	(1)	(2)
Immediate benefits	-0.028	-0.017
	(0.101)	(0.094)
Delayed benefits	0.013	-0.004
	(0.113)	(0.112)
Present-biased	**-0.278*** **	**-0.272*** **
	(0.076)	**(0.093)**
Immediate x Present-biased	0.194	0.139
	(0.186)	(0.204)
Delayed x Present-biased	0.187	0.184
	(0.172)	(0.172)
Age		0.003
		(0.003)
Female		-0.025
		(0.085)
Sole-decision-maker		**0.144***
		(0.077)
Bachelor's or higher		0.024
		(0.074)
Income > 40,000 UAH		-0.059
		(0.088)
Own dwelling		-0.046
		(0.085)
Detached house		0.089
		(0.075)
Prior interest in solar energy		**0.064***
		(0.035)
Knowledge about solar energy		**0.080****
		(0.040)
Risk attitude		**-0.092*** **
		(0.032)
Anxiety about outages		0.022
		(0.034)
Constant	0.278***	-0.125
	(0.076)	(0.212)
Observations	138	138
R2	0.033	0.239
Adjusted R2	-0.004	0.138

Note: The dependent variable is signup for a free informational session on solar energy (1=signup). Column (1) reports the baseline specification without controls. Column (2) includes demographic, housing, attitudinal, and comprehension controls. Robust standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

At the same time, when we restrict the sample, we risk getting the results with reduced statistical power and potential selection bias. Individuals who pass the comprehension check may differ systematically from those who do not (for example, in terms of cognitive ability, motivation, or engagement with the survey). As a result, such estimates may not be fully representative of the broader population.

Taken together, the two specifications capture different dimensions of the treatment effect. The full-sample analysis corresponds to an intention-to-treat (ITT) specification. It preserves the original randomized assignment and reflects the average effect of the informational intervention in the overall sample. In contrast, the restricted-sample specification can be interpreted as a per-protocol analysis, and it focuses on respondents who successfully passed the comprehension checks and, thus, showed a good understanding of the treatment information. While the restricted sample shows stronger behavioral effects that are associated with present bias, these estimates may reflect a more attentive and engaged subgroup of respondents. For this reason, we report the results of the full-sample specification as the primary analysis, while including the restricted-sample results as a supplementary robustness check.

In addition to the main LPM specification, given the full sample, we also estimate the logit and probit models as robustness checks. The average marginal effects (AMEs) for both models are shown in Appendix C. Overall, the results of these specifications are consistent with the results of estimation of the baseline linear model. In particular, neither immediate-benefit nor delayed-benefit framing has a statistically significant effect on signup behavior. Although results show that present-biased individuals are approximately 11 percentage points less likely to sign up, this finding is not statistically meaningful ($p = 0.33$-0.39). The coefficients on interaction terms show no significant results either, suggesting that there is no robust evidence that

immediate or delayed framing mitigates the effect of present bias. Similarly to the main findings, prior interest in solar energy is a strong and statistically significant predictor of engagement. A one-point increase in baseline interest is associated with approximately an 8-9 percentage-point increase in signup probability. In addition, higher risk aversion is associated with a lower likelihood of signup (approximately 6-7 percentage points). Prior knowledge of solar energy is positively associated with engagement and is marginally significant at 10% level.

In our research, we test not only the primary outcome variable of signup engagement but also examine the impact of the interventions on the secondary outcome variable – post-treatment interest in solar energy – which is measured on a 5-point scale. The regression results are reported in Appendix D and show a somewhat different pattern from the one detected in the main specification with the primary signup intention. Several interesting insights appear when we turn to control variables. First, age is positively associated with interest. The coefficient of 0.012 implies that a 10-year increase in age is associated with approximately a 0.12-point increase in interest on the 1-5 scale. So, this suggests that older individuals tend to be slightly more interested in solar energy. Secondly, consistent with the main specification, prior interest in solar energy emerges as the strongest predictor of post-treatment interest. One-point increase in baseline interest is associated with approximately a 0.48-point increase in reported interest after reading the informational treatment ($p < 0.01$). Higher risk aversion is negatively associated with interest, while the prior knowledge is positively associated with interest, although the latter effect is not statistically significant.

A counterintuitive pattern emerges in the interaction term between delayed-benefits framing and present bias. The results show that exposure to the delayed-benefits framing among present-biased individuals is associated with

an increase of approximately 0.52 points in reported interest on a 5-point scale, relative to non-present-biased individuals in the control group. However, this finding should be interpreted with caution. Since the analysis involves multiple estimated coefficients and exploratory secondary outcome, there is a risk of getting isolated statistically significant effects which may reflect sample variation rather than a stable underlying relationship. Furthermore, the examined interest in solar does not indicate the actual behavior but rather shows the attitudes of people. Therefore, we view these results as exploratory evidence which suggests that long-term framing may influence attitudes differently from concrete behavioral commitment decisions.

In addition to the main analysis, we also examine potential heterogeneity in treatment effects using the full sample. In particular, we explore differences across subgroups defined by age, education, and decision-making responsibility. The results of this analysis are presented in Appendix E. A notable pattern emerges in the negative interaction between being aged 45+ and exposure to the delayed-benefits framing. The coefficient on it is relatively large in magnitude (-0.278) and statistically significant at the 10% level. This suggests that older individuals are substantially less likely to express willingness to sign up for a free informational session on solar energy when the benefits of solar adoption are framed as occurring in the future, compared to younger respondents. One possible interpretation is that older individuals may exhibit stronger preferences for immediacy or shorter planning horizons. However, this finding should be interpreted with caution because the heterogeneity analysis is exploratory and the relatively small subgroup samples were included in the experiment. So, this evidence is suggestive rather than confirmatory.

Overall, the findings suggest that informational framing alone may not significantly affect engagement in the full-sample specification. Likewise, the estimated effects of present bias become substantially attenuated once we

include respondents who failed the comprehension checks in the analysis. This indicates that data quality and treatment comprehension play an important role in identifying behavioral effects. At the same time, the restricted-sample estimates provide suggestive evidence that present bias may reduce signup intention among respondents who accurately understood the treatment information.

Moreover, attitudinal characteristics such as perceived interest in solar energy and risk attitudes appear to play an important role in explaining variation in engagement, while structural and financial constraints may also shape households' decisions. In addition, the exploratory secondary-outcome analysis suggests that framing effects may differ between stated attitudes and actual behavioral commitment decisions.

Therefore, these findings indicate that in order to increase the engagement of households with solar energy, there should be a combination of behaviorally informed communication strategies with policies aimed to reduce the structural barriers of solar panel adoption, with structural constraints appearing to play the more important role. While informational framing alone does not appear sufficient to increase signup behavior, policies that reduce perceived risk and improve affordability may be more effective in encouraging engagement.

Chapter 6

CONCLUSIONS AND POLICY RECOMMENDATIONS

This study provides exploratory experimental evidence on the role of present bias and informational framing in shaping energy-related decisions of Ukrainian households. Using data from a randomized online survey experiment, we find no statistically significant effect of informational framing on signup behavior in the full sample, while estimated effects of present bias remain weak and statistically imprecise. At the same time, attitudinal characteristics, such as prior interest in solar energy and risk attitudes, appear to be associated with engagement.

Supplementary analyses suggest that there may be variation of behavioral effects across respondent groups and outcome measures. In particular, the restricted-sample estimates among respondents who passed the comprehension checks show statistically significant association between present bias and signup intention, while exploratory secondary-outcome results indicate that informational framing may affect stated attitudes differently from concrete behavioral commitment decisions. Overall, the findings suggest that informational interventions alone may be insufficient to overcome barriers to solar adoption, as concerns about affordability, risk, and practical feasibility remain important considerations in household decision-making.

From a policy perspective, the findings suggest that informational campaigns alone are unlikely to be effective in increasing households' engagement with solar energy. Instead, policies that focus on combining the behavioral communication strategies with the interventions aimed to reduce structural and perceived barriers to adoption (easier access to financing and greater investment certainty) may lead to more effective outcomes.

A few limitations should be noted for this study. First, the primary outcome variable captures willingness to register for a free informational session rather than actual solar adoption behavior. Although signup decisions represent a meaningful low-commitment behavioral step, they may not translate into real investment decisions afterwards. Second, the experimental treatments rely on a one-time informational exposure which is delivered in an online survey setting, while in real world households make decisions by repeatedly exposing to information. Therefore, the estimated treatment effects may not fully capture how framing operates in actual adoption environments. Third, the informational treatments vary not only in framing emphasis but also in the presentations of financial information itself. Consequently, we cannot fully isolate pure framing effects from potential differences in information salience or perceived magnitude of benefits. Fourth, approximately 35% of respondents failed the comprehension check. This suggests that a large share of participants may not have fully understood the treatment information. As a result, we report results for both full-sample intention-to-treat specification and restricted sample of comprehension-passers. Furthermore, the stronger effects among those respondents who passed the comprehension check indicate that limited attention or understanding may attenuate estimated behavioral effects in the full sample. Fifth, we measure present bias using a simplified two-question intertemporal choice task rather than a full multiple price list (MPL) elicitation. Although this approach is consistent with simplified designs that are commonly used in survey research, it may underestimate the prevalence of present-biased preferences relative to studies which use richer elicitation methods. Sixth, although the survey includes respondents from different regions of Ukraine, the sample is not fully representative because some regions have just a few respondents, and high-income households are underrepresented. This limits the external validity and generalization of the findings to the broader population. Finally, the study is not sufficiently powered to detect small interaction effects.

With a given sample size of 213 respondents and the relatively small proportion of present-biased individuals (18%), the effective subgroup sizes in the interaction analysis are limited. The post-hoc power analysis suggests that the design is capable of reliably detecting only relatively large treatment effects.

Therefore, future research should rely on larger and more representative samples to improve statistical power and external validity. Given the current study's minimum detectable effect of approximately 23 percentage points with a sample of 213 respondents, detecting smaller but policy-relevant effects on the order of 10 percentage points would likely require a sample closer to 1,800-2,000 respondents under a similar experimental design. It would also be beneficial to focus on actual behavioral outcomes such as detecting whether individuals proceed with solar panel installation, request consultation, or engage with financing programs. In addition, future studies could employ more detailed and robust elicitation techniques for measuring time preferences, such as MPL tasks or incentivized choices, to obtain more precise measures of present bias. Finally, future research may also explore other behavioral frictions that may affect individuals' decisions – including risk aversion, loss aversion, trust in institutions – which could play an even more important role than present bias in shaping solar adoption decisions.

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Appendix A. Survey Experiment Design

Dear Respondent,
We are conducting a short survey about **household energy decisions** in Ukraine.
The survey takes about **10-15 minutes**.
Your answers are **anonymous** and will be used for academic research only.
Thank you for your time.

Section 1. General information.

Q1.1. What is your age?

If the age < 18, end survey

Q1.2. Do you currently live in Ukraine?

- Yes
- No *(if no, end survey)*

Q1.3. What type of home do you live in?

- Detached house
- Semi-detached or townhouse
- Apartment in multi-unit building

Q1.4. Who makes decisions about major home improvements in your household (e.g., heating systems, renovations)?

- I make these decisions alone
- I make these decisions together with others
- Someone else makes these decisions (*end survey*)

Section 2. Demographics.

Q2.1. What is your gender?

- Female
- Male

- Other / Prefer not to say

Q2.2. What is your highest completed education?

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

Q2.3. What is your monthly household income after taxes?

- < 12,000
- 12,000-24,999
- 25,000-39,999
- 40,000-59,999
- 60,000-89,999
- 90,000+
- Prefer not to say

Q2.4. Which of the following best describes your household's current financial situation?

- We cannot afford enough food and basic necessities
- We can afford food and basic necessities, but not clothing and shoes when needed
- We can afford food and clothing, but not small appliances (e.g., phone, microwave)
- We can afford small appliances, but not large purchases (e.g., furniture, TV)
- We can afford large purchases, but not very expensive items (e.g., car, major renovation)
- We can afford very expensive items if needed

Q2.5. What is your region of residence?

- West / Center / East / South / Kyiv City

Q2.6. Do you own your dwelling?

- Own
- Rent
- Live with family / other arrangement

Section 3. Baseline energy attitudes.

Q3.1. What are your average monthly electricity expenses?

- 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 concerned are you about electricity outages?

- Not at all (1) … Very concerned (5)

Q3.3. How familiar are you with rooftop solar systems for homes?

- Not at all (1) … Very familiar (5)

Q3.4. 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 → *[end survey]*

Q3.5. How interested are you in installing solar panels at your home?

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

Q3.6. Do you personally know anyone who has installed solar panels?

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

Q3.7. How many years do you think it takes for solar panel savings to cover the installation cost?

Slider (bounded but continuous)

| *How many years to pay back?* |----●----------| 0 - 30

Q3.7.1. How confident are you in this estimate?

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

Q3.8. How much do you think it costs to install a typical rooftop solar system?

[Slider: 50,000 - 400,000 UAH]
|----●----------|

Q3.8.1. How confident are you in this estimate?

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

Q3.9. How much do you think a household could save per month with solar panels?
Slider (bounded but continuous)

|----●----------| 0 - 5000 UAH

Q3.9.1. How confident are you in this estimate?

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

Q3.10. How risky do you think it is to invest in solar panels in Ukraine right now?

- Not at all risky (1) … Very risky (5)

Section 4. Attention check.

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

What is your favorite color?

- Blue
- Green
- Red
- Yellow
- Other

Section 5. Time preferences, risk assessment, and present bias module.

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

Q5.1. 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)

Q5.2. 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)

Q5.3. 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

Q5.4. Which option would you choose?

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

Q5.5. Which option would you choose?

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

Section 6. Information scenario (randomized).

Section 6A. Control (Neutral).

Please read some interesting information about solar panels below.

What are residential solar panels?
Solar photovoltaic (PV) systems convert sunlight into electricity for household use. For houses, panels are typically installed on the roof, and most residential systems range from 5 to 10 kW. For apartments, smaller balcony solar systems (300-800W)

can be mounted on balconies and connected directly to the home's electrical system. Both types generate power during hours when there is daylight.

Why should you consider solar energy?
Solar panels can give you a degree of energy independence. This is particularly relevant in today's Ukrainian context, where we have constant blackouts and grid instability. Solar panels reduce reliance on the centralized grid during daylight hours. If you have excess electricity, you can easily store it in batteries or, if this is an option, sell it back to the grid under net metering arrangements.

How do installation and maintenance look?
To install solar panels, you typically should wait for about 1-3 days if this is a residential rooftop system. If you want to install balcony systems, they are simpler and can often be self-installed. Afterwards, solar panels require minimal maintenance. In particular, you should occasionally clean them and periodically check the inverter.

What are the costs and savings?
You should pay an upfront installation cost to install a typical solar system, and it will help you reduce electricity bills later. The average expected lifespan of a solar PV system is about 25 years or more. Your costs and savings may vary because they depend on different characteristics such as system size, household consumption, and local conditions. You can reach certified installers for more information.

Comprehension Questions:

Q6A.1. Based on the text you've read, what is the typical capacity of residential rooftop systems?
a) 300-800 W
b) 1 to 3 kW
c) 5 to 10 kW ✓
d) 15 to 20 kW

Q6A.2. Based on the text you've read, note one reason why solar panels are highly relevant in Ukraine nowadays.
a) Ukraine has more sunshine than other European countries

b) There are subsidies for installation offered by the government
c) In war conditions, there are constant blackouts and grid instability ✓
d) Prices for natural gas are rising

Q6A.3. Based on the text you've read, how long should you wait for installation of a typical rooftop system?
a) A few hours
b) 1-3 days ✓
c) 1-2 weeks
d) About a month

Q6A.4. Based on the text you've read, how should you maintain the solar panels?
a) Monthly professional inspections are required
b) I must replace panels every 5 years
c) Regular battery replacement is mandatory
d) It's enough to occasionally clean them and periodically check the inverter ✓

Q6A.5. Based on the text you've read, what factors should you consider to calculate the costs and savings of solar panel installation?
a) Only the brand of solar panels matters
b) System size, household consumption, and local conditions should be considered simultaneously ✓
c) The colour of the roof is important
d) The season when I will install solar panels

Then, we move to the outcome section.

Section 6B. Immediate Benefits Frame (Treatment 1)

Please read some interesting information about solar panels below.

What are residential solar panels?
Solar photovoltaic (PV) systems convert sunlight into electricity for household use. For houses, panels are typically installed on the roof, and most residential systems range from 5 to 10 kW. For apartments, smaller balcony solar systems (300-800W)

can be mounted on balconies and connected directly to the home's electrical system. Both types generate power during hours when there is daylight.

Why should you consider solar energy?
Solar panels can give you a degree of energy independence. This is particularly relevant in today's Ukrainian context, where we have constant blackouts and grid instability. Solar panels reduce reliance on the centralized grid during daylight hours. If you have excess electricity, you can easily store it in batteries or, if this is an option, sell it back to the grid under net metering arrangements.

How do installation and maintenance look?
To install solar panels, you typically should wait for about 1-3 days if this is a residential rooftop system. If you want to install balcony systems, they are simpler and can often be self-installed. Afterwards, solar panels require minimal maintenance. In particular, you should occasionally clean them and periodically check the inverter.

What are the costs and savings?
You should pay an upfront installation cost to install a typical solar system, and it will help you reduce electricity bills later. The average expected lifespan of a solar PV system is about 25 years or more. What is important, your electricity bills will decrease by approximately 1,000-2,000 UAH/month from the very first month after installation (amount depends on the consumption of your household and the installed solar system size).

Comprehension Questions:

Q6B.1. Based on the text you've read, what is the typical capacity of residential rooftop systems?
a) 300-800 W
b) 1 to 3 kW
c) 5 to 10 kW ✓
d) 15 to 20 kW

Q6B.2. Based on the text you've read, note one reason why solar panels are highly relevant in Ukraine nowadays.
a) Ukraine has more sunshine than other European countries

b) There are subsidies for installation offered by the government
c) In war conditions, there are constant blackouts and grid instability ✓
d) Prices for natural gas are rising

Q6B.3. Based on the text you've read, how long should you wait for installation of a typical rooftop system?
a) A few hours
b) 1-3 days ✓
c) 1-2 weeks
d) About a month

Q6B.4. Based on the text you've read, how should you maintain the solar panels?
a) Monthly professional inspections are required
b) I must replace panels every 5 years
c) Regular battery replacement is mandatory
d) It's enough to occasionally clean them and periodically check the inverter ✓

Q6B.5. Based on the text you've read, by how much may your monthly electricity bills decrease?
a) 500-1,000 UAH/month
b) 1,000-2,000 UAH/month ✓
c) 2,000-4,000 UAH/month
d) 5,000-10,000 UAH/month

Then, we move to the outcome section.

Section 6C. Long-term Benefits Frame (Treatment 2).

Please read some interesting information about solar panels below.

What are residential solar panels?
Solar photovoltaic (PV) systems convert sunlight into electricity for household use. For houses, panels are typically installed on the roof, and most residential systems range from 5 to 10 kW. For apartments, smaller balcony solar systems (300-800W) can be mounted on balconies and connected directly to the home's electrical system. Both types generate power during hours when there is daylight.

Why should you consider solar energy?

Solar panels can give you a degree of energy independence. This is particularly relevant in today's Ukrainian context, where we have constant blackouts and grid instability. Solar panels reduce reliance on the centralized grid during daylight hours. If you have excess electricity, you can easily store it in batteries or, if this is an option, sell it back to the grid under net metering arrangements.

How do installation and maintenance look?

To install solar panels, you typically should wait for about 1-3 days if this is a residential rooftop system. If you want to install balcony systems, they are simpler and can often be self-installed. Afterwards, solar panels require minimal maintenance. In particular, you should occasionally clean them and periodically check the inverter.

What are the costs and savings?

You should pay an upfront installation cost to install a typical solar system, and it will help you reduce electricity bills later. The average expected lifespan of a solar PV system is about 25 years or more. What is important, over this expected 25-year lifespan, you can save from 300,000 to 600,000 UAH on your electricity bills (amount depends on the consumption of your household and the size of the installed solar system).

Comprehension Questions:

Q6C.1. Based on the text you've read, what is the typical capacity of residential rooftop systems?

a) 300-800 W

b) 1 to 3 kW

c) 5 to 10 kW ✓

d) 15 to 20 kW

Q6C.2. Based on the text you've read, note one reason why solar panels are highly relevant in Ukraine nowadays.

a) Ukraine has more sunshine than other European countries

b) There are subsidies for installation offered by the government

c) In war conditions, there are constant blackouts and grid instability ✓
d) Prices for natural gas are rising

Q6C.3. Based on the text you've read, how long should you wait for installation of a typical rooftop system?
a) A few hours
b) 1-3 days ✓
c) 1-2 weeks
d) About a month

Q6C.4. Based on the text you've read, how should you maintain the solar panels?
a) Monthly professional inspections are required
b) I must replace panels every 5 years
c) Regular battery replacement is mandatory
d) It's enough to occasionally clean them and periodically check the inverter ✓

Q6C.5. Based on the text you've read, how much will you save on the electricity bills over the solar system's lifespan?
a) 50,000-150,000 UAH
b) 150,000-300,000 UAH
c) 300,000-600,000 UAH ✓
d) 600,000-1,000,000 UAH

Section 7. Outcome.

Q7.1. Would you like to register for a free online consultation about how to install solar panels in your home?

- Yes → Q7.2
- No → Q7.3

Q7.2. Please provide your email or phone number: _____

Q7.3. How interested are you in installing solar panels at your home?

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

Q7.4. 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

Q7.5. How affordable do you think solar panels are for a typical Ukrainian household?

1 ○—○—○—○—○ 5 *(Not at all affordable — Very affordable)*

Q7.6. How worthwhile do you think installing solar panels would be as a long-term investment?

1 ○—○—○—○—○ 5 *(Not at all worthwhile — Very worthwhile)*

Q7.7. How risky do you think it is to invest in solar panels in Ukraine right now?

1 ○—○—○—○—○ 5 *(Not at all risky — Very risky)*

Section 8. Credibility and feedback.

Q8.1. How credible do you find the information provided about solar panels?

1 ○—○—○—○—○ 5
(1 = Not at all credible, 5 = Very credible)

Q8.2. Do you have any comments or feedback about this survey?

[Open text box]

Thank you for taking the time to complete this survey and for contributing to this academic study. Your participation is greatly appreciated and helps advance research on household energy decisions in Ukraine.

Appendix B. Probit and Logit Model Specifications

Since our main specification has a binary primary outcome variable, we additionally estimate logit and probit models as robustness checks to the linear probability model.

For both models, we use the following equation, which employs the same independent variables as in the main LPM specification:

$$Y_i = F(\alpha + \beta_1 * Current_i + \beta_2 * Delayed_i + \\ + \gamma * PresentBias_i + \delta_1 * (Current_i * PresentBias_i) + \\ + \delta_2 * (Delayed_i * PresentBias_i) + X_i * \theta), \quad \text{(B.1)}$$

where $F = \Lambda(\dots)$ showing the logistic CDF for the logit model and $F = \Phi(\dots)$ showing the normal CDF for the probit model.

Here, we have the following observed outcome:

$$SignUp_i = \begin{cases} 1 \; if \; Y_1 > 0 \\ 0 \; if \; Y_1 \leq 0 \end{cases} \quad \text{(B.2)}$$

We estimate parameters via maximum likelihood and report the average marginal effects (AMEs) to improve interpretability of the results.

Appendix C. Results of the Probit and Logit Models Estimation

Table 6. Average marginal effects from logit model

	AME	SE	p
Immediate benefits	0.003	0.072	0.971
Delayed benefits	-0.009	0.075	0.906
Present-biased	-0.111	0.131	0.395
Immediate x Present-biased	0.186	0.177	0.293
Delayed x Present-biased	0.066	0.177	0.710
Age	0.001	0.003	0.747
Female	0.053	0.057	0.354
Sole-decision-maker	0.079	0.057	0.166
Bachelor's or higher	-0.068	0.059	0.253
Income > 40,000 UAH	0.061	0.080	0.444
Own dwelling	0.056	0.062	0.373
Detached house	0.031	0.056	0.585
Prior interest in solar energy	**0.086*** **	**0.027**	**0.001**
Knowledge about solar energy	**0.042***	**0.025**	**0.092**
Risk attitude	**-0.067*** **	**0.025**	**0.007**
Anxiety about outages	0.032	0.027	0.235
Comprehension failure	-0.045	0.058	0.444

Note: N=213. The table reports average marginal effects (AMEs) with standard errors. *p<0.1; **p<0.05; ***p<0.01

Table 7. Average marginal effects from probit model

	AME	SE	p
Immediate benefits	0.003	0.072	0.971
Delayed benefits	-0.001	0.075	0.906
Present-biased	-0.111	0.131	0.395
Immediate x Present-biased	0.186	0.177	0.293
Delayed x Present-biased	0.066	0.177	0.710
Age	0.001	0.003	0.668
Female	0.052	0.057	0.354
Sole-decision-maker	0.079	0.057	0.166
Bachelor's or higher	-0.068	0.059	0.253
Income > 40,000 UAH	0.061	0.080	0.444
Own dwelling	0.056	0.062	0.373
Detached house	0.031	0.056	0.585
Prior interest in solar energy	**0.086*** **	**0.027**	**0.001**
Knowledge about solar energy	**0.042***	**0.025**	**0.092**
Risk attitude	**-0.067*** **	**0.025**	**0.007**
Anxiety about outages	0.032	0.027	0.228
Comprehension failure	-0.045	0.058	0.444

Note: N=213. The table reports average marginal effects (AMEs) with standard errors. *p<0.1; **p<0.05; ***p<0.01

Appendix D. Results of The Linear Regression on the Secondary Outcome Variable (Interest)

Table 8. Estimation results on secondary outcome variable (interest)

	Interest in solar
Immediate benefits	-0.015
	(0.161)
Delayed benefits	-0.061
	(0.174)
Present-biased	-0.252
	(0.243)
Immediate x Present-biased	-0.206
	(0.377)
Delayed x Present-biased	**0.521***
	(0.312)
Age	**0.012***
	(0.006)
Female	-0.042
	(0.129)
Sole-decision-maker	-0.065
	(0.149)
Bachelor's or higher	-0.135
	(0.121)
Income > 40,000 UAH	0.220
	(0.158)
Own dwelling	-0.066
	(0.131)
Detached house	0.190
	(0.129)
Prior interest in solar energy	**0.478*** **
	(0.068)
Knowledge about solar energy	0.106
	(0.067)
Risk attitude	**-0.139****
	(0.057)
Anxiety about outages	0.075
	(0.066)
Comprehension failure	-0.026
	(0.140)
Constant	1.241***
	(0.475)
Observations	213
R2	0.455
Adjusted R2	0.407

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix E. Results of the Heterogeneity Analysis

Table 9. Heterogeneity analysis by subgroup

	Age 45+	Bachelor+	Sole decision-maker
Immediate benefits	-0.006	-0.059	-0.009
	(0.089)	(0.110)	(0.083)
Delayed benefits	0.158	-0.076	0.034
	(0.109)	(0.111)	(0.089)
Age 45+	0.141		
	(0.153)		
Immediate x Age 45+	0.057		
	(0.144)		
Delayed x Age 45+	**-0.278***		
	(0.148)		
Bachelor+		-0.122	
		(0.106)	
Immediate x Bachelor+		0.131	
		(0.146)	
Delayed x Bachelor+		0.156	
		(0.150)	
Sole decision-maker			0.099
			(0.120)
Immediate x Sole decision-			0.043
maker			(0.163)
Delayed x Sole decision-maker			-0.085
			(0.164)

Note: N=213. The dependent variable is signup. Standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

Appendix F. Results of Heteroskedasticity and Multicollinearity Tests for the Main Specification (full sample)

Table 10. Heteroskedasticity test results

	Statistic	df	p-value
Breusch-Pagan test	9.83	13	0.708

As we can observe from the table above, we cannot reject the null hypothesis of homoskedasticity. Therefore, no heteroskedasticity is found.

Table 11. Variance Inflation Factors (VIF) test results

	VIF
Immediate benefits	1.67
Delayed benefits	1.78
Present-biased	2.88
Immediate x Present-biased	1.99
Delayed x Present-biased	2.37
Age	1.13
Female	1.08
Sole-decision-maker	1.12
Bachelor's or higher	1.18
Income > 40,000 UAH	1.17
Own dwelling	1.04
Detached house	1.12
Comprehension failure	1.06

Since all VIF values are below 5, there is no multicollinearity issue indicated.