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ARTICLE

Behavioral preferences and contract choice in the residential solar PV market

Christine L. Crago[1] | Rong Rong[2]

[1]Department of Resource Economics and Commonwealth Honors College, University of Massachusetts Amherst, Amherst, Massachusetts, USA

[2]Department of Resource Economics, University of Massachusetts Amherst, Amherst, Massachusetts, USA

Correspondence
Rong Rong, Department of Resource Economics, University of Massachusetts Amherst, Amherst, MA, USA.
Email: rrong@umass.edu

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Abstract

Greater adoption of renewable energy technologies by households is a key component of decarbonization and energy transition goals. Although existing literature has examined how sociodemographic characteristics, "green" preferences, and peer effects impact adoption of new energy technology, the role of behavioral preferences has not been adequately studied. In this paper, we examine the effect of two types of behavioral preferences, namely the degree of risk tolerance (risk preference) and attitude toward delayed reward (time preference) on the contract decision to lease or own a solar photovoltaic (PV) system. We develop a theoretical framework to show that the effect of risk and time preferences on the relative utilities from the two contracts is monotonic: Lower risk aversion and lower discount rate (more patience) imply a higher chance of solar PV ownership. To test these predictions empirically, we first estimate preference parameters (risk aversion and discount rate) from laboratory data collected from solar PV adopters. We then combine the parameter estimates with data on actual solar PV contract choice to examine the relationship between solar PV adopters' time and risk preferences and their lease-versus-own choice. Our regression results confirm that less risk averse individuals have a higher tendency to choose the ownership option, whereas more patient individuals are (weakly) more likely to own their solar PV systems. These findings contribute to a greater understanding of the role of behavioral factors in household decisions related to energy technologies.

KEYWORDS

energy technology adoption, lease-versus-own, risk preferences, solar PV, time preferences

JEL CLASSIFICATION
C91, Q42

1 | INTRODUCTION

Many national and regional economies around the world are undergoing energy transition, replacing fossil fuel energy sources with clean and renewable energy sources like wind and solar. The U.S. Energy Information Agency estimates that by 2050, 42% of electricity will be sourced from renewable energy sources, which primarily will be wind and solar (Nalley & LaRose, 2021). The drivers behind this transition are myriad, including concerns about climate change, health, and environmental impacts of fossil-based energy, falling costs, and geopolitics. One distinguishing characteristic of renewable energy sources is that electricity production is more decentralized, compared to conventional coal or gas-fired power plants. In particular, for solar power, a significant share of electricity will be produced from rooftop solar photovoltaic (PV) installations, which include residential systems. The shift from centralized generation to a more distributed energy generation (and storage) structure puts electricity production under the direct control of households. In this new energy landscape, household-level decisions regarding the adoption and use of solar energy will have far-reaching impacts on the broader energy market. For this reason, it is increasingly important to understand the factors affecting household decisions in the solar PV market.

Earlier literature has examined many observable household characteristics, such as income, education, and pro-environment preference, and found that they are correlated with households' choices in the energy domain (De Groote et al., 2016; Jacksohn et al., 2019; Schelly & Letzelter, 2020). Unobservable yet crucially important factors, such as behavioral preferences and decision anomalies, have not been adequately studied. The importance of including these "unobservables" in explaining real-world decision making is demonstrated by a large and growing behavioral economics literature under a variety of domains, including the labor market, health, and personal finance (Anderson & Mellor, 2008; Elston et al., 2005; Lusk & Coble, 2005). In this study, we aim to capture behavioral preference parameters using state-of-the-art experiments and structural estimation techniques. We then use these parameters to explain household contract choices in the solar PV market. In particular, we examine two types of behavioral preferences, namely the degree of risk tolerance (risk preference measured by risk aversion) and attitude toward delayed reward (time preference measured by the discount rate). Using these two preference measures, we aim to explain contract choice in the solar PV market, which can be broadly categorized into either a leasing contract or an ownership contract (hereafter, "lease-versus-own" contract).

We focus our attention on risk and time preferences, as they are the most relevant decision parameters that distinguish a solar ownership contract from a solar leasing contract. To own the solar PV outright, one must pay a high upfront installation cost. The ownership option, therefore, requires the decision maker to be patient, which is a strong willingness to trade off short-term losses with long-term gains. Solar PV owners also face a more volatile stream of financial returns, which suggests that owners may be a select group of individuals who have higher risk tolerance. In contrast to ownership, leasing solar panels involves little upfront cost and delivers predictable benefits over time. Hence, it is not necessary for someone to possess the same high level of risk tolerance and patience to become a solar lessee.

In addition to the implications of the lease-versus-own decision on individual household welfare, this choice has important implications for policies that support renewable energy. For example, when households choose ownership, more of the financial benefits accrue to the local economy. This is because ownership of solar panels typically results in the hiring of local installers and local sourcing of equipment compared to leasing solar panels from a third-party owner, which tends to operate nationally and sources materials from outside the state. Moreover, the tax credit for solar installation is given to the owner of the panels. If a household owns its panels, the financial benefit of the tax credit is more likely to go to the local economy (MA-DOER, 2013). Knowing whether the choice to own is correlated with behavioral and demographic factors can help policymakers design better policies to localize the benefits of solar adoption.

We formally model the above-mentioned tradeoffs between leasing and owning using a framework that involves both firm and consumer optimization. We assume firms who offer both leasing and owning contracts to be risk neutral and discount with ongoing market interest rate. We establish that there is an equilibrium leasing fee that equalizes the firm's profit from the two contracts. We then specify the household's utility function from owning and leasing based on the equilibrium leasing fee. Our model allows households to have flexible utility functions under various behavioral assumptions: Households may have heterogeneous risk parameters and a discount rate that differs from the market interest rate. We obtain analytical expressions to show that the effect of risk and time preferences on the relative utilities from the two options is monotonic. Lower risk aversion implies a higher chance of choosing ownership. Similarly, a lower discount rate (more patient individual) implies a higher chance of ownership. To our knowledge, our model constitutes the first attempt to formally model household contract choice in the solar PV market.

To properly test the model's predictions, it is crucial to obtain accurate measures of owners' and lessees' risk and time preferences. We obtain these measures by applying state-of-the-art experimental design to elicit these preferences using a sample of solar adopters from the state of Massachusetts.[1] In particular, we implement an "incentive-compatible" experimental design with subjects recruited from actual solar PV adopters. Incentive compatibility ensures that the choices subjects make in the laboratory reflect their actual risk and time preferences in both theoretical and empirical contexts. The carefully designed laboratory tasks also involve repeated decisions from each subject in two types of decision environments, one involving risky lotteries and the other delayed rewards. With multiple decisions collected from each subject, it is possible to infer risk and time preferences for each individual using both nonparametric count data and structurally estimated utility parameters under a variety of parametric utility assumptions (e.g., expected utility and rank dependent utility). Additionally, our experimental design allows joint estimation of the risk and time preference parameters, which is key to avoiding upward bias of the discount rate when risk neutrality is imposed on risk averse individuals (Andersen et al., 2008; Andreoni & Sprenger, 2012).

Combining robust laboratory inferences with data on actual contract choice of households, we empirically examine the relationship between solar adopters' time and risk preferences, and their lease-vs-own decision. We find that solar lessees are on average more risk averse than solar owners. The difference in the risk parameter between owners and lessees is statistically significant. Our result can be interpreted as evidence of risk preference playing a role in solar contract choice; More risk-averse individuals favor the less risky solar leasing contract. Our results on the effect of an individual's time preference on their lease-versus-own decision are a bit mixed. In the nonparametric analysis, patient individuals who chose larger later payment options have a higher tendency to own their panels. This result is significant and robust across multiple specifications with or without controls. The parametric analysis, however, does not yield similar statistical significance. That is, we find that individuals with lower discount rates (those who are more patient) are no more likely to own their solar PV systems.

There are some studies that have linked risk and time preferences with household decisions in energy and environmental settings (Qiu et al., 2014; Qiu et al., 2017; Schleich et al., 2019). These studies are primarily empirical. We add to the literature by providing a theoretical decision model in the context of renewable energy adoption. Moreover, our empirical strategy largely differs from the above-mentioned literature. Schleich et al. (2019) obtain their the preference parameters by numerically solving for them in an equation system. This approach limits the number of parameters to be solved, which in turn imposes a strict assumption on the utility functional form. Qiu et al. (2014,

[1]In 2022, Massachusetts ranked eighth in the nation for net generation from solar energy (U.S. Energy Information Administration, 2023).

2017) infer the range of parameters from raw data and assign the midpoint value. Their inference, therefore, is less precise and not applicable for decisions that involve multiple switching.[2] To improve upon these limitations, we apply maximum likelihood structural estimations to obtain preference parameters. In particular, we jointly estimate the optimal value for a large set of parameters to maximize the chance of observing a particular pattern of choices from each individual. The main advantage of adopting such an approach is that it (1) allows for a variety of flexible utility assumptions to establish robust inferences, (2) accounts for multiple switching by modeling decision noise, and (3) can avoid biasing the time preference parameter by jointly estimating it with the risk preference parameter.

Our work is related to research that examines household lease-versus-own decision in the solar PV market. Existing studies primarily focus on nonbehavioral factors, such as demographic differences (Drury et al., 2011; Rai & Sigrin, 2013), information search (Pless et al., 2020), and cashflow constraints (Rai & Sigrin, 2013). Although our focus is on behavioral factors, we take nonbehavioral factors into account by including them in our regressions as control variables.

We also contribute to the experimental economics literature that link the behavioral preferences to decision making. Although previous literature has demonstrated the linkage between risk and time preferences, and individual choices in various domains (e.g., agricultural technology [Liu, 2013], financial decisions [Belzil & Sidibé, 2016], and health [Anderson & Mellor, 2008]), our study provides a novel example where risk and time preferences play an important role in determining households' long-term environmental and energy choices.

Finally, we contribute to the growing literature on the adoption of green energy technologies by bringing attention to important and understudied behavioral factors. Previous studies have identified the importance of policy incentives (Crago & Chernyakhovskiy, 2017; Hughes & Podolefsky, 2015), peer effects (Bollinger & Gillingham, 2012), uncertainty (Bauner & Crago, 2015), and pro-environmental preferences (Dastrup et al., 2012) in the decision to adopt solar panels. Our study is the first to examine the role of risk and time preferences in the context of solar PV adoption. Moreover, we are the first to develop a theoretical framework for solar adopters' lease versus own decisions and to derive testable hypotheses. We test our theoretical predictions using a novel experimental approach with data collected from real-world solar adopters.

2 | BACKGROUND ON CONTRACT CHOICE FOR RESIDENTIAL SOLAR PV

Owning and leasing are two contract types available to households who want to install solar PV systems on their residential properties. These two contracts have significantly different features. Owning entails paying for the solar PV system upfront and being responsible for operation and maintenance costs throughout the approximately 25-year lifespan of the solar PV system. Solar PV owners are eligible for rebates and tax incentives offered by state and federal governments. In states where they are available, owners also receive solar renewable energy certificates (SRECs) generated by the PV system and can sell those in the SREC marketplace.[3] Finally, owners also have complete control of their equipment and do not face constraints of checking with the third-party owner (TPO) of their solar PV system when they need to make modifications to the panels or conduct home maintenance that may affect solar panels.

[2]The experiments in Qiu et al. (2014, 2017) are applications of the design in Holt and Laury (2002) in which rational utility maximizers are assumed to only switch once from the low risk lottery to the high risk lottery as the expected return monotonically increases for the latter. If subjects switch back and forth, one cannot infer their range of risk aversion using the switching point. This limitation similarly applies to time preference experiments that rely on a single switch point.

[3]The state of MA had an SREC program until 2018. All participants in our study installed solar PV systems in years when the SREC program was active. The SREC program (also called solar "carve out") allows owners of solar PV systems to obtain a credit for every 1 MWh of solar electricity produced for 10 years. This credit can then be sold in the SREC market where the price is determined by supply and demand for SRECs. SREC holders can also sell their SRECs at the state managed Solar Credit Clearinghouse Auction (SCCA) at a predetermined price.

TABLE 1 Risks borne by solar PV owners and lessees.

Risk	Own	Lease
Underproduction of electricity from panels	×	×
Lower than expected electricity price	×	×
Lower than expected SREC price	×	
Equipment failure	×	

Leasing arrangements fall into two categories: paying a monthly fee to rent the solar panels and equipment (equipment lease option) or entering into a power purchase agreement (PPA) with a third-party-owner (PPA option). With both leasing options, there is little to no upfront cost. The TPO installs the system and is responsible for any maintenance issues that come up over the lifetime of the solar PV system. Lessees are not eligible to receive rebates, tax credits, and SRECs, which go to the TPO.[4] Lessees also have to coordinate with the TPO of their solar PV system for any home maintenance that will impact the panels.

Adopting a new technology involves some risk, and solar PV technology adopters (both owners and lessees) accept risk in varying degrees when they decide to adopt solar PV technology. Table 1 shows the different risks borne by solar PV owners and lessees. All solar PV households bear the risk of lower electricity prices. If electricity prices are lower than expected, the savings from having solar-generated electricity becomes smaller. Owners and lessees also bear the risk of lower than expected electricity production of the solar panels—say due to a long gray winter.[5]

There are also risks that are unique to the ownership option. These include the risk of equipment failure and damage, and lower than expected SREC prices. The risk of equipment failure is statistically low (UMass CFARE, 2020).[6] The volatility of SREC prices is another risk to which owners are uniquely subject. Figure 1 shows considerable variation in SREC prices, especially in the early part of the program. This early time period is important for the study, as SREC trends in these early years may have formed the basis of solar adopters' beliefs about the risks associated with SREC prices. SREC revenue accounted for 57%–95% of the net present value (NPV) of financial return from solar PV investment in the years 2014 to 2018, which is when our subjects installed their solar PV systems.[7] Due to the variability in future SREC prices, owners of solar PV systems incur the risk of facing lower than expected SREC prices, which could decrease the value of their solar investment.

In terms of financial returns from owning or leasing, owning yields greater financial benefits based on net present value calculations alone. Based on data from Massachusetts, the NPV of a 7 kWC system installed in 2019 is about $22,000 if the system is owned, and $6000 if the system is leased (Crago et al., 2023). NPV calculations assume that the decision maker is risk neutral and discounts using the ongoing market rate. However, these two assumptions rarely hold (Elston et al., 2005; Frederick et al., 2002). Hence, we investigate the role of risk and time preferences in this particular contract choice. Of course, there may be reasons other than financial gain that motivate households to lease rather than own. Households may be motivated to adopt solar panels for other nonfinancial reasons such as the desire to help the environment as well as to obtain a "warm glow" for contributing to the public good (Dastrup et al., 2012; Sexton & Sexton, 2014; Sun et al., 2020). In our empirical analysis, we control for these nonfinancial motivators.

[4]Lessees may indirectly benefit from these policies to the extent that TPOs pass some of those benefits to households in the form of lower lease payments.

[5]Lessees under a PPA option do not face the risk of lower electricity prices as they are only obligated to buy the electricity that is produced by the solar panels.

[6]Solar panel equipment typically carries a warranty on the panels' level of electricity production for 20–25 years on average. In addition, solar panels can be covered under a home insurance policy.

[7]Source: Authors' calculations based on data from MA in years 2014–2018.

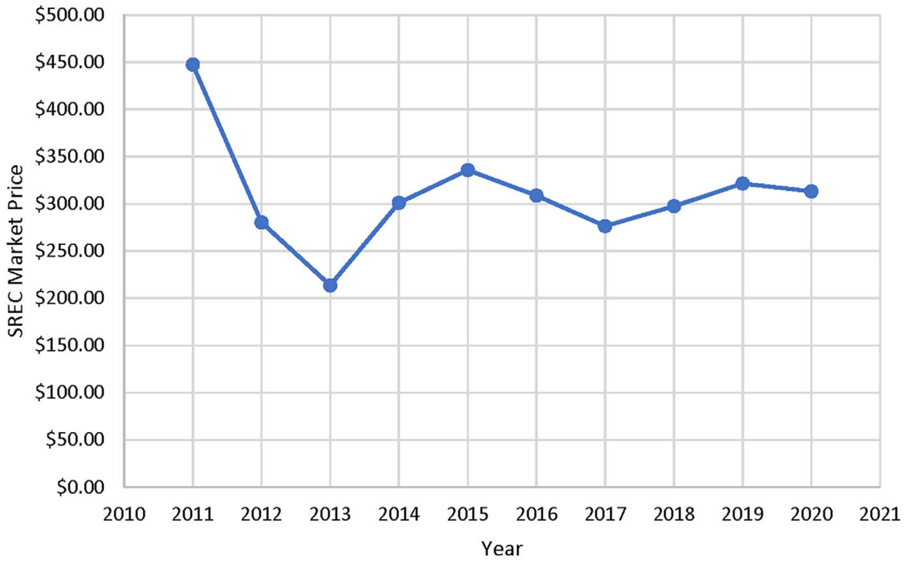

FIGURE 1 Average annual solar renewable energy certificate (SREC) market prices in Massachusetts. Data Source: SRECTrade.com.

3 | THEORETICAL FRAMEWORK

In this section, we model the tradeoffs between leasing and owning using a framework that involves both firm and consumer optimization. In Section 3.1, we establish the equilibrium leasing fee assuming that firms are risk neutral and discount with the ongoing market interest rate. Based on the equilibrium leasing fee, we then specify the household's utility function from owning and leasing in Section 3.2. We obtain analytical expressions to show that the effect of time and risk preferences on the relative utilities of owning and leasing is monotonic in Sections 3.3 and 3.4.

3.1 | Firm behavior

Assume a representative firm that offers contracts to provide solar PV systems to consumers. The firm is risk neutral and uses the market interest rate in calculating the value of future payoffs. The firm supplies solar PV systems based on the profit maximizing condition that its marginal cost to install a complete solar PV system is equal to I, the price of a solar PV system.[8] In addition to selling complete systems to consumers, the firm also offers leasing contracts. Under a leasing contract, the firm retains ownership of the system and collects applicable incentives, including rebates and SRECs. The lessee pays a leasing fee to the firm specified in the leasing contract.[9] As shown in Equation (1), the firm prices the leasing option such that its revenue from selling a complete solar system is the same as its revenue from offering a lease contract.[10]

[8]This is inclusive of all hardware, equipment, fees, and labor.

[9]Some lessees only pay for electricity produced by solar panels under a power purchase agreement (PPA). The standard leasing model can be modeled equivalent to a PPA because the electricity rate discount under a PPA can be set to yield revenue equal to the firm's revenue under a standard leasing contract.

[10]We have assumed that the firm equalizes returns from leasing and selling complete solar PV systems to make the model tractable. This assumption implies that all rebate and SREC benefits are passed on to the consumer. If firms do not pass on rebate and SREC benefits to the consumer, the leasing rate will be higher and will result in the utility of ownership being greater than the utility of leasing even under risk neutrality and equal discount factors for the firm and consumer. Even in this case, our theoretical results still hold: Consumers having a greater degree of risk aversion and a lower discount factor relative to the firm leads to a decrease in the relative utility of ownership compared to leasing. In other words, more risk averse and less patient individuals will be less likely to own.

$$I = R + \sum_{t=1}^{N} \delta_f^t \left(L + E_f\left[p_t\right]\right) \tag{1}$$

The left hand side of Equation (1) is the firm's revenue from selling a solar PV system, whereas the right hand side is the firm's revenue from leasing the system to a customer.[11] In the case of direct sale to the customer, the firm receives I from the customer. In the case of leasing to the customer, the firm receives available upfront financial incentives or rebates (R) and a stream of payments consisting of the annual lease payment (L) and annual SREC revenues. $E_f\left[p_t\right]$ is the expected value of annual SREC revenues, which depends on the random variable p denoting SREC prices (the subscript f in E_f denotes expectations by the firm). SREC payments depend on the SREC price, the capacity of the solar PV system, and the electricity production of solar panels. Capacity and electricity production can be predicted with a fair amount of accuracy over N periods, whereas the SREC price is subject to market volatility arising from the market. Without loss of generality, we set capacity and electricity production to 1. We assume that the firm makes rational predictions about future SREC prices and payments based on available information at the time of installation. Annual lease payments and SREC revenues over N periods are discounted using the discount factor δ. Solving for the equilibrium leasing rate L^* yields:

$$L^* = \frac{\left(I - R - \sum_{t=1}^{N} \delta_f^t E_f\left[p_t\right]\right)}{\frac{1-\delta_f^{N+1}}{1-\delta_f} - 1}. \tag{2}$$

3.2 | Household behavior

Assume a representative consumer who chooses to install solar panels. The consumer may be risk neutral, risk averse, or risk seeking. The consumer has the choice to purchase the solar PV system outright from the firm or to enter into a leasing contract with the firm. The cost of purchasing a solar PV system outright (net of rebates) is $I - R$. The annualized value of this upfront cost over the lifetime of the solar panels is $\frac{I-R}{\frac{1-\delta_c^{N+1}}{1-\delta_c}-1}$.[12] The utility from owning (U_O) is given by:

$$U_O = u(w) + \sum_{t=1}^{N} \delta_c^t E_c\left[u\left(e_t - \left(\frac{I-R}{\frac{1-\delta_c^{N+1}}{1-\delta_c} - 1}\right) + p_t\right)\right] \tag{3}$$

The first term on the right-hand side of Equation (3) is the utility from background wealth w, whereas the second term is the present value of expected financial return from installing solar PV. The dollar value of annual energy savings from solar panels is denoted by e. The annualized cost of the solar PV system is given by $\left(\frac{I-R}{\frac{1-\delta_c^{N+1}}{1-\delta_c}-1}\right)$, and p_t represents annual SREC revenues that depend on the realizations of the random variable p representing SREC prices. As in Section 3.1, other determinants of SREC revenue, such as electricity production and system capacity, are set to 1. The

[11]The cost of providing an owned system and a leased system is the same, hence equating revenue is equivalent to equating profit.

[12]Note that the cost of purchasing with own capital and taking out a loan to purchase the solar PV system is equivalent, assuming that the present value of forgone interest from the capital investment is the same as the present value of interest paid to the lender. Equivalently, this implies that the interest rate of investments is equal to the loan interest rate.

consumer discounts future financial payoff using the discount factor δ_c. Similar to the firm, consumers make rational predictions about future SREC prices and payments based on available information at the time of installation. Realizations of p are subject to volatility. Thus u in the second term of Equation (3) is enclosed by the expectation operator E_c, where the subscript c denotes expectations by the consumer.

The utility from leasing (U_L) is given by:

$$U_L = u(w) + \sum_{t=1}^{N} \delta_c^t u(e_t - L^*) \tag{4}$$

Substituting the equilibrium leasing price L^* from Equation (2) yields:

$$U_L = u(w) + \sum_{t=1}^{N} \delta_c^t u \left(e_t - \frac{(I-R) - \sum_{t=1}^{N} \delta_f^t E_f[p_t]}{\frac{1-\delta_f^{N+1}}{1-\delta_f} - 1} \right) \tag{5}$$

Or equivalently,

$$U_L = u(w) + \sum_{t=1}^{N} \delta_c^t u \left(e_t - \left(\frac{I-R}{\frac{1-\delta_f^{N+1}}{1-\delta_f} - 1} \right) + \frac{\sum_{t=1}^{N} \delta_f^t E_f[p_t]}{\sum_{t=1}^{N} \delta_f^t} \right) \tag{6}$$

Similar to Equation (3), the first term on the right hand side of Equation (6) is the utility from background wealth w, whereas the second term is the present value of utility from the expected financial return from leasing a solar PV system. The leasing rate reflects the firm's financial cost of installing solar PV as well as its expected revenue from selling SRECs. Unlike in Equation (3) where utility depends on annual realizations of p, the utility from leasing is not subject to market volatility and depends on the firm's expected SREC revenues as reflected in the leasing rate.

Note that for every period, the last term in Equation (6) is just $E_f[p_t]$. Thus, the expressions for utility from owning and leasing for each period, $t=1$ to $t=N$, are:

$$U_{Ot} = u(w)_t + \delta_c^t E_c \left[u \left(e_t - \left(\frac{I-R}{\frac{1-\delta_c^{N+1}}{1-\delta_c} - 1} \right) + p_t \right) \right] \tag{7}$$

$$U_{Lt} = u(w)_t + \delta_c^t u \left(e_t - \left(\frac{I-R}{\frac{1-\delta_f^{N+1}}{1-\delta_f} - 1} \right) + E_f[p_t] \right) \tag{8}$$

Our model focuses on the risk associated with SREC price changes, which is the major source of risk in our setting. Risks borne by owners and the leasing company from unexpected costs due to repairs and maintenance are not explicitly modeled. However, if one views $E[p_t]$ as the net SREC revenue after accounting for unexpected costs due to repairs in maintenance, the model can capture these risks as well.

3.3 | Effect of risk preference on utility of owning and leasing

We are interested in examining the relative utility of owning versus leasing under different assumptions of consumer risk preference. To isolate the effect of risk preference from time discounting in comparing the utility of owning and leasing, we assume for the moment that the firm and consumer have the same discount factor, or $\delta_c = \delta_f = \delta$. To simplify our expressions, we express the annual financial flows as $A(p_t) = e_t - \left(\frac{I-R}{\frac{1-\delta_c^{N+1}}{1-\delta_c}-1}\right) + p_t$ in Equation (7) and $A(E[p_t]) = e_t - \left(\frac{I-R}{\frac{1-\delta_f^{N+1}}{1-\delta_f}-1}\right) + E_f[p_t]$ in Equation (8). We now have the following equations for each time period t:

$$U_{Ot} = u(w)_t + \delta E_c[u(A(p_t))] \tag{9}$$

$$U_{Lt} = u(w)_t + \delta u(A(E[p_t])) \tag{10}$$

Note that the degree of risk aversion determines the curvature of the utility function. Risk neutrality implies a linear utility function, whereas risk aversion (seeking) implies concave (convex) utility. Based on Equations (9) and (10), assuming that the consumer and firm have the same expectations about the realizations of SREC payments, the linear form of u implies that $U_{Ot} = U_{Lt}$ (and thus, $U_O = U_L$). In other words, risk neutral consumers will be indifferent toward owning or leasing. If the consumer is risk averse and the utility function is concave, Jensen's Inequality results in $E_c[u(A(p_t))] \leq u(A(E[p_t]))$. Consequently, $U_{Ot} < U_{Lt}$ ($U_O < U_L$) for risk averse consumers. This result implies that all else being equal, risk averse consumers will be more likely to choose the leasing option rather than ownership. If the consumer is risk seeking, the convexity of u leads to $E_c[u(A(p_t))] \geq u(A(E[p_t]))$ by Jensen's Inequality. Thus, $U_{Ot} > U_{Lt}$ ($U_O > U_L$) for risk seeking consumers, that is, absent other considerations for owning or leasing, risk seeking consumers will be more likely to choose ownership rather than leasing.

3.4 | Effect of time preference on utility of owning and leasing

To isolate the effect of time preference on the utility of owning and leasing, assume for now that consumers are risk neutral. Based on Equations (7) and (8), if the firm is more patient or has a higher discount factor than the consumer ($\delta_f > \delta_c$), the cost of installing solar panels net of rebates will be lower for the firm compared to the consumer $\left(\frac{I-R}{\frac{1-\delta_f^{N+1}}{1-\delta_f}-1}\right) < \left(\frac{I-R}{\frac{1-\delta_c^{N+1}}{1-\delta_c}-1}\right)$. This results in $U_{\mathrm{Ot}} < U_{\mathrm{Lt}}$ ($U_O < U_L$). The intuition is that with the cost of capital being lower for the firm, the firm will be able to offer a more favorable leasing rate to consumers. Conversely, if the consumer is more patient or has a higher discount factor than the firm ($\delta_f < \delta_c$), the firm's leasing rate will be less favorable and will lead to the utility of owning being greater than the utility of leasing. In sum, all else being equal, more patient consumers are more likely to choose the ownership option. Under the special case where the consumer is risk neutral like the firm, and the discount factor is the same for the consumer and the firm, consumers will be indifferent between the owning and leasing options.

4 | EXPERIMENT

4.1 | Design principles

Because the aim of our study is to examine the relationship between solar contract choice and individual preferences, it is critical to incorporate design principles that maximize our ability to precisely estimate these individual risk and time preferences. The first principle is to reduce choice complexity. Asking subjects to conduct complex calculations and produce numerical answers (of probabilities, payment amounts, time horizons, etc.) can be overwhelming. Participants may have diverse levels of educational attainment and ability to conduct numerical calculations. To make the choice transparent and easy to understand, we adopt a simple binary choice procedure to elicit risk and time preferences. That is, subjects are asked to select one preferred option out of two available options. To capture risk preferences, each option is a lottery where the prizes and probability of winning the prizes vary. To capture time preferences, each option is a payment amount to be delivered at a specific payment date. We specify the details of these options in Section 4.2 below.

The second principle is to relax the assumption of linear utility. Earlier experimental work on time preferences assumed that utility is linear (which can be interpreted as the risk neutrality assumption). Recent work by Andersen et al. (2008) and Andreoni and Sprenger (2012) established empirical evidence that imposing linear utility leads to largely overestimated discount rates, making patient and risk-averse subjects appear to be impatient and risk neutral. With one set of decisions on risk and the other on time, we can adopt the approach in Andersen et al. (2008) to jointly estimate risk and time preference parameters. Our results confirm the importance of allowing for utility concavity when estimating time preference.

The third principle is to ensure that the credibility of payments is constant across all payment dates, as any doubt in receipt of future payments implies a higher transaction cost, which could translate into overestimated discount rates. To minimize the differences in the transaction cost, we designed the time tasks to always include a delay of either 1 or 4 months for the sooner payment. We provided a promissory note that clearly stated the amount and date of payments and included the signature, full name, and contact information of the lead researchers. In addition, the payment recipients were asked to write their own name and address on the envelope that was used to mail all future check payments. Finally, in our survey, we asked participants to indicate on the 0–100 scale, "How much do you trust that the researchers will make the payment to you in [1, 2, 4, or 7] month(s)?" The mean choice ranges from 95.2 to 96.6, with a median of 100.

4.2 | Laboratory tasks

1Guided by the above principles, we designed each laboratory session to include three major stages: risk preference stage, time preference stage, and survey stage. Each subject went through the above three stages in sequence.[13]

The risk preference stage included 40 tasks. Each task is a binary decision between two lotteries, similar to the original design that first appeared in Loomes and Sugden (1998) and Coller and Williams (1999). Our design is a variation of the original design, in which we optimize the selections of probabilities and prizes to ensure robust inferences on a wide range of a subject's preference parameters. In particular, we create each lottery to be composed of three different prizes with its corresponding probabilities.[14] One important constraint on the lottery parameters is that one lottery always has a lower variance than the other. We call the former the "safer" lottery and the latter the

[13]The complete experiment instructions can be found in the Online Supplementary Appendix A.

[14]It is possible that one or two out of the three probabilities in a given lottery equals to zero. In that case, subjects see fewer than three prizes. This design helps to simplify the decision complexity.

"riskier" lottery. This additional constraint allows us to draw nonparametric conclusions on subjects' risk preferences by simply counting the number of chosen "safer" lotteries. The actual numerical values for lotteries used in the experiment are presented in Appendix Table A.1.

To facilitate the understanding of the lottery choice, we presented the lotteries visually with two pie charts (see Appendix Figure A.1 for an example screenshot). The pie is divided into colored areas that are proportional to the probability of winning each prize. Once a subject submits her choice, the unselected pie chart disappears, and the selected pie starts to spin and then stops randomly. The subject wins the prize corresponding to the colored area where a stationary white pin rests inside the pie chart. After that, the new lottery pair appears on the screen and the process repeats until the subject has submitted her decisions for all 40 lottery pairs. At the end of all 40 tasks, we randomly chose one task and paid the subject the prize for that specific task.[15] To avoid the order effect, we also randomized the sequence of the 40 tasks[16] and the location where the "safer" lottery is displayed on each screen.

The second stage of the experiment includes 40 time preference elicitation tasks. Each task is a binary choice between two payment options. Each option includes a payment amount and payment date. We chose the payment amounts and dates so that one of the options implies a sooner and smaller payment, whereas the other implies a later and larger payment. The sooner payment can occur either 1 or 4 months after the date of the experiment.[17] The later payment can occur either 2, 4, or 7 months after the experiment. The combination of these delayed dates yields four sets of decision environments (1 vs. 2 months, 1 vs. 4 months, 1 vs. 7 months, and 4 vs. 7 months).[18] Within each set, we implemented 10 binary tasks with the earlier payment always equal to 200 US dollars and the later payment varying from 201 to 253 US dollars. These payment amounts were carefully chosen so that the implied annual interest rates vary from 5.06% to 79.59%. These interest rate offers allow us to make robust inferences on individuals' discount rates over a wide parameter range and for various delay lengths. Appendix Table A.2 lists all parameters used in the time preference tasks.

To make it easier for subjects to perceive the time delay, we displayed a calendar on the decision screen. We highlighted the experiment date, sooner payment date, and later payment date on the same calendar using different colors. The payment amount for each future date was placed directly below the corresponding calendar month (see Appendix Figure A.2 for an example). The instructions emphasized to the subjects that they can only receive one of the two payments and never both. After completing all 40 time preference tasks, one task is randomly selected for payment. Each subject has a 1 in 10 chance to receive the actual payment.[19] Similar to the risk preference tasks, we also randomized the sequence of the 40 tasks and displayed them one at a time on the computer screen.

The third and final part of the experiment is a detailed survey. We collected demographic information as well as the key decision variable, the lease-versus-own decision, in this survey.[20] In terms

[15]The design of the above risk-elicitation procedure corresponds to the "Pay One Randomly, Played Out Sequentially" method (PORpos) in (Cox et al., 2015). Their paper clarifies the superiority of the PORpos payment scheme by demonstrating that the choice pattern under PORpos highly resembles the ideal but costly "One Task" mechanism. In a similar context, Brown and Healy (2018) demonstrate that when each binary choice is shown on a separate screen with random order and one of the choices is randomly selected for payment, incentive compatibility is best recovered.

[16]Note that the design feature of the random ordering means that the lottery tasks are not presented to subjects with monotonically increasing or decreasing pattern. This certainly makes transitivity violations possible in observed choices. Brown and Healy (2018) argue that these intransitivities are part of the human decision process. With structural estimation, we can account for these violations by including a parameter for decision error as part of the estimation model.

[17]We carefully exclude the possibility of immediate payment in time preference tasks. This helps to equalize the transaction cost of all delayed payments.

[18]We chose these delay dates so that we can estimate a hyperbolic discounting model. However, we did not find any evidence for hyperbolic discounting from the decision data, so we combined decisions from all delay dates in the analysis section and estimated the discount rates assuming exponential discounting.

[19]An experimenter placed nine white balls and one yellow ball in an opaque box in front of all the subjects. Each subject was asked to draw one ball from the box (with replacement). This design is common in economic experiments and allows us to increase the stake of the task while maintaining a reasonable research budget.

[20]We also have access to official state data on whether each subject owns or leases their solar PV system. Out of the 247 subjects, self-reported and state data on solar PV ownership do not match for nine subjects. Our main analysis uses self-reported own or lease status because we deem this as more reliable. Using the state data on own or lease status does not meaningfully affect our results for estimated coeffcients and statistical significance.

of demographics, our survey collected data on age, education, political affiliation, and household income range. We also collected variables that can act as proxies for "green choices," such as practice of recycling and composting, ownership of hybrid or electric vehicles, and membership in or donation to environmental organizations. In addition, we asked whether subjects had a third party renewable energy supplier prior to installing solar panels. We also collected data on the number of households that have installed solar panels prior to the participant's adoption decision among the participant's circle of family, friends, and acquaintances. We use the information as a proxy for "peer effect." We control for these factors in our analysis.

Subjects participated in one of the 12 experiment sessions between September 2018 and November 2018. Each session lasted ~2.5 h. All participants were promised a "show up bonus" of 50 US dollars, which they received at the end of the experiment session. They also received 2 US dollars for completing the survey and payments related to earnings from the risk and time preferences tasks. The average payment received from the risk preference tasks was 11.15 US dollars. Payments from the time preference tasks were realized with a 1 in 10 chance. The delayed payment amount was on average 212 US dollars. As of November 2019, all checks for delayed payments have been mailed and cashed with no issues.

4.3 | Recruitment procedure and sample description

The subjects were identified using a dataset of all solar adopters provided by the Massachusetts Department of Energy and Resources. The dataset is administrative; hence, it included all the physical addresses of residential solar adopters at the time of recruitment. We sent invitation letters to adopters within Hampshire County, MA, so that potential participants are within driving distance of the experimental lab. The invitation letter asked the person most responsible for the decision to install solar panels to participate in the study. No further restriction was applied to the recruitment list. A total of 2644 postal letters were sent, and 247 subjects completed the study.

Table 2 shows key characteristics of the study participants, who are homeowners who have adopted solar panels either by owning or leasing. A wide range of income groups are represented, with the majority of the respondents belonging to the middle household income category. Over 25% of the owners had a household income of at least $160,000, compared to under 8% for lessees. Over half of the participants have a graduate degree (51%). Of those that do not, 60% have a bachelor's degree. Most respondents engaged in environmentally conscious behaviors such as contributing to environmental organizations, recycling, and composting. A larger share of owners have a hybrid or electric vehicle, and a larger share of owners had a prior contract with a third party renewable energy supplier prior to installing solar PV. Owners also appear to have spent more effort on the solar adoption decision. Compared to lessees, more owners had more than one installer visit their property. Owners also appear to have larger exposure to solar PV in their social network with owners having more peers that have already installed solar panels. Table 2 also shows the number of solar systems installed each year for owners and lessees. Owners tended to adopt solar PV earlier than lessees. In general, solar installation has increased over time, peaking in the years 2015 and 2016 in our data. This trend is consistent with statewide solar installation trends in the state of Massachusetts (Crago et al., 2023). We control for these differences among owners and lessees in our empirical analysis.

5 | EMPIRICAL STRATEGY AND RESULTS

A key advantage of our experimental design is that it allows for the joint estimation of multiple preference parameters under various flexible utility assumptions. In Section 5.1, we present the likelihood function used in the structural estimation. We explain how individual level estimations are implemented to exploit the full potential of the repeated decision data. In Section 5.2, we present the

TABLE 2 Summary statistics for study participants.

	All	Own	Lease
	Frequency		
Income[a]			
Less than $50,000	29	12	17
$50,000–$159,000	171	91	80
$160,000–$199,999	23	17	6
$200,000 and above	24	22	2
Education[a]			
Less than bachelor's degree	48	22	26
Bachelor's degree	72	37	35
Graduate degree	127	83	44
Year born			
1925–1945	28	19	9
1964–1964	133	75	58
1965–1980	71	42	29
After 1980	12	5	7
Peers with solar[a]			
None	70	31	39
1–5	154	94	60
6–10	11	9	2
More than 10	12	8	4
Number of installer visit			
Only 1	126	64	62
2–3	107	68	39
4–7	13	10	3
8–10	1	0	1
Year of PV installation[a]			
2012	2	2	0
2013	1	1	0
2014	43	28	15
2015	83	47	36
2016	83	38	45
2017	35	26	9
	Mean		
Binary variables			
Democrat	0.6	0.6	0.5
Contributes to environmental org[b]	0.6	0.7	0.4
Owns hybrid vehicle[b]	0.3	0.4	0.1
Always recycles	1	1	1
Always composts	0.5	0.6	0.5
Third party renewable energy	0.2	0.3	0.2

[a]Significantly different at 5% using chi2 test for independence for categorical variables.
[b]Significantly different at 5% using *t*-test comparison of means.

results of logistic regressions to examine the correlation between individuals' preference parameters and their decisions to own or lease their solar PV systems. One potential drawback of implementing structural parameter estimation is that the results may depend on the imposed structural assumptions. To check robustness of our findings, in Section 5.3, we present analysis using raw decision data. We confirmed that absent structural assumptions about the functional form of the utility function of subjects, the number of risky options and longer delayed payoffs chosen are correlated with solar PV ownership, similar to the result in Section 5.2.

5.1 | Structural estimation of risk and time preference parameters

Using data generated from the laboratory experiment, we estimated risk and time preference parameters using the maximum likelihood approach.[21] We jointly estimated the risk and time preference parameters by maximizing the joint log likelihood function for the risk and time preference tasks.

We define the log likelihood function for risky lotteries as:

$$lnL^{\text{risk}}(r,\mu|y,\mathbf{X})=\sum\left(\left(ln\left(\frac{U_A^{\frac{1}{\mu}}}{U_A^{\frac{1}{\mu}}+U_B^{\frac{1}{\mu}}}\right)|y_i=1\right)+\left(ln\left(\frac{U_B^{\frac{1}{\mu}}}{U_A^{\frac{1}{\mu}}+U_B^{\frac{1}{\mu}}}\right)|y_i=-1\right)\right) \tag{11}$$

where $y_i=1(-1)$ denotes the choice of the Option A (B) lottery in risk preference task i, r is the risk preference parameter, $\mathbf{X}$ is a vector of individual characteristics, and μ is a structural "noise parameter" that allows errors to enter the deterministic utility model (Wilcox, 2011). $U_j(j=A,B)$ refers to the utility for a particular lottery within a pair of risk lotteries. U_j is further defined as $U_j=\sum_{k=1,2,3}(p(M_k)\times U(M_k))$, in which $U(M_k)$ and $p(M_k)$ refer to the utility of receiving a particular prize M_k and its corresponding probability weighting. With standard expected utility (EU) assumptions, U_j takes on the simple form where $p(M_k)$ is the probability of winning the prize M_k, specified in the parameter table (Appendix Table A.1). With the constant relative risk aversion (CRRA) assumption, the utility of receiving prize M_k can be written as $U(M_k)=M_k^{(1-r)}/(1-r)$, where r is the CRRA risk preference parameter. We apply these standard assumptions of EU and CRRA in our main analysis. Our structural estimation, however, is flexible enough to allow for other utility assumptions. In particular, when the rank dependent utility (RDU) model is assumed, $p(M_k)$ can be replaced with the RDU probability weighting function.

Similarly, we define the log likelihood function for time preference tasks as follows:

$$lnL^{\text{time}}(r,d,\nu|y,\mathbf{X})=\sum\left(\left(ln\left(\frac{\mathrm{PV}_A^{\frac{1}{\nu}}}{\mathrm{PV}_A^{\frac{1}{\nu}}+\mathrm{PV}_B^{\frac{1}{\nu}}}\right)|y_i=1\right)+\left(ln\left(\frac{\mathrm{PV}_B^{\frac{1}{\nu}}}{\mathrm{PV}_A^{\frac{1}{\nu}}+\mathrm{PV}_B^{\frac{1}{\nu}}}\right)|y_i=-1\right)\right) \tag{12}$$

where $y_i=1(-1)$ denotes the choice of the Option A (B) in time preference task i, r is the risk preference parameter, d is the time preference parameter or discount rate (note that $\delta=\frac{1}{(1+d)}$.), $\mathbf{X}$ is a vector of individual characteristics, and ν is a noise parameter for the choices made in the time preference tasks. $\mathrm{PV}_j(j=A,B)$ refers to the time-discounted utility for a chosen option in a particular time preference task. PV_j is further defined as $\mathrm{PV}_j=(\delta(t)\times U(M_k))$, $t=1,2,4,7$ in which $U(M_k)$ refers to the instant utility of receiving the payment of M_k. Because M_k is always paid after a period

[21]Note that these parameters are obtained from objectives measures of risk and time preference, as opposed to subjective measures obtained from simply asking subjects to report how risk averse or impatient they are. An important feature of our objective measures of risk and time preferences is that they are consistent with economic theory and numerical results can be compared across studies. Objective measures using lotteries and delayed payments also ensure a uniform context for measuring these parameters, whereas in subjective measures, the context may vary for each individual. For example, one subject may think of risk in terms of financial risk whereas another may relate risk to risky physical activities.

of delay (either 1, 2, 4, or 7 months), the discounted utility of option j is the instant utility multiplied by a discount factor $\delta(t)$. One of the common structural assumptions on $\delta(t)$ is exponential discounting, where $\delta(t) = 1/(1+d)^{t/12}$ and d is the annual discount rate, the key parameter we intend to estimate. For brevity, our baseline analysis for time preference assumes exponential discounting and EU, although our model allows for other forms of discounting.

We assemble both log likelihood functions into the joint log likelihood:

$$lnL^{\text{joint}}(r,d,\mu,\nu|y,\mathbf{X}) = lnL^{\text{risk}}(r,y,\mathbf{X},\mu) + lnL^{\text{time}}(r,d,y,\mathbf{X},\nu) \tag{13}$$

When we maximize the above joint log likelihood function using all decision data from all subjects, it yields a group-aggregate average risk aversion and time preference parameters. When we maximize the joint log likelihood using data from each individual, we obtain individual risk and time preference parameters.

The group-aggregate average constant relative risk aversion (CRRA) parameter for our sample is 0.74, suggesting a moderate risk aversion level similar to the results found in other laboratory risk attitude calibration studies (Charness et al., 2020; Harrison & Rutström, 2008). After adjusting for risk aversion, the average annual discount rate for the full sample is estimated to be 5.7%. The average discount rate we found is in the range of current ongoing market interest rates and similar to those found in previous literature where risk aversion is controlled for (Anderson et al., 2008; Andreoni & Sprenger, 2012; Imai et al., 2021; Matousek et al., 2022).

The group level analysis yields reasonable estimates for risk and time preference parameters. Our main task, however, requires us to explore individual heterogeneity in risk and time preference parameters. We do so by estimating risk and time preference parameters for each individual subject. To do that, we take advantage of the variations within the 80 decisions made by a particular subject. Using Equation (13) we ran a separate maximum likelihood estimation using each subject's own decisions. In an ideal case, we would like to recover individual risk and time preference parameters for all of the subjects. One critical obstacle to achieving this ideal is the issue of nonconvergence in maximum likelihood estimations. It is possible that individuals could adopt drastically different strategies and heuristics when making their decisions in the risk and time preference tasks. They may also make "corner" decisions. That is, in the risk preference tasks, a participant may choose the safer option (or risky option) for all 40 lottery pairs. Similarly, for the time preference tasks, a subject may choose all sooner payments or all later payments for all 40 binary tasks. These are reasons that could lead to difficulties in recovering multiple preference parameters using structural estimation. In our case, the experimental design and careful calibration approach resulted in high quality decision data: Most subjects' decisions achieved convergence using maximum likelihood estimation coupled with standard utility function assumptions. For 191 out of the total 247 subjects, individuals' choices led to convergence with joint estimation on both time and risk preferences. For an additional 48 subjects, convergence is achieved using only decisions in risk preference tasks but not the time preference tasks.[22] We also vary the utility functional form in both groups of estimations to be either EU or RDU. The majority of our subjects made decisions that can be explained with EU assumptions. The more flexible RDU models only added six more subjects whose estimations did not converge under EU. Finally, there is a small set of subjects (8 out of 247 individuals, 3.24%) whose choices cannot be reasonably rationalized under any standard utility assumptions, whether we consider their choices in both risk and time tasks or in risk tasks only.

The above procedure led to a 96.76% recovery rate for risk preference parameters and 77.33% recovery rate for time preference parameters. A closer inspection of the choices made by the 56 subjects who did not converge on time preference estimation revealed that 42 of them chose either all sooner payments or all later payments for each of the 40 time preference tasks. Theoretically (and

[22]We chose not to estimate the discount rate using time preference tasks alone. Recall that estimating the discount rate using decisions made in time preference tasks alone forces one to assume risk neutrality, which will lead to a biased result.

TABLE 3 Number and percentage of subjects by convergence types.

Type	Risk preference r	Time preference d	Utility form	# of subjects	% of subjects
1	Estimated	Estimated	EU	185	74.90%
2	Estimated	Estimated	RDU	6	2.43%
3	Estimated	Lower bound	EU	38	15.38%
4	Estimated	Not exist	EU	10	4.05%
5	Not exist	Lower bound	-	4	1.62%
6	Not exist	Not exist	-	4	1.62%
Total				247	100%

Abbreviations: EU, expected utility; RDU, rank dependent utility.

empirically), it is impossible to recover the time preference parameter for these 42 subjects. However, it is possible to assign a lower bound discount rate for these subjects. In particular, for the highly impatient subjects who chose all 40 sooner payments, it is reasonable to infer that their discount rate is at least as high as the highest interest rate we offered, which is 79.59%. Thus, we set those subjects' discount rate to 79.59%. For the subjects who are highly patient and chose all 40 later payments, it is reasonable to assume that their discount rate is likely to be small and bounded from below by 0%. For those subjects, we set the discount rate to 0%. These assigned discount rates are conservative, which means that if we find significant results under these assumptions, the significance of the results is likely to be stronger under the true discount rates.

Table 3 shows the number and percentage of individuals who achieved convergence using data from both risk and time tasks, and from risk tasks only. We also separated the count for those who did not converge in time preference by whether it is possible to assign a lower bound for their discount rate. Only four subjects (1.62% of the sample, Table 3, Row 6) did not achieve convergence on both parameters, nor could they be assigned a lower bound discount rate based on their raw decision data.

5.2 | Analysis using estimated preference parameters

In this section, we link estimated risk and time preference parameters with the decision to own or lease solar panels. Define Y as:

$$Y = \begin{cases} 1, & \text{if owned, with probability } q. \\ 0, & \text{if leased, with probability } 1-q. \end{cases} \tag{14}$$

The probability of owning (denoted by q) is parameterized by an index function $\mathbf{x}\beta$, where $\mathbf{x}$ is a vector of regressors and β is a vector of coefficients to be estimated. $q = \Pr(y=1|x) = F(\mathbf{x}\beta)$, where $F(*)$ is the specific parametric function of $\mathbf{x}\beta$. Our base specification uses the logit model, that is, $F(\mathbf{x}\beta) = \Lambda(\mathbf{x}\beta) = e^{\mathbf{x}\beta}$, the cumulative distribution function of the logistic distribution. In all specifications discussed below, we include the risk aversion parameter (r) and time discount rate (d) as the main regressors. Statistically significant coefficients on these preference parameters indicate that risk and time preferences between owners and lessees are different. We also include a large set of control variables as well as installation year fixed effects to control for time varying factors that may affect the choice between ownership and leasing.[23]

[23]In addition to the control variables shown in Table 4, variables such as age of respondent and level of education were also used as explanatory variables in our regressions, but these variables were not significant and did not improve model fit, and were thus not included in the final specification.

Table 4 presents the marginal effects from the logistic regressions.[24] Our main specifications in Columns (1)–(3) impose conservative lower bound inferences on the discount rate of subjects who chose either all sooner payments or all later payments for the entire list of 40 tasks ($d = 79.59\%$ for those who choose all sooner payments; $d = 0\%$ for those who choose all later payments). Imposing lower bounds allowed us to include 92.7% of the subjects (227 individuals) in the regression.[25] Columns (4)–(6) show results when we do not impose any bounds on the discount rate of participants who choose to receive either all sooner or all later payments for the entire set of 40 binary choices. We find that subjects who are more risk averse are less likely to own their solar panels. The marginal effect size in Column (1) suggests that for every unit increase in the subject's CRRA risk aversion parameter, the likelihood of ownership decreases by 18.4%. Recall that for CRRA utility, when the risk parameter equals 0, the individual is risk neutral. For most empirical studies, the risk aversion parameter falls between 0 and 1. A shift of the CRRA parameter from 0 to 1, therefore, should be interpreted as a comparison between those who are risk neutral and extremely risk averse. For a moderate decrease in risk preference, say a decrease in the CRRA parameter of 0.1, our results show an average 1.84% increase in the probability of choosing the ownership option. In summary, our logit regression detects a negative relationship between risk aversion and solar ownership. The effect is statistically significant and the significance persists with a large set of control variables and year fixed effects.

Another result from our regressions is that the effect of the discount rate is negative as predicted but not statistically significant in most specifications. In Column (1), when no control variables are present, a 0.1 unit increase in the annual discount rate (subject becoming less patient) leads to a 3.21% decrease in the probability of ownership. The parameter is statistically significant at the 10% level. The statistical significance goes away once we added control variables. We hesitate to draw any strong conclusions regarding the effect of the discount rate on the ownership choice. The reason is that for the results in Columns (1)–(3), the discount rates took the most conservative lower bound value. It is quite likely that subjects who chose all sooner payments hold higher discount rates than 79.59%. Our lower bound inference may contribute to the lack of statistical significance observed in this case.

For robustness check, we also report the regression results without imposing any bounds on the discount rates for those who made all 40 choices that are either all sooner or all later payments (see Columns (4)–(6) in Table 3). Recall that this analysis is not ideal as 38 subjects are dropped. The much smaller sample size may make it harder to detect an existing effect. With this smaller sample, we continue to observe the negative effect of the risk parameter on solar PV ownership. The effect size is larger at −0.326 in Column (4) and −0.206 in Column (6), though the statistical significance level decreases from 5% to 10% in the specification without controls (Column 4) and is not significant in the specification with full controls (Column 6). The effect of time preference on ownership is not significant in these specifications.

We include a large set of control variables, including measures of household income, education, age, political orientation, peer effect, pro-environmental preferences, and year-of-installation fixed effects. We report the results in Columns (2), (3), (5), and (6). These controls were included based on findings from previous literature about factors that affect solar PV adoption as well as leasing versus owning.[26] Income is represented by yearly income categories (low income, less than \$50,000; middle income, \$50,000–\$159,999; high income, \$160,000–\$199,999; highest income, \$200,000 and above) based on the income categorizations used by the Pew Research Center (2021). Income

[24]These are average partial effects.

[25]Three more subjects are dropped in Column (2) due to missing information in the survey data.

[26]Only a few studies exist on the determinants of the choice to own or lease solar panels. Rai and Sigrin (2013) and Pless et al. (2020) found little to no difference in terms of demographics between owners and lessees in Texas and California respectively. This is in contrast with an earlier study by Drury et al. (2011), who found that third party ownership opened up the PV market to younger, less affluent, and less educated market segments. Because the geographic location of our study is different, and because there is no consensus in the literature about the likely demographic correlates of owning versus leasing, we include variables that have been shown to be correlated with solar PV adoption, including income, peer effect, and different measures of pro-environmental behavior (Crago & Chernyakhovskiy, 2017).

TABLE 4 Marginal effects from logistic regressions using estimated r and d parameters.

Dependent variable $Y = 1$ if own	With bounds			No bounds		
	(1)	(2)	(3)	(4)	(5)	(6)
CRRA parameter r	−0.184**	−0.149**	−0.130**	−0.326*	−0.161	−0.206
	(0.072)	(0.069)	(0.066)	(0.176)	(0.163)	(0.152)
Annual discount rate d	−0.321*	−0.144	−0.122	−0.335	0.129	0.050
	(0.193)	(0.173)	(0.169)	(0.471)	(0.436)	(0.419)
Base: Income less than $50,000						
$50,000–$159,999		0.141	0.121		0.151	0.132
		(0.101)	(0.100)		(0.111)	(0.108)
$160,000–$199,999		0.351**	0.333**		0.360**	0.345**
		(0.146)	(0.144)		(0.156)	(0.152)
$200,000 and above		0.480***	0.457***		0.546***	0.520***
		(0.121)	(0.124)		(0.119)	(0.124)
Base: Peers with solar equal to 0						
1–5		0.112+	0.144**		0.110	0.115+
		(0.068)	(0.069)		(0.078)	(0.079)
5–10		0.244+	0.287*		0.269*	0.281*
		(0.154)	(0.148)		(0.153)	(0.150)
More than 10		0.189	0.284**		0.136	0.256*
		(0.144)	(0.133)		(0.165)	(0.148)
Base: Number of installer visits equal to 1						
2–3		0.083	0.105*		0.088	0.109+
		(0.063)	(0.062)		(0.069)	(0.067)
4–7		0.232*	0.266**		0.227+	0.273**
		(0.119)	(0.111)		(0.139)	(0.129)
8–10		0.000	0.000		0.000	0.000
		(.)	(.)		(.)	(.)
Democrat		0.025	0.011		0.029	−0.001
		(0.062)	(0.062)		(0.067)	(0.068)
Contributes to envt org		0.118*	0.108*		0.117*	0.117*
		(0.064)	(0.064)		(0.070)	(0.071)
Owns hybrid vehicle		0.139*	0.135*		0.076	0.052
		(0.077)	(0.074)		(0.085)	(0.082)
Always recycles		0.069	0.125		0.157	0.227
		(0.181)	(0.172)		(0.232)	(0.222)
Always composts		0.097+	0.094+		0.076	0.083
		(0.060)	(0.059)		(0.066)	(0.064)
Third party renewable energy		0.059	0.046		0.051	0.053
		(0.073)	(0.070)		(0.082)	(0.077)
N	229	225	222	191	188	185

Note: Variables age and education level are also included in the regressions but their coefficients are not significant and are not reported for brevity.
$^{+}p < 0.15$;
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

variables are used to account for cash liquidity or access to financing under the assumption that higher income households have more available capital to spend on purchasing solar panels and have easier access to finance for their solar PV systems. The peer effect variable indicates the number of households among friends, family, and acquaintances that have installed solar panels prior to the subject installing solar panels. Variables that represent pro-environmental preferences include contributing to environmental organizations, driving an electric or hybrid vehicle, the practice of recycling and composting, as well as contracting with a third-party renewable energy supplier prior to the installing solar panels. Attention to the solar adoption decision is captured by the number of installers that visited the property prior to installation of solar panels. Finally, year fixed effects capture time varying factors common to all solar adopters in our sample, including solar installation costs and other market conditions that affect the favorability of owning versus leasing.

We find that households with an annual income above $160,000 are more likely to choose the ownership option. It is well known that risk aversion is correlated with wealth, where wealthy individuals tend to be less risk averse (e.g., (Tanaka et al., 2010)). However, after controlling for income, our main specification shows that the effect of risk preference remains statistically significant. We also find positive and significant coefficients on the peer effect variable indicating that the knowledge of solar panels through social networks increases the probability of owning, and the effect is generally larger as the number of peers who also have solar panels increases. Finally, those who drive an electric or hybrid vehicle and those who donate or contribute to environmental organizations are more likely to own their panels. Note that compared to other pro-environmental behaviors (such as recycling and composting, which were also included as controls), these two behaviors involve significant financial commitment. The significance of these two variables matches well with our expectations given that the ownership of solar panels is also an environmentally friendly action that requires financial investment.

5.3 | Robustness check with raw decision data

In this section, we conduct additional logistic regressions using the raw decision data from the experiment as main regressors. For each subject, the raw decision data that we use are the count of the number of choices for the safer option in the risk preference tasks and the count of the choices for sooner payment option in the time preference tasks.

There are two main advantages of using raw data collected from the risk and time preference tasks as regressors. First, we are able to include all subjects in our experiment in the raw data analysis. Second, we significantly reduce the assumptions needed during the parameter estimation stage. In particular, we remove the assumption that the subject's utility follows a specific function form. Subjects may not be maximizing standard utility functions in EU or RDU frameworks. These nonstandard utility maximizers did not yield convergence in the maximum likelihood procedure as shown in previous sections. Their raw decision data, however, still carry important information regarding their aversion to risk and patience toward delayed rewards. Recall that for each paired risky lottery choice, we chose the parameter values for the prizes and probability of winning prizes in such a way that one of the two lotteries always has a lower variance than the other. We name this lottery with lower variance as the "safer" lottery. The count of safer lottery a subject chooses, therefore, carries the meaningful interpretation of how risk averse the subject is without the need to impose any parametric structure on how the choice over the lottery is made. This nonparametric count of safer lottery choices takes a value between 0 and 40. Similarly, we can interpret the choice made in the time preference tasks in a nonparametric way. In particular, the number of times a subject chose the smaller sooner payment is a continuous measure of how impatient she is. The more of these sooner payments are chosen, the more impatient is the subject.

Despite these advantages, caution must be taken in interpreting the results from the raw data analysis because of these limitations: (1) Choices in time preference tasks are confounded by risk aversion, and thus it is impossible to separate the two, and (2) the coefficients from the raw data analysis cannot be directly interpreted for out-of-the-sample interpretation. This is contrary to the parameters obtained from structural estimation: CRRA risk parameters and annual discount rates presented in earlier sections are fundamental elements of general utility functions and can be readily used for out-of-the-sample interpretation. Hence, the purpose of this additional analysis is to provide a robustness check for our main results. We show that without structural assumptions about the utility function, the directional predictions made in our model continue to hold.

In Table 5, we first present the marginal effects from logit regressions where we regress solar ownership on the number of safe choices made by each subject in the risky lottery tasks (Columns (1) to (3)). The number of safe choices provides a rough measure of risk aversion without making any assumptions about the form of the utility function and nature of risk aversion. The results show that the number of safe choices has a negative coefficient. This provides additional evidence of a negative relationship between one's risk aversion and the decision to own. The result is statistically significant and robust to additional control variables and year fixed effects. In Columns (4) to (6), we add the raw data from the time preference tasks, the count of sooner payment option chosen by each subject as an additional regressor. Recall that when subjects choose between a sooner smaller and later larger payment, such a choice is reflective of not only their attitude toward delayed reward but also their tendency to avoid higher risk implied by choosing the later payment. We find that the coefficient for the count of sooner payment is negative and statistically significant at the 5% level with controls and year fixed effects (Column 6), whereas the coefficient of the count of safe choices remains negative and statistically significant at 15%. We take these results in Table 5 as additional supporting evidence for the main results in Table 4 and Section 5.2.

6 | CONCLUSIONS AND POLICY IMPLICATIONS

In this study, we provide novel evidence that risk preference is an important factor that affects contract choice in the solar PV market. Specifically, more risk tolerant individuals are more likely to own their solar panels. We also find some evidence based on nonparametric analysis that time preference plays a role in solar contract choices, where more patient individuals are more likely to own their panels. These results highlight the importance of behavioral factors in households' green energy decisions.

Our experimental data are collected in the state of Massachusetts, which is one of the leading states in small-scale solar deployment (ranked fourth in the nation as of 2022 [Dutzik et al., 2024]). The new insights from our study can be applied more broadly toward understanding residential solar adoption in other US states because households in the US face similar financial portfolios and trade-offs in solar contract choice described in this study. However, we will refrain from generalizing our findings to decisions made by firms in commercial-scale or utility-scale solar adoption settings.

One of the limitations of the current research method is that we are only able to capture people's risk and time preferences at a particular moment. If these preference changes are idiosyncratic, our regressions will still be able to capture the true correlation between risk and time preferences and solar contract choice. It is also possible that there has been a level shift over the years: As people become older, they become less risk averse and more patient. However, it can be argued that such a shift has occurred more or less universally to all of our subjects as they aged. If so, our analysis can still capture the relative difference in people's risk attitudes and patience and their impact on solar contract choice. Although the longitudinal dynamics of risk and time preferences are an important consideration, it is beyond the scope of this study. Despite this shortcoming, we believe that our experimental design is still optimized to document the essential connection between behavioral preferences and an important choice in the green energy domain.

The availability of the option to own or lease may facilitate self-selection of customers to each option depending on their risk and time preferences. In this regard, the market may be functioning

TABLE 5 Marginal effects from logistic regressions using raw decision data.

Dependent variable $Y = 1$ if own	(1)	(2)	(3)	(4)	(5)	(6)
# Safe lotteries	−0.008*	−0.007+	−0.008*	−0.007+	−0.006	−0.006+
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
# Sooner Payments				−0.005**	−0.004+	−0.004*
				(0.002)	(0.002)	(0.002)
Base: Income less than $50,000						
$50,000–$159,999		0.120	0.085		0.112	0.077
		(0.097)	(0.095)		(0.096)	(0.094)
$160,000–$199,999		0.278**	0.254*		0.267*	0.244*
		(0.139)	(0.136)		(0.138)	(0.133)
$200,000 and above		0.467***	0.429***		0.453***	0.418***
		(0.116)	(0.119)		(0.117)	(0.118)
Base: Peers with solar equal to 0						
1–5		0.118*	0.157**		0.132**	0.176***
		(0.067)	(0.066)		(0.067)	(0.067)
5–10		0.269*	0.313**		0.291**	0.342**
		(0.151)	(0.146)		(0.148)	(0.142)
More than 10		0.136	0.243*		0.165	0.287**
		(0.144)	(0.135)		(0.143)	(0.133)
Base: Number of installer visit equal to 1						
2–3		0.070	0.093+		0.071	0.093+
		(0.061)	(0.059)		(0.060)	(0.059)
4–7		0.211*	0.252**		0.184+	0.224*
		(0.120)	(0.111)		(0.125)	(0.115)
8–10		0.000	0.000		0.000	0.000
		(.)	(.)		(.)	(.)
Democrat		0.025	0.015		0.025	0.013
		(0.061)	(0.060)		(0.061)	(0.059)
Contributes to envt org		0.128**	0.114*		0.126**	0.113*
		(0.062)	(0.062)		(0.062)	(0.062)
Owns hybrid vehicle		0.168**	0.157**		0.162**	0.152**
		(0.072)	(0.069)		(0.072)	(0.069)
Always recycles		0.146	0.195		0.154	0.201
		(0.177)	(0.166)		(0.178)	(0.165)
Always composts		0.096+	0.086+		0.087+	0.074
		(0.059)	(0.057)		(0.059)	(0.057)
Third party renewable energy		0.074	0.064		0.070	0.056
		(0.072)	(0.070)		(0.071)	(0.069)
N	247	243	240	247	243	240

Note: Standard errors in parentheses. Raw decision data for each individual consists of the count of safe lottery choices in the risk preference tasks and count of sooner payment choices in the time preference tasks. Variables age and education level are also included in the regressions but their coefficients are not significant and are not reported for brevity.

$^{+}p < 0.15$;

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

well to bring about an optimal outcome: Those willing to bear the risk of owning and are more patient are rewarded with higher financial payoff, whereas those who are more risk averse and less patient have the option to choose a less risky option with immediate benefit, albeit with overall lower financial payoff. Without knowing the exact financial condition of each individual (income, access to credit, return to other financial investments, etc), it would be impossible to judge whether an individual has indeed made the optimal contract choice. This type of investigation is outside of the scope of this paper. Although making judgments on whether a particular contract choice is optimal at the individual level is difficult, there may be some scenarios where policy intervention to encourage ownership of solar PV is warranted. Studies show that benefits to local and state governments are better localized with ownership compared to leasing (MA-DOER, 2013). In Massachusetts, 70% of benefits stay in state when solar systems are owned, compared with 50% for leased systems. A study by Crago et al. (2023) found that with leased systems, homeowners only get 30% of the 20-year net present value of financial returns from installing homeowner-owned solar panels. If there is a desire to localize benefits from state solar incentives, our results suggest that it could be helpful to devise state policies that (1) lower the risks of owning solar panels and (2) provide expanded access to credit and low-interest loans. Recently, issues of equity in renewable energy markets have gained prominence in the social discourse. For example, the Inflation Reduction Act of 2022 carries significant provisions to address energy equity (U.S. Environmental Protection Agency, 2023). Because lower income status has been empirically linked to greater risk aversion and less patience for delayed financial rewards, these policies may also increase access of low and middle income households to solar PV ownership. Given that owning one's solar panels provides significantly more financial benefits compared to leasing, and that wealthier households tend to own, such policies may work to distribute gains from the solar market in a more equitable manner.

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REFERENCES

Andersen, Steffen, Glenn W. Harrison, Morten I. Lau, and E. Elisabet Rutström. 2008. "Eliciting Risk and Time Preferences." *Econometrica* 76(3): 583–618.

Anderson, Lisa R., and Jennifer M. Mellor. 2008. "Predicting Health Behaviors with an Experimental Measure of Risk Preference." *Journal of Health Economics* 27(5): 1260–74. https://doi.org/10.1016/j.jhealeco.2008.05.011.

Anderson, Lisa R., Jennifer M. Mellor, and Jeffrey Milyo. 2008. "Inequality and Public Good Provision: An Experimental Analysis." *Journal of Socio-Economics* 37(3): 1010–28.

Andreoni, James, and Charles Sprenger. 2012. "Risk Preferences Are Not Time Preferences." *American Economic Review* 102(7): 3357–76. https://doi.org/10.1257/aer.102.7.3357.

Bauner, Christoph, and Christine L. Crago. 2015. "Adoption of Residential Solar Power under Uncertainty: Implications for Renewable Energy Incentives." *Energy Policy* 86: 27–35.

Belzil, Christian, and Modibo Sidibé. 2016. "Internal and External Validity of Experimental Risk and Time Preferences." *Economic Research Initiatives at Duke (ERID)* Working Paper (237).

Bollinger, Bryan, and Kenneth Gillingham. 2012. "Peer Effects in the Diffusion of Solar Photovoltaic Panels." *Marketing Science* 31(6): 900–912.

Brown, Alexander L., and Paul J. Healy. 2018. "Separated Decisions." *European Economic Review* 101: 20–34.

Charness, Gary, Thomas Garcia, Theo Offerman, and Marie Claire Villeval. 2020. "Do Measures of Risk Attitude in the Laboratory Predict Behavior under Risk in and outside of the Laboratory?" *Journal of Risk and Uncertainty* 60(2): 99–123.

Coller, Maribeth, and Melonie B. Williams. 1999. "Eliciting Individual Discount Rates." *Experimental Economics* 2: 107–127.

Cox, James C., Vjollca Sadiraj, and Ulrich Schmidt. 2015. "Paradoxes and Mechanisms for Choice under Risk." *Experimental Economics* 18: 215–250.

Crago, Christine L., Emma Grazier, and Dwayne Breger. 2023. “Income and Racial Disparities in Financial Returns from Solar PV Deployment.” *Energy Economics* 117: 106409.

Crago, Christine Lasco, and Ilya Chernyakhovskiy. 2017. “Are Policy Incentives for Solar Power Effective? Evidence from Residential Installations in the Northeast.” *Journal of Environmental Economics and Management* 81: 132–151.

Dastrup, Samuel R., Joshua Graff Zivin, Dora L. Costa, and Matthew E. Kahn. 2012. “Understanding the Solar Home Price Premium: Electricity Generation and ‘Green’ Social Status.” *European Economic Review* 56(5): 961–973. https://doi.org/10.1016/j.euroecorev.2012.02.006.

De Groote, Olivier, Guido Pepermans, and Frank Verboven. 2016. “Heterogeneity in the Adoption of Photovoltaic Systems in Flanders.” *Energy Economics* 59: 45–57. https://doi.org/10.1016/j.eneco.2016.07.008.

Drury, Easan, Paul Denholm, and Robert Margolis. 2011. *Impact of Different Economic Performance Metrics on the Perceived Value of Solar Photovoltaics*. Working paper. Golden: National Renewable Energy Lab.(NREL).

Dutzik, Tony, Abigail Ham, and Johanna Neumann. 2024. *Rooftop Solar on the Rise*. Frontier Group. https://environmentamerica.org/center/resources/rooftop-solar-on-the-rise/.

Elston, Julie A., Glenn W. Harrison, and E. Elisabet Rutström. 2005. “Characterizing the Entrepreneur Using Field Experiments.” *Max Planck Institute of Economics* Working Paper.

Frederick, Shane, George Loewenstein, and Ted O’Donoghue. 2002. “Time Discounting and Time Preference: A Critical Review.” *Journal of Economic Literature* 40(2): 351–401.

Harrison, Glenn W., and E. Elisabet Rutström. 2008. “Risk Aversion in the Laboratory.” In *Risk Aversion in Experiments*, Vol 12, edited by J. C. Cox and G. W. Harrison, 41–196. Bingley: Research in Experimental Economics.

Holt, Charles A., and Susan K. Laury. 2002. “Risk Aversion and Incentive Effects.” *American Economic Review* 92(5): 1644–55.

Hughes, Jonathan E., and Molly Podolefsky. 2015. “Getting Green with Solar Subsidies: Evidence from the California Solar Initiative.” *Journal of the Association of Environmental and Resource Economists* 2(2): 235–275.

Imai, Taisuke, Tom A. Rutter, and Colin F. Camerer. 2021. “Meta-Analysis of Present-Bias Estimation Using Convex Time Budgets.” *Economic Journal* 131(636): 1788–1814.

Jacksohn, Anke, Peter Grösche, Katrin Rehdanz, and Carsten Schröder. 2019. “Drivers of Renewable Technology Adoption in the Household Sector.” *Energy Economics* 81: 216–226.

Liu, Elaine M. 2013. “Time to Change What to Sow: Risk Preferences and Technology Adoption Decisions of Cotton Farmers in China.” *Review of Economics and Statistics* 95(4): 1386–1403.

Loomes, Graham, and Robert Sugden. 1998. “Testing Different Stochastic Specificationsof Risky Choice.” *Economica* 65(260): 581–598.

Lusk, Jayson L., and Keith H. Coble. 2005. “Risk Perceptions, Risk Preference, and Acceptance of Risky Food.” *American Journal of Agricultural Economics* 87(2): 393–405.

MA-DOER. 2013. Task 4 Report: Comparative Regional Economic Impacts of Solar Ownership/Financing Alternatives https://www.mass.gov/doc/post-400-task-4/download

Matousek, Jindrich, Tomas Havranek, and Zuzana Irsova. 2022. “Individual Discount Rates: A Meta-Analysis of Experimental Evidence.” *Experimental Economics* 25(1): 318–358.

Nalley, Stephen, and Angelina LaRose. 2021. Annual Energy Outlook 2021 [Presentation Slides] https://www.eia.gov/pressroom/presentations/AEO2021_Release_Presentation.pdf

Pew Research Center. 2021. Defining Income Tiers https://www.pewresearch.org/politics/2021/09/23/biden-economy-appendix/

Pless, Jacquelyn, Harrison Fell, and Ben Sigrin. 2020. “Information Searching in the Residential Solar PV Market.” *Energy Journal* 41(4): 255–278.

Qiu, Yueming, Gregory Colson, and Carola Grebitus. 2014. “Risk Preferences and Purchase of Energy-Efficient Technologies in the Residential Sector.” *Ecological Economics* 107: 216–229.

Qiu, Yueming, Yi David Wang, and Jianfeng Wang. 2017. “Soak up the Sun: Impact of Solar Energy Systems on Residential Home Values in Arizona.” *Energy Economics* 66: 328–336.

Rai, Varun, and Benjamin Sigrin. 2013. “Diffusion of Environmentally-Friendly Energy Technologies: Buy Versus Lease Differences in Residential PV Markets.” *Environmental Research Letters* 8(1): 014022.

Schelly, Chelsea, and James C. Letzelter. 2020. “Examining the Key Drivers of Residential Solar Adoption in Upstate New York.” *Sustainability* 12(6): 2552.

Schleich, Joachim, Xavier Gassmann, Thomas Meissner, and Corinne Faure. 2019. “A Large-Scale Test of the Effects of Time Discounting, Risk Aversion, Loss Aversion, and Present Bias on Household Adoption of Energy-Efficient Technologies.” *Energy Economics* 80: 377–393.

Sexton, Steven E., and Alison L. Sexton. 2014. “Conspicuous Conservation: The Prius Halo and Willingness to Pay for Environmental Bona Fides.” *Journal of Environmental Economics and Management* 67(3): 303–317.

Sun, Pi-Chuan, Hsueh-Mei Wang, Hsien-Long Huang, and Chien-Wei Ho. 2020. “Consumer Attitude and Purchase Intention toward Rooftop Photovoltaic Installation: The Roles of Personal Trait, Psychological Benefit, and Government Incentives.” *Energy and Environment* 31(1): 21–39.

Tanaka, Tomomi, Colin F. Camerer, and Quang Nguyen. 2010. “Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam.” *American Economic Review* 100(1): 557–571.

U.S. Energy Information Administration. 2023. Massachusetts State Profiles and Energy Estimates https://www.eia.gov/state/?sid=MA

U.S. Environmental Protection Agency. 2023. Inflation Reduction Act Environmental and Climate Justice Program https://www.epa.gov/inflation-reduction-act/inflation-reduction-act-environmental-and-climate-justice-program

UMass CFARE. 2020. *Considering a Solar Photovoltaic Array for your Home*. Amherst, MA: University of Massachusetts Amherst Center for Agriculture, Food, and the Environment https://ag.umass.edu/clean-energy/fact-sheets/considering-solar-photovoltaic-array-for-your-home.

Wilcox, Nathaniel T. 2011. "'Stochastically More Risk Averse': A Contextual Theory of Stochastic Discrete Choice under Risk." *Journal of Econometrics* 162(1): 89–104.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX A

TABLE A.1 Lottery parameters in 40 risk preference tasks.

No	Option A						Option B					
	Safe						Risky					
	Prize 1	Prob Prize 1	Prize 2	Prob Prize 2	Prize 3	Prob Prize 3	Prize 1	Prob Prize 1	Prize 2	Prob Prize 2	Prize 3	Prob Prize 3
1	$1	0%	$5	100%	$10	0%	$1	50%	$5	0%	$10	50%
2	$1	0%	$5	40%	$10	60%	$1	20%	$5	0%	$10	80%
3	$1	10%	$5	90%	$10	0%	$1	40%	$5	0%	$10	60%
4	$1	0%	$5	60%	$10	40%	$1	20%	$5	0%	$10	80%
5	$2	10%	$10	90%	$20	0%	$2	40%	$10	0%	$20	60%
6	$2	0%	$10	60%	$20	40%	$2	20%	$10	0%	$20	80%
7	$2	0%	$10	100%	$20	0%	$2	50%	$10	0%	$20	50%
8	$2	0%	$10	40%	$20	60%	$2	20%	$10	0%	$20	80%
9	$1	10%	$10	90%	$15	0%	$1	40%	$10	0%	$15	60%
10	$1	0%	$10	60%	$15	40%	$1	20%	$10	0%	$15	80%
11	$1	0%	$10	70%	$15	30%	$1	20%	$10	0%	$15	80%
12	$1	30%	$10	70%	$15	0%	$1	50%	$10	0%	$15	50%
13	$1	0%	$10	100%	$15	0%	$1	20%	$10	0%	$15	80%
14	$1	50%	$10	50%	$15	0%	$1	60%	$10	0%	$15	40%
15	$1	50%	$10	50%	$20	0%	$1	80%	$10	0%	$20	20%
16	$1	0%	$10	100%	$20	0%	$1	60%	$10	0%	$20	40%
17	$1	0%	$10	100%	$20	0%	$1	40%	$10	0%	$20	60%
18	$1	50%	$10	50%	$20	0%	$1	70%	$10	0%	$20	30%
19	$1	0%	$10	60%	$20	40%	$1	20%	$10	0%	$20	80%
20	$1	40%	$10	60%	$20	0%	$1	60%	$10	0%	$20	40%
21	$1	0%	$10	100%	$20	0%	$1	20%	$10	0%	$20	80%
22	$1	50%	$10	50%	$20	0%	$1	60%	$10	0%	$20	40%
23	$1	0%	$10	100%	$25	0%	$1	80%	$10	0%	$25	20%
24	$1	20%	$10	50%	$25	30%	$1	60%	$10	0%	$25	40%
25	$1	50%	$10	50%	$25	0%	$1	80%	$10	0%	$25	20%
26	$1	0%	$10	100%	$25	0%	$1	60%	$10	0%	$25	40%
27	$1	0%	$15	100%	$30	0%	$1	40%	$15	0%	$30	60%
28	$1	50%	$15	50%	$30	0%	$1	70%	$15	0%	$30	30%
29	$1	0%	$15	90%	$30	10%	$1	20%	$15	0%	$30	80%
30	$1	10%	$15	90%	$30	0%	$1	30%	$15	0%	$30	70%
31	$5	0%	$10	100%	$20	0%	$5	80%	$10	0%	$20	20%
32	$5	20%	$10	50%	$20	30%	$5	60%	$10	0%	$20	40%
33	$5	20%	$10	30%	$20	50%	$5	40%	$10	0%	$20	60%
34	$5	0%	$10	60%	$20	40%	$5	20%	$10	30%	$20	50%
35	$5	0%	$10	100%	$20	0%	$5	40%	$10	0%	$20	60%
36	$5	50%	$10	50%	$20	0%	$5	70%	$10	0%	$20	30%
37	$5	50%	$15	50%	$25	0%	$5	80%	$15	0%	$25	20%
38	$5	0%	$15	100%	$25	0%	$5	60%	$15	0%	$25	40%
39	$5	0%	$15	100%	$25	0%	$5	40%	$15	0%	$25	60%
40	$5	50%	$15	50%	$25	0%	$5	70%	$15	0%	$25	30%

TABLE A.2 Parameters used in 40 time preference tasks.

	Option A		Option B		Calculated annual interest rate not shown to subjects
	Sooner date (month)	Sooner payment (USD)	Later date (month)	Later payment (USD)	
1	1	200	7	205	5.06%
2	1	200	7	210	10.25%
3	1	200	7	215	15.56%
4	1	200	7	221	22.10%
5	1	200	7	226	27.69%
6	1	200	7	231	33.40%
7	1	200	7	237	40.42%
8	1	200	7	242	46.41%
9	1	200	7	248	53.76%
10	1	200	7	253	60.02%
11	1	200	4	203	6.14%
12	1	200	4	205	10.38%
13	1	200	4	208	16.99%
14	1	200	4	210	21.55%
15	1	200	4	213	28.65%
16	1	200	4	215	33.55%
17	1	200	4	218	41.16%
18	1	200	4	220	46.41%
19	1	200	4	223	54.56%
20	1	200	4	225	60.18%
21	1	200	2	201	6.17%
22	1	200	2	202	12.68%
23	1	200	2	203	19.56%
24	1	200	2	204	26.82%
25	1	200	2	205	34.49%
26	1	200	2	206	42.58%
27	1	200	2	207	51.11%
28	1	200	2	208	60.10%
29	1	200	2	209	69.59%
30	1	200	2	210	79.59%
31	4	200	7	203	6.14%
32	4	200	7	205	10.38%
33	4	200	7	208	16.99%
34	4	200	7	210	21.55%
35	4	200	7	213	28.65%
36	4	200	7	215	33.55%
37	4	200	7	218	41.16%
38	4	200	7	220	46.41%
39	4	200	7	223	54.56%
40	4	200	7	225	60.18%

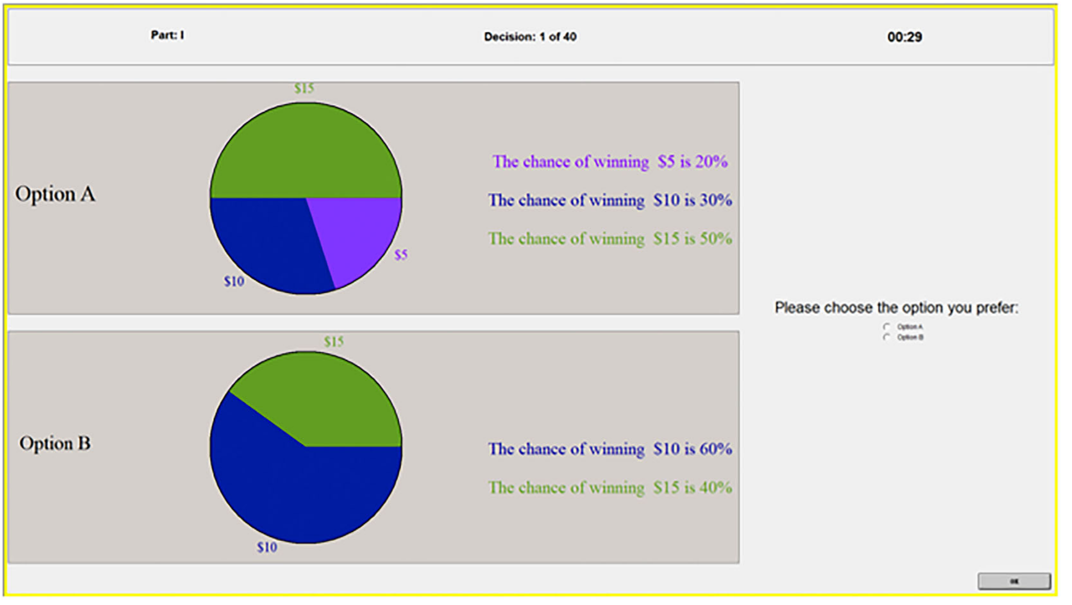

FIGURE A.1 Screenshot of risk task.

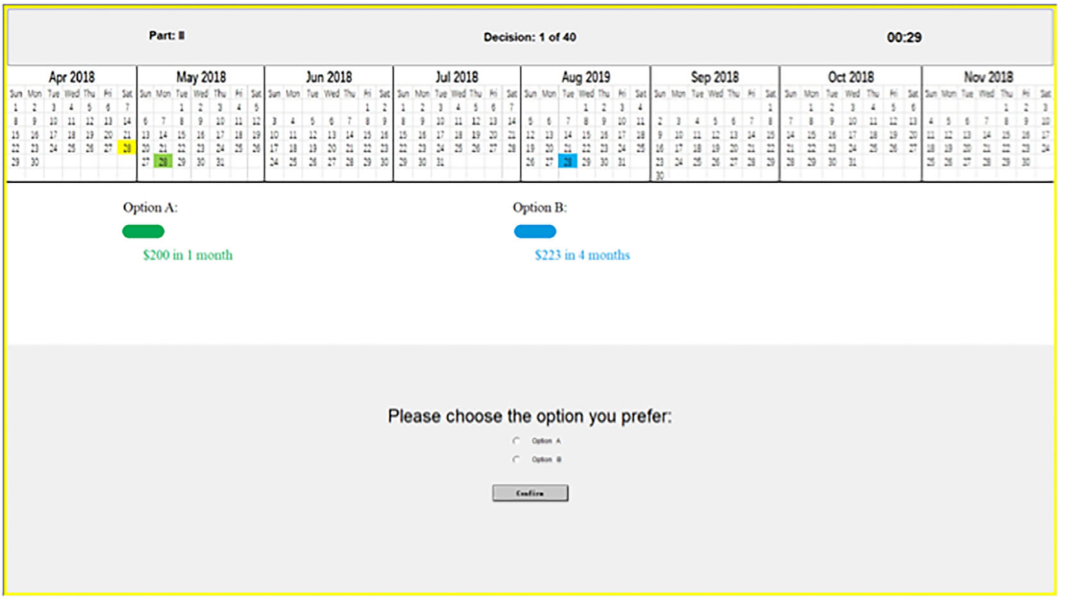

FIGURE A.2 Screenshot of time task.