# Economics of Individual Decision-Making: Buy vs. Lease Differences in the Adoption of Residential Solar

Varun Rai<sup>1,2,\*</sup> and Benjamin Sigrin<sup>1</sup>

 $1$  LBJ School of Public Affairs, The University of Texas at Austin <sup>2</sup> Mechanical Engineering Department, The University of Texas at Austin

Contact information: Varun Rai Assistant Professor, LBJ School of Public Affairs and Mechanical Engineering The University of Texas at Austin 2315 Red River Street, SRH 3.256, Austin, Texas, 78712 Email: raivarun@gmail.com. Phone: 512.471.5057. Fax: 512.471.4697

# **Abstract**

We use a uniquely rich dataset from the rapidly growing residential photovoltaic (PV) sector to study individual decisionmaking. We focus on what financial metrics and information decision makers base their decisions on, and how their decision is affected by the structuring of rebates and business models. In particular, we study how the leasing and buying models affect individual choices. We find that in the early market we studied (Texas), a majority of PV adopters use payback period not net present value (NPV) as the decision-making financial criterion. Those who opt to buy PV systems display a systematic optimism in the value of solar. On the contrary, those who lease typically have a tighter cash flow situation, which in addition to less uncertainty about technological performance when leasing, are the main reasons for them to lease. We also are able to calculate individual-level discount rate using a measure of implied net present value. Across a range of scenarios, buyers of PV systems have discount rates of 8-21% *lower* than the leasees. Overall, our results suggest that the leasing business is able to address informational requirements of consumers more effectively than the buying model, and that the leasing model has also opened up the residential PV market to a new, and potentially a very large, consumer segment—those with a tight cash flow situation.

*Keywords*: Residential Solar PV; Discount Rates; Solar Business Models; Individual Decision-making.

#### **1. Introduction**

!!

Two questions prompted the work we report in this paper. First, and somewhat specific in scope, what can be learned from the diffusion of solar photovoltaics (PV) so far for improving the existing solar rebate programs and for the design of yet others in newer markets? This is especially relevant as market support (incentives, rebates, etc.) for these technologies is waning down, increasing the pressure for incentive programs to become more efficient. Second, and more generally, what lessons could the residential solar PV market shed on the individual decision-making process? The scale of capital investment for solar PV is quite high—it is a relatively big investment compared to most other household investments in technology.<sup>1</sup> So, presumably, the choice to adopt PV would force individuals to consider the (alternative

VR would like to acknowledge support from the Elspeth Rostow Memorial Fellowship and from the Center for International Energy and Environmental Policy (CIEEP) at UT Austin. Any remaining errors are ours alone.

<sup>&</sup>lt;sup>1</sup> Other energy-related decisions at the household level include choice of electric appliances (and their efficiency), automobile selection, and behavioral choices (for example, temperature settings for AC units), but perhaps only automobile purchase comes even close to a PV system in terms of the initial investment requirement. While energy considerations are certainly a factor in automobile choice, this process involves several other factors and is not primarily an energy choice.

investment) options more carefully than when they are making most other investment decisions. Unpacking the decision process to adopt PV, then, might provide promising insights into the nature of the individual decision-making process.

Understanding the nature of the decision-making process has important practical implications for the design of mechanisms that incentivize reduction of harmful emissions resulting from energy use. With 22.2% consumption of primary energy and 21.4% of the total greenhouse gas (GHG) emissions (EIA, 2010) the residential sector is one of the key targets for reducing both energy demand and GHG emissions. Among other strategies—such as the adoption of energyefficient appliances and building design and construction—diffusion of microgeneration technologies, particularly rooftop solar PV, represents a key option in meeting demand and emissions reductions in the residential sector (EPRI, 2007). As different actors (policymakers, electricity utilities, program managers, conservation enthusiasts) have tried to design programs and incentives to spread the adoption of more efficient and environmentally-friendly consumption and generation devices, the nature of the decision-making process has come to sharper focus recently in the context of energy choices of households (Drury *et al.*, 2011a; DOE, 2008). As we see a wave of new energy innovations such as electric vehicles (EVs), home energy management systems (HEMS), and smart thermostats and meters, the last few years of experience with residential PV provides an early and unique opportunity to refine our understanding of how individual decision-making impacts technology diffusion.

Three lines of inquiry in the literature are particularly relevant to the work reported here. First, decision-making at the individual level. While the predominant neoclassical microeconomic theory is based upon the assumption of rational individual decision makers who are information prescient, more recently there is increasing evidence that the individual decision-making process and the information that feeds that process depart significantly from the neoclassical model (Frederick *et al.*, 2002; Wilson & Dowlatabadi, 2007; Margolis and Zuboy, 2006). Second, empirical evidence of the use of higher discount rates for returns farther into the future. Expectations of rapid technological change, information barriers, and other non-monetary costs are some of the factors that give rise to this phenomenon. In general, this phenomenon discourages the adoption of technologies whose benefits are spread over a long time horizon. Researchers have proposed the use of upfront capital subsidies as a way to overcome this barrier to the adoption of technologies (Timilsina *et al.*, 2011; Johnson *et al.*, 2011; Guidolin and Mortarino, 2009; Margolis and Zuboy, 2006). Third, business models for accelerating the deployment of technologies by addressing market barriers facing individual decision makers, and in particular the leasing (renting) model. Several researchers suggest that the option to lease (rent) a technology may also offer an effective means to address the high discount rate problem as well as some of the information failures associated with new technologies (Coughlin & Cory, 2009; Taylor, 2008; Hart, 2010).

#### **2. Data and Methodology**

Our basic strategy is to compare the payback period that PV adopters report as having used to evaluate their investment decision with an "objective" model we have built to calculate those same metrics. Actual metrics used by PV adopters in their decision and other related financial and behavioral aspects of their decision-making process were obtained through a survey of PV owners in Texas (see Section 2.2). To enable a comparison, we built a financial model that calculates the lifecycle expected costs and revenues associated with ownership of a residential PV system for the buying and leasing business models (discussed in detail below). Two factors make our model unique. First, our uniquely

comprehensive dataset allows us to make detailed cost and revenue calculations for *each* respondent (decision maker). Second, our model includes several detailed features of *household-level* electricity consumption, electricity rates, and PVbased electricity generation, including time-of-day and monthly variations. Our temporal resolution is at the hourly level, aggregated for all days of a months; that is, the given hour represents that hour for all days in that specific month.

#### **2.1 Calculation of Financial Metrics: Cash Flow Model**

For each PV adopter in the dataset we calculated a series of monthly expected costs  $C_k$  and revenues  $R_k$  that are incurred every month over the lifetime of the PV system, where *k* is the number of months since the PV system was installed. For leasees the system life is the length of the lease contract (typically 15 years) and for buyers it is 20 to 25 years, which is the standard length of warranty coverage on the PV modules. Therefore, monthly cash flows  $(CF_k)$  in month *k* of the investment are:

$$
CF_k = R_k - C_k \t\t(1)
$$

and the lifetime cash flow is given simply by  $\sum_k CF_k$ . Details of how  $C_k$  and  $R_k$  are calculated are provided below. Using these cash flows we calculate a number of standard financial metrics for each household's investment, including NPV (using a 10% annual discount rate), NPV per DC-kW, and payback period. Further, as we discuss later, we also estimate each individual's unique implicit discount rate.

Next we detail the process of calculating costs and revenues. Let  $c_{ijk}$  be the electrical consumption and  $g_{ijk}$  be the system's generation in hour  $i$  (1 – 24,) month j of the year (1 – 12), and k be the number of months since the system was installed. Note that  $j = k \mod 12$ , but the index is preserved to emphasize intermonthly variation. System generation is adjusted by a monthly system loss factor  $l$ :

$$
g_{ijk+1} = g_{ijk} * (1 - l). \tag{2}
$$

Furthermore, f is a function that calculates electricity costs such that  $f_{BAU}(c_{ijk})$  is the business-as-usual (BAU) electric bill prorated for period *ijk* and  $f_{PV}(c_{ijk} - g_{ijk})$  is the PV electric bill for the same period. The electricity bill function is numerically calculated based on the individual's rate plan and electricity tariffs are escalated by an annual growth rate, which is a parameter in the model.

Therefore, revenue associated with system ownership in month  $k$  after system installation is:

$$
R_k = \sum_{i}^{24} f_{BAU}(c_{ijk}) - f_{PV}(c_{ijk} - g_{ijk}).
$$
\n(3)

Costs of the system  $(C_k)$  consist of three monthly components: (a) system payments  $(C_{system_k})$ —either lease payments or the initial down payment, (b) operations and maintenance costs  $(C_{O\&M_k})$ , and (c) cost of inverter replacement( $C_{\text{Inverter}_k}$ ) such that

$$
C_k = C_{system_k} + C_{0\&M_k} + C_{Inverter_k} \,. \tag{4}
$$

*2.1.1 Buyer's Costs*

For buyers, system payments comprise of the system down payment in the first period and any amortized costs if the system is financed. The net system cost is calculated as the total installed cost less the utility rebate reported in the program data. Last, 30% of the remaining balance is subtracted to account for Federal Tax Credits (FTC). We assume that buyers will be required to make periodic operation and maintenance-related (O&M) expenses which range from 0%/year to 0.75%/year of the system's installed cost and are expensed equally each month. Inverters comprise a substantial portion of a system's installed cost and are assumed to require replacement after 15 years of use. Thus, buyers pay 70 $\ell$  to 95 $\ell$  per DC-Watt in real costs in the fifteenth year of ownership to represent this cost. In Section 2.3 below we develop a set of scenarios that are used to systematically vary these parameters.

#### *2.1.2 Leasees's Costs*

As defined by their contractual agreement, solar leasees are not obligated to pay O&M or inverter replacement costs. Therefore, the only costs of ownership they incur are either monthly lease payments that escalate by 2.5% a year, or, as in the case of the majority of leases, a single payment incurred in the first period known as a *pre-paid lease*. For all 68 leased systems in our dataset we use the actual lease payments being made by the leasees.

#### **2.2 Data**

Our analysis uses a new household-level dataset we have built through two complementary data streams: (i) a survey of residents who have already adopted PV and (ii) solar program data for these *same* PV adopters obtained from electric utilities that administer rebate programs for residential PV. The survey sought to study the experience in selecting and installing a solar PV system by those who have installed PV at their homes. Only households that have already adopted PV were part of this survey. A summary of the overall findings from the survey can be found elsewhere (Rai and McAndrews, 2012). The survey was administered electronically (online) in Texas during August-November 2011. The total number of complete responses received was 365, or about 40% of the 922 PV owners contacted. Of these we could get the complementary program data for 210 respondents. Accordingly, unless otherwise noted, all the results reported in this paper use the full data for 210 PV adopters in Texas who installed their systems between 2009-2011. The program data provided us with several detailed data points, including (i) installed cost of the system, (ii) price and structure of lease payments if the system was leased, (iii) size of the system, (iv) amount of rebates disbursed, (v) compiled or estimated annual household electricity consumption from the prior year, (vi) retail electricity provider (REP) and electric plan as well as their marginal cost of electric consumption and plan structure just prior to PV installation, and (vii) projected annual electricity generated by the system based on orientation, derating factor, and geography.

#### *2.2.1 Electricity Consumption Profiles*

Given the seasonal and hourly variations of both solar generation and electric rate structure, we modeled household electric consumption to include both hourly and monthly factors. Ideally, our model would include the actual time-series of historic consumption patterns to project future consumption for each respondent. This proved infeasible, as we did not have consumption data at that level of resolution. This will be the purview of our future work.

Therefore, the best indication of each respondent's electricity use was their historic annual electricity consumption in kilowatt-hours (kWh) as provided in the program data. The challenge, however, is to disaggregate annual consumption

into hourly intervals of consumption. We make the necessary assumption, given these constraints, that each respondent's intraday pattern of electrical consumption follows profiles released by the Electricity Reliability Council of Texas (ERCOT) representing average residential consumption patterns in north-central Texas in 2010 (ERCOT, 2010). The ERCOT profiles recognize two types of consumers as defined by the ratio of their peak summer to peak winter consumption. These consumers, Low Winter Ratio (LoWR) and High Winter Ratio (HiWR) respectively, correspond to households using either natural gas or electricity as a winter heat fuel source. Based on information from the consumer's electricity bill, we assigned each consumer a low or high winter ratio consumption profile; where no information was present, a HiWR was assumed.

Furthermore, we assume that profiles of electricity consumption are invariant over the lifetime of the PV system and that each consumer follows the same *pattern* of consumption. With that assumption, the specific consumption profile for each consumer takes into account their actual annual electricity consumption over the past year. While the ERCOT data was expressed in 15-minute intervals, we aggregated the profiles into an hour-month scale, that is, where all consumption within a given month is expressed in terms of a 24-value vector corresponding to each hour of the day (Fig. 1).

## [FIGURE 1 ABOUT HERE]

Obviously, this is not a robust assumption, per se, since we do not capture household-level patterns of consumption that differ from the average consumption patterns or patterns that evolve over time. But, since the goal is to *compare* the objective and reported financial metrics, as opposed to evaluating the impact of the absolute amount of electricity consumed, we believe that this is a robust enough assumption for the purposes of our analysis.

#### *2.2.2 PV Generation Profiles*

Calculating profiles for the electricity generated by the photovoltaic system (Fig. 1) presents a similar challenge as disaggregating electric consumption, because hourly generation will depend on geography and system orientation characteristics that are unique to each respondent. Orientation of the system is the driving variable in these calculations since it determines the magnitude and profile of generation. Complicating these calculations are factors relating to rooftop availability, angle, and shading factors unique to each rooftop. We employ a generic generation profile for the Dallas-Ft. Worth area taken from the PVWATTS model created by the U.S. National Renewable Energy Laboratory (NREL). Like the consumption profiles, the generation profile is aggregated to an hour-month scale, normalized, and then scaled by the expected annual production of specific PV systems under consideration. The expected, annual system production reported in the program data, which we use here, already incorporates orientation and geographic factors.

Depending upon the specific scenario, purchased systems are assumed to have 20-25 years of production and leased system are assumed to be functional for the length of the lease contract. All systems experience a 0.5% annual loss in system production as the equipment ages. This is the baseline parameter, and as discussed in Sections 2.3 and 4, we also explore the changes in financial return to more pessimistic or optimistic values.

#### *2.2.3 Electricity Rates*

PV systems generate value for their owners by reducing electricity expenses during the life of the system. Therefore, the difference between monthly electric bills the owner would have incurred without the system and those with the PV system installed can be thought of as a monthly stream of revenues. The value of these revenues is dependent on the structure and rates of the consumer's electric bill with the PV system (PV electric bill**)** as well as the bill the consumer would have paid without the system (Business-As-Usual (BAU) electric bill**)**. We have data regarding each respondent's electricity rates and bill structure at the time of (just prior to) PV installation. These rates inform the BAU bill calculations; that is, we assume that in the BAU calculations the customer would have remained on their current electricity rate plan for the lifetime of their PV system.

Calculating the PV bill—projections of the electricity bill with PV system installed—is more complicated and requires careful treatment. Within the ERCOT deregulated electricity market customers may freely choose retail electricity service among a variety of providers with varying rates, available bill structures, and percent of electricity sourced from renewable energy sources. Standard bill structures such as flat-rate and tiered-rate plans are prolific as well as plans with a seasonal or a Time-of-Use (ToU) tariff differentiation. More important for solar owners is whether their Retail Electricity Provider (REP) offers a plan which will offer credit for any moment-to-moment excesses of PV generation over consumption that are outflowed to the grid. Unlike many retail choice states, REPs within the ERCOT market are not required to provide credit for these 'outflows' and may set the outflow rate if they choose to offer it. Current practice is for REPs to offer at least one 'solar plan' characterized by outflows that are credited at a rate below the marginal price of electricity. As an example, a popular 'solar plan' is structured as a time-of-use plan with peak  $(1pm - 7pm)$ , off-peak  $(7am - 7pm)$ – 1pm, 7pm - 11pm), and night rates (11pm – 6am) of 21.9¢/kWh, 9.2¢/kWh, and 6.8¢/kWh respectively, and 7.5¢/kWh credited for all outflows.

While it is tempting to assume that consumers will select retail electricity plans which offer the highest value for their PV system, it is not obvious what depth of information finding and analysis decision-makers go through to find out which REP provides this greatest value. For example, is the highest value achieved through a plan which offers the lowest marginal electricity prices but no outflow reimbursement? Or, is it achieved through a ToU plan that has high outflow rates in conjunction with high peak-consumption rates? It is unlikely that consumers will possess sufficient technical expertise, interest, and time to make such a detailed calculation and, therefore, may elect to remain with their current REP as a default option. As discussed below, we account for this dilemma through a set of scenarios.

#### *2.2.4 Electricity Prices*

A driving parameter in the projected value of a residential PV system is the expected increase in future retail electricity prices. Excluding unexpected maintenance costs, the financial costs of solar ownership can be well-predicted at the time of purchase. Investment in a PV system, therefore, acts as a hedge against uncertain electricity price increases. Our baseline mode assumes a 2.6% annual increase in electricity, as this was the average increase in residential retail electricity prices in Texas since market deregulation (1990 - 2010). Needless to say, the value of future prices is uncertain. So, a range of plausible annual price escalations from 0% to 5%, were used in a set of scenarios.

## **2.3 Scenarios**

To recognize uncertainty in the values of parameters that drive PV investment profitability, we structured our calculations as a series of five scenarios (Very Conservative, Conservative, Baseline, Optimistic, and Very Optimistic) with progressively more optimistic assumptions (i.e., increasing value of solar to the consumer) for the value of the parameters

(Table 1). Additionally, it is an insightful exercise on its own to see how the consumer's bottom line might be affected across these scenarios for the buying and the leasing business models. Parameters varied in the scenarios were (i) the annual growth rate in retail electricity price (0-5%); (ii) lifetime of the system (20 or 25 years); (iii) system loss rate (0.75- 0.25%/year); (iii) maintenance costs as a percentage of installed costs incurred per year  $(0.5 - 0\%$ /year); and (iv) inverter replacement cost (\$0.95/W - \$0/W).

## [TABLE 1 ABOUT HERE]

The final parameter varied across the scenarios is the customer's retail electricity plan *post-installation*, which impacts the availability and value of outflow sales. Scenario 1, the most conservative scenario, assumes that the consumer will remain on their current BAU plan for the entirety of their system's lifetime. This means that they will not be credited for outflows. Scenario 2 assumes that consumers will adopt the 'solar' plan if one is offered by their current REP,<sup>2</sup> but will not transfer REPs otherwise even if there is a better solar plan from a different REP. Scenario 3, the baseline scenario, has the additional assumption that consumers will be credited 7.5¢/kWh for outflows if their current REP does not offer a solar plan. Our logic behind this design is our belief that nearly all REPs will offer an outflow credit in the future. Scenario 4 and 5 both assume that consumers will consider plans and REPs beyond their current rate plan and will adopt the plan with the highest overall value (as defined by minimizing their electricity bill post-installation for the life of the PV system) from among their current (BAU) plan and other current solar plans.

## **3. Results**

We found no statistically significant difference between buyers and leasers on the size of their system, annual consumption of electricity, or average electricity rates (Table 2) as well as on a number of demographic factors including income, age, education, and race. Based on the results which follow, our main conclusion is that buyers and leasers *do not*  represent different demographic groups, but that they represent *different consumer segments* within the residential PV market.

#### [TABLE 2 ABOUT HERE]

## **3.1 Installed Cost and Cost of Ownership**

!!

Even though the installed costs on a capacity scale  $(\text{S/W})$  for leasees (M = 8.292, SD = 0.529) was significantly more than those of buyers ( $M = 6.155$ ,  $SD = 1.387$ ),  $t(201) = 16.083$ ,  $d = 2.036$  (Fig. 2), this is the final installed cost and is not necessarily reflective of the leasee's cost of ownership. Consider that it is the *lessor* (the leasing company) that pays the installed cost, which is then passed through to the *leasee* in the form of lease payments. However, in the current policy environment, *leasing companies* are able access additional financial incentives which ultimately translates into lease payments made by the leasees being substantially lower than those that could otherwise be explained by amortization of the installed cost of the system.

#### [FIGURE 2 ABOUT HERE]

 $2$  Our data allows us to know who the current REP is for particular households. Therefore, it was possible to determine if each respondent had access to a 'solar' plan and, if so, its rate and structure.

Reflecting this market peculiarity, we found that leased systems had a statistically significant greater NPV per capacity ratio (NPV/DC-kW) than buyers in all but Scenario 5 (Fig. 3a-c; only results for the Conservative, Baseline, and Optimistic scenarios are shown). Again, this is not because leased systems are installed at a lower cost than bought ones, but that some market elements (such as accelerated depreciation and economies of scale, among other factors) currently exist which permit lessors to market their systems at prices lower than could be explained by the installed cost alone.

## [FIGURES 3a-c ABOUT HERE]

#### **3.2 Payback Period Comparison**

!!

Consistent with previous research (Ross, 1986; Camerer *et al.*, 2004; Kirchler *et al.*, 2008), the majority of respondents reported using payback period as one of the methods used for evaluating the financial attractiveness of their investment (66%) as opposed to NPV (7%), IRR (27%), Net monthly savings (25%), or "Other methods" used (6%) (Table  $3$ .<sup>3</sup> 10% of respondents indicated they made no estimate of the financial attractiveness of their investment. Respondents were subsequently asked to report the values of the metrics they used to evaluate their investment. From these responses we are able to compare reported metric values (reported) to the values generated from the financial model (modeled) based on the value of the parameters known for each respondent.

#### [TABLE 3 ABOUT HERE]

Because most respondents used payback period to assess their investment—and listed the actual value they used, payback proved to be the best financial metric to compare respondent's *reported* paybacks to those calculated using the financial *model* (Fig. 4a-c; only results for the Conservative, Baseline, and Optimistic scenarios are shown). Further, in order to compare the difference between modeled and reported payback values, we calculated the average absolute difference between reported and modeled payback period values for the entire sample and for buyers and leasers separately, excluding responses more than  $3\sigma$  from the mean (Table 4). For buyers, Scenario 4 (M = 2.613 years, SD = 2.409) minimized the average absolute difference, followed by Scenario 5 (M = 3.051, SD = 1.918). For leasees, Scenario 3 (M = 1.140, SD =  $0.725$ ) was the best fit, followed by Scenario 2 (M = 1.296, SD = 0.704). Scenario 1 was a very poor fit overall.

## [FIGURES 4a-c ABOUT HERE]

## [TABLE 4 ABOUT HERE]

Since the SSE—defined as the sum of squared differences between the modeled and reported payback periods for buyers is minimized in Scenario 5 (2764.32), this suggests that buyers likely assumed parameters similar to those of Scenario 5 when making their investment valuation. That is, buyers were optimistic or very optimistic when assessing the likely revenues and costs associated with their investment decision. By the same argument, since the SSE for leasers is minimized for Scenario 3 (816.65), leasees were more realistic to slightly pessimistic (conservative) when making their

<sup>&</sup>lt;sup>3</sup> Note that because respondents were permitted to indicate more than one metrics the percentages do not sum to 100%.

investment decision. The standard deviation of buyers' mean difference was greater than that of leasees, which indicates that leasees were more precise in their financial evaluation of the PV system. This is consistent with the fact that leasees receive much of this financial information from leasing companies, who use very detailed and sophisticated financial models.

Thus, our model indicates that leased systems have a lower mean payback period than that of bought systems across all scenarios. However, this statement must be understood in the context that from a financial perspective the two modes of investments operate on different time considerations—for leased system it is 15 years, the length of the lease contract, and for bought systems it is the lifetime of the system i.e.  $20 - 25$  years. A far better comparison of the financial profitability of the investment is the NPV DC-kW, which incorporates differences in the duration of investment. But, as we have discussed above, a majority of (individual) decision-makers do not use NPV as the evaluation metric.

#### **3.3 Implied Discount Rate**

For all previous calculations of NPV we used a 10% annual discount rate. In this section we present calculations of the discount rate at the individual level as implied by investment behavior. Specifically, as discussed below, we use a measure of implied NPV to back calculate discount rate using Eq. 5. To determine the implicit discount rate that respondents used when assessing their investment, respondents were asked to rate how strongly they agreed with the following five statements: (i) "I would not have installed the PV system if it had cost me **\$1000** more", (ii) "I would not have installed the PV system if it had cost me **\$2000** more" … (v) "I would not have installed the PV system if it had cost me **\$5000** more." For each question respondents marked 'Strongly Agree', 'Agree', 'Neither agree nor disagree', 'Disagree', or 'Strongly disagree'. One would expect a respondent to reply to this series of questions by *increasingly agreeing* that they would NOT have installed the PV system as the price increased. For example, one might respond that they would willingly have paid \$1000 more, been indifferent to paying \$2000 more, but forgone the investment if it had cost \$3000 more than they actually paid for their PV system.

Indeed, the real purpose of this question is to ascertain the implicit NPV of the respondent's investment. Based on the series of responses, we can extrapolate how much more the consumer would have been willing to pay for their system before becoming indifferent to purchasing the system or forgoing the investment—this amount is the implied NPV. In the above example, the implied NPV is \$2000. Of the total of 210 respondents in our full dataset, we excluded 82 responses from these calculations—59 whose extrapolated NPV was outside the range tested, that is, between \$0 - \$5000, 7 responses which implied an increasing willingness to have paid more for the system, and 16 non-responses. Of these excluded respondents, 55 respondents indicated that they would have been willing to pay at least \$5000 more for their system—76% were buyers and 24% leasers. That is, a significant percent of the population did consider their investment to be financially sound, but were otherwise not captured within this calculation. In total, after excluding the 82 responses as just outlined, we are left with 81 buyers and 38 leasers for the implied discount rate analysis.

The difference of normalized implied NPV ( $\frac{\text{S}}{\text{K}}$ ) for buyers (M = 511.16, SD = 308.27) and leasers (M = 447.14, SD = 282.59) was statistically insignificant from zero:  $t(85) = 1.16$ , p = 0.249 two-tailed, d = 0.216 (Fig. 5). This suggests that, overall, buyers and leasers expected similar (normalized) returns on their investment.

#### [FIGURE 5 ABOUT HERE]

Using the implied NPV, one can determine the consumer's implied discount rate, since the model calculates an expected series of cash flows. Consider that:

$$
NPV_{implied} = \sum CF_k = \sum \frac{[R_k - C_k]}{(1 + r_m)^k} \tag{5}
$$

where  $r_m$  is the monthly implied discount rate. Using an optimization routine, we can determine (a positive)  $r_m$ and annualize it, where *r* is the implied annual discount rate:

$$
r = (1 + r_m)^{12} - 1 \tag{6}
$$

Assuming Scenario 3 (Baseline) parameters, the mean discount rate for all buyers was 6.6% and that for all leasers was 21.4% (Tables 5 and 6). Rates are generally higher for the optimistic scenarios and lower for the pessimistic ones, because, as scenarios become more optimistic, the cash flows also increase. So, a higher implied rate is required to discount the cash flows to equal the *implied NPV* (which is constant across scenarios). A robust finding is that the implied discount rate for leasees is significantly greater than those of buyers—leasees discount rates are higher by 8% - 21% across all scenarios and income levels (Tables 5 and 6).

#### [TABLE 5 and 6 ABOUT HERE]

Given that there is little demographic or implied NPV differences between buyers and leasers, the conclusion one can make is that buyers and leasers do not represent difference demographic groups, but that they represent *different consumer segments* within the residential PV market. Each group expects to receive a similar (normalized) NPV for their investment, but have different availabilities of investment capital, and so has differing cash urgencies. Leasers appear to favor investments with a short return on capital because they are cash-poor, whereas buyers are able to consider longer-term investments because their cash needs are less urgent.

Previous literature (starting with Hausman, 1979) suggests that an inverse relationship likely exists between a consumer's discount rate and household income. That is, poorer consumers have more urgent needs for their cash than wealthy ones. At higher incomes, however, where one presumably has a greater quantity of spare income, the rate of return of one's investments (and hence, their discount rate) should converge to those available within the market. Our results have mixed agreements with these earlier findings.

A one-tailed t-test comparing the difference in mean discount rate among sequential income groups for the baseline scenario was performed using the hypothesis H<sub>0</sub>: DR<sub>1</sub> = DR<sub>2</sub>, H<sub>a</sub>: DR<sub>1</sub> ≥ DR<sub>2</sub>, where DR<sub>1</sub> is the mean implied discount rate for income group 1.<sup>4</sup> This test was performed for both sequential income pairs i.e.  $DR_1 \geq DR_2 DR_2 \geq DR_3$  since it is expected that the implied discount rate will monotonically decrease.

Results of the significance test indicate a much weaker relationship between income and discount rate than has been detected in previous research. We find no trend among buyers and income, and, while there may be an inverse trend

!!

 $4$  Income groups were: Income 1:  $$0 - $84,999$  / year; Income 2:  $$85,000 - $149,999$ / year; Income 3:  $$150,000 +$  / year

along income for leasers, it is statistically insignificant using a 90% confidence interval. Small sample size, particularly for leasers in each income group, is the main hurdle in detecting significant changes in discount rate along income. In agreement with previous literature, we do, however, find that the discount rate for buyers in the conservative, baseline, and optimistic scenarios (Scenarios 2-4) ranges between 7-13%, which is close to market interest rates. This further supports the point we made earlier that buyers of PV systems are in a relatively comfortable cash-flow position.

## **4. Sensitivity Analysis**

A sensitivity analysis was conducted to determine the influence of model parameters on the model-calculated NPV/kW output for the 'Optimistic' (Scenario 4), 'Baseline' (Scenario 3), and 'Conservative' scenarios (Scenario 2). Typically, sensitivity analyses compare the effect that a percentage change in inputs has on the corresponding percentage change in output. Since many of the modeled-calculated NPVs were centered around \$0, a small change in parameters produced a modest relative change in NPV, but a large percentage change. That is, suppose changing a parameter increases the NPV from \$10/kW to \$15/kW—a relative increase of \$5/kW, but a 50% percentage increase. Reporting these changes in percentage terms is somewhat difficult to grasp considering that the overall costs of the system could easily exceed \$10,000. Therefore, we only consider the *relative change* in NPV/kW, not the percentage change, as compared to the default NPV/kW for each scenario.

Six variables were tested in the sensitivity analysis: (i) Annual percentage escalation in retail electricity costs, (ii) Annual O&M costs as percentage of gross installed cost, (iii) Inverter replacement cost, (iv) Annual percentage loss in system output, (v) Minimum outflow reimbursement price, and (vi) Lifetime of system (only applicable to buyers). Each parameter was flexed over plausible values and were analyzed for impact on the Conservative, Baseline, and Optimistic scenarios.

Holding all else constant, the NPV/kW is most sensitive to changes in the annual percentage increase in electricity costs, followed by annual O&M costs, and the lifetime of the system. NPV is therefore relatively insensitive to inverter replacement cost, annual production efficiency losses, and the rate credited for outflows. It is interesting that the profitability of the PV system is most dependent on the future costs of electricity, as this is precisely the reason many consumers choose to invest in PV—to hedge against uncertain increases in electricity costs.

#### **5. Conclusion**

In this paper we report on the economics of decision-making in the adoption of residential solar PV. Using a comprehensive data set comprised of two complementary data sources (survey and program data) for 210 adopters of PV in Texas, we delve into the individual decision-making process. Four main insights emerge from this study. First, a majority of PV adopters report using *payback period* as the key financial metric they employ in judging the financial attractiveness of investing in PV. This is consistent with other studies of consumer decision-making in a wide range of settings. The use of payback period as a decision criteria is noteworthy given that these early adopters are some of the most sophisticated decision makers—they are far more educated, wealthier, and information savvy than the median household/individual. It also suggests that decision-makers are not nearly as sophisticated as the intertemporal utility optimizer (the rational actor), who at the very least would base the decision on a net present value (NPV) calculation, if not compare that NPV to alternative investment options.

Second, we compare the reported payback that PV adopters report as having used to evaluate their investment decision with an "objective" model we have built to calculate those same metrics. Our model includes several detailed features of household-level electricity consumption, electricity rates, and PV-based electricity generation, including timeof-day and monthly variations. This comparison of reported and objective metrics allows us to unpack the differences in risk perceptions between buyers and leasers of PV. Assuming the same annual discount rate (10%) for all adopters, we find that across a range of plausible scenarios buyers are more optimistic in their outlook about the costs and benefits of PV than leasers.

Third, through optimizing our model to match the reported implied net present value ("How much more would you have paid for your PV system?"), we were able to calculate discount rate for each household (decision-maker) separately. We find that across a range of scenarios, the discount rate for buyers varies between 6-18% and that for the leasees varies between 20-35%. This further confirms that buyers are in general more optimistic about the value of solar. We do not find any significant variation between buyers and leasees on any socio-demographic dimension (age, home value, income, etc.).

Taken together, these findings suggest that the leasing model is making PV adoption possible for households with a tight cash-flow situation. From this perspective, the leasing model has opened a new market segment at existing prices and supply chain conditions, and represents a business model innovation.

Fourth, and related to the previous two points, we find that for the period of the study (2009-11) cost of leasing appears to be significantly lower than that of buying. We believe that this is due to certain additional benefits such as accelerated depreciation and economies of scale (warrantees and cost of financing) accessible by the leasing companies only through the leasing model, but not the buying model. Further, leasees typically do not have to worry about maintenance and performance, which are included as part of the contract with the leasing company. For buyers, uncertainties around these represent significant non-monetary costs. Given the apparent cost and informational advantages of the leasing option, then, one would expect decision-makers to opt for the buying option only when their discount rate is very low, or equivalently, when they are very optimistic about the benefits of adopting PV. It is axiomatic that such households are vastly outnumbered by households with higher discount rates. This would imply that in the broader market and policy context of 2009-11, leasing models should be the predominant form of PV adoption. Market data, especially from California—the largest PV market in the U.S.—and elsewhere, confirm this.

### **References**

- Camerer C, Loewenstein G, Rabin M, eds, 2004. Advances in Behavioral Economics. Princeton, NJ: Princeton University Press.
- Conlisk J, 1996. Why bounded rationality? *Journal of Economic Literature,* Vol. 34, pp 669–700.
- Coughlin, J., and K. Cory, 2009. Solar Photovoltaic Financing; Residential Sector Deployment. National Renewable Energy Laboratory Technical Report. NREL/TP-6A2-44853, March 2009.
- Dietz, T., 2010. Narrowing the US Energy Efficiency Gap. *Proceeding of the National Academy of Sciences*, Vol. 107, No. 37, September 2010.
- Drury, E. et al, 2011a. The Transformation of Southern California's Residential Photovoltaic Market Through Third-Party Ownership, *Energy Policy*, Vol. 42, No. 3, pp 681-690.
- Drury, E., R. Margolis, and P. Denholm, 2011b. Metric Dependence of PV Economics. National Renewable Energy Technology Laboratory. Accessed 05/08/2012 at: http://www.nrel.gov/analysis/pdfs/solar2011\_pv\_econ.pdf.
- EIA, 2010. *Annual Energy Review*. Accessed 8 July 2011 at: http://www.eia.gov/totalenergy/data/annual/index.cfm.
- ERCOT Backcasted (Actual) Load Profiles Historical. (2010). Retrieved September 15th, 2011, from http://www.ercot.com/mktinfo/loadprofile/alp/.
- Faiers, A., Neame, C. 2006. Consumer Attitudes Toward Domestic Solar Power Systems. *Energy Policy*, Vol. 34, No. 14, September 2006.
- Frederick, S., Loewenstein G. & O'Donoghue T, (2002). "Time Discounting and Time Preference: A Critical Review," *Journal of Economic Literature*, American Economic Association, Vol. 40. No. 2, pp 351-401.
- Gigerenzer G, Todd P, 1999. Simple Heuristics that Make Us Smart. Oxford: Oxford University Press.
- Guidolin, M., And C. Mortarino, 2009. Cross-country Diffusion of Photovoltaic Systems: Modeling Choices and Forecasts for National Adoption Patterns. *Technological Forecasting and Societal Change*, Vol. 77, Iss. 2, July 2009.
- Hart, D.M. 2010. Making, Breaking, and (Partially) Remaking Markets: State Regulation and Photovoltaic Electricity in New Jersey. *Energy Policy*, No. 38, pp. 6662-6673.
- Hassett, K. A., Metcalft, G.E, 1993. Energy Conservation Investment: Do Consumers Discount the Future Correctly?, *Energy Policy*, Vol. 21, No. 6, June 1993, Pages 710-716.
- Howarth, R.B., Sanstad, A.H., 1995. Discount Rates and Energy Efficiency. *Contemporary Economic Policy,* Vol. 13, No. 3. July 1995, pp 101.
- Johnson, K., *et al*., 2011. Lessons Learned from the Field: Key Strategies for Implementing Successful on-the-bill Financing Programs. *Energy Efficiency*, Vol. 5, January 2011.
- Kirchler, E., Hoelzl, E., & Kamleitner B., 2008. Spending and credit use in the private household, *Journal of Socio-Economics*, Vol. 37, No. 2, pp 519-532.
- Margolis, R. and J. Zuboy, 2006. Nontechnical Barriers to Solar Energy Use: Review of Recent Literature. National Renewable Energy Technology Laboratory Technical Report. NREL/TP-520-40116, September 2006.
- Mont, O., 2004. Product-service Systems: Panacea or Myth? Ph.D. Dissertation, Lund University, Sweden.
- Nelson, P., 1970. Information and Consumer Behavior. *The Journal of Political Economy*, Vol. 78, No. 2, pp 311-329.
- Rai, V. and McAndews, K., 2012. Decision-Making And Behavior Change In Residential Adopters Of Solar PV. *Proceedings of the World Renewable Energy Forum*, Denver, Colorado, May 2012.
- Rogers, E.M., 2003. Diffusion of Innovations,  $5<sup>th</sup>$  ed. New York: Free Press 2003.
- Ross, Marc. 1986. Capital Budgeting Pracices of Twelve Large Manufacturers. *Financial Management*. Vol. 15, No. 4, pp 15-22.
- Shih, L.H., and T.Y. Chou, 2011. Customer Concerns about Uncertainty and Willingness to Pay in Leasing Solar Power Systems. *International Journal of Environmental Science and Technology*, Vol. 8, No. 3, pp 523-532.

Simon HA, 1997. Empirically Grounded Economic Reason. Cambridge, MA: MIT Press.

- Taylor, M. 2008. Beyond Technology-Push and Demand-Pull: Lessons from California's Solar Policy. *Energy Economics*. No. 30, pp 2829-2854**.**
- Timilsina, G.R., *et al.* 2011. A Review of Solar Energy: Markets, Economics, and Policies. Work Bank Policy Research Working Paper No. 5845, October 2011.
- Todd P. & Gigerenzer G, 2003. Bounding Rationality to the World. *J. Econ. Psychol.* Vol. 24, pp 143–65.
- U.S. Department of Energy. (2008). Multi Year Program Plan 2008 2012. Washington, D.C.: Government Printing Office.
- Wilson, C. & Dowlatabadi, H., 2007. Models of Decision Making and Residential Energy Use. *Annual Review of Environment and Resources*, Vol. 32, November 2007.
- Zeimthaml, V.A. Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence. *The Journal of Marketing*, Vol. 53, No. 3, July 1988.



Table 1. Description of the scenarios analyzed and their respective parameters.

<i>Buy</i> $(n = 142)$ Lease $(n = 68)$	Electric Consumption (kWh/yr)		System Size (DC- kW		Cost of Electricity $(\phi/kWh)$	
	Buy	Lease	Buy	Lease	Buv	Lease
Mean	21,122	20,738	6.192	6.569	0.1401	0.1274
<b>SD</b>	12,202	11,704	2.884	1.966	0.0959	0.0215
df	137		184		168	
t Stat	0.2196		$-1.108$		1.505	
$P(T \le t)$ two-tail	0.8265		0.269		0.134	
t Critical two-tail	1.977		1.973		1.974	

Table 2. Student t-test comparing mean electricity consumption, system size, and cost of electricity for buyers and leasers.

Table 3. Financial metrics used by survey responders to assess the financial attractiveness of their system and the sources of help (if any) used to determine the value of these metrics. Note: not all percentages sum to 100% because respondents may have used more than one metric or source of information.



Table 4. Mean difference between reported and modeled payback periods for buyers and leasers with ±1σ. Differences are minimized (bold rows) for leasers in baseline scenario and in the optimistic scenario for buyers.



Table 5. Mean implied discount rate for buyers along income and scenarios with  $\pm 1\sigma$ .

<b>Buyers</b>	Implicit Annual Discount Rate						
Annual Income	<b>All Incomes</b>	$$0 - $85k$$	$$85k - $150k$	$$150k+$			
N	81	22	37	22			
Scen 2: Conservative	$6\% \pm 6\%$	$6\% \pm 5\%$	$6\% \pm 8\%$	$7\% \pm 6\%$			
Scen 3: Baseline	$7\% \pm 5\%$	$7\% \pm 4\%$	$6\% \pm 6\%$	$7\% \pm 6\%$			
Scen 4: Optimistic	$13\% \pm 6\%$	$12\% \pm 5\%$	$13\% \pm 6\%$	$13\% \pm 7\%$			
Scen 5: V. Optimistic	$18\% \pm 7\%$	$17\% \pm 5\%$	$18\% \pm 7\%$	$17\% \pm 8\%$			

Table 6. Mean implied discount rate for leasers along income and scenarios with  $\pm 1\sigma$ .





**Figure 1**: Consumption, generation, and net consumption profiles for hypothetical consumer during the month of August. Profiles are unique to each consumer and have hourly, monthly, and annual variation.



**Figure 2**: Distribution of system installed costs (\$/W) for buyers and leasers. Buyers installed costs ( $M = 6.155$ , SD = 1.387) were significantly less ( $p = 5.85e-38$  two-tailed) than leasers ( $M = 8.292$ , SD = 0.529) though the cost of ownership are the opposite.



**Figure 3a**: Distribution of modeled system installed costs per W (\$/W) for buyers and leasers assuming *conservative* model parameters.



**Figure 3b**: Distribution of modeled system installed costs per W (\$/W) for buyers and leasers assuming *baseline* model parameters.



**Figure 3c**: Distribution of modeled system installed costs per W (\$/W) for buyers and leasers assuming *optimistic* model parameters.



**Figure 4a**: Comparison of payback period calculated by model to the period reported by consumer in our survey using *conservative* parameters assumptions. Mean difference between modeled and consumer payback period: Buyers = 8.9 yrs; Leasers  $= 1.3$  years.



**Figure 4b**: Comparison of payback period calculated by model to the period reported by consumer in our survey using *baseline* parameters assumptions. Mean difference between modeled and consumer payback period: Buyers = 7.1 yrs; Leasers  $= 1.1$  years.



**Figure 4c**: Comparison of payback period calculated by model to the period reported by consumer in our survey using *optimistic* parameters assumptions. Mean difference between modeled and consumer payback period: Buyers = 2.6 yrs; Leasers  $= 1.8$  years.



**Figure 5**: Difference between implied NPV/kW between buyers and leasers was not significantly different than zero; Both groups implied a mean NPV/kW close to \$500.