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Household Changes in Electricity Consumption Behavior Post Solar PV-Adoption

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Household Changes in Electricity Consumption Behavior Post Solar PV-Adoption

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Abstract

Household Changes in Electricity Consumption Behavior Post Solar PV-Adoption

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I combine quantitative data on minute-resolved electricity-consumption profiles and survey data with qualitative interviews of PV adopters to create a holistic understanding of how PV adoption influences behavioral change of electricity use. In particular, I examine the information and heuristics consumers use to make energy-related choices and evaluate how consumption behavior affects the total amount and timing of electricity use. Consumption behavior post adoption can significantly alter the environmental benefits of solar PV. Post-adoption changes such as decreases in energy consumption or load shifting from times of high peak demand to times of lower peak demand increase the amount of solar PV generation that is exported to the grid. Higher outflows may reduce the need for less efficient peaking generation units during peak demand, particularly in the summer when solar PV is at its highest generation capacity and electricity demand is greatest.

I find that PV adoption does trigger increases in awareness of electricity use. However, while adopters report small or insignificant decreases in household consumption post-adoption, examination of actual records shows both significant increases and decreases in consumption post-PV adoption at the household level. I explain this seeming discrepancy by noting that these households were already energy-conscious prior to PV adoption and had newer, more energy efficient homes, which could offset effects of increased awareness. Supporting this, a majority of respondents considered PV adoption as one action within a larger electricity conservation campaign initiated prior to system adoption. Because they had already implemented several energy efficiency measures, respondents could not easily identify additional ways to reduce electricity use. Most respondents have a method of monitoring consumption, but their attentiveness to monitoring declines after installation-- which could explain the awareness gap as well as the consumption increase. In addition, exogenous factors such as the purchase of an electric vehicle and changes in household size may explain increases in consumption. While I find changes in total consumption after adoption of solar PV at the individual household level, the aggregate mean consumption for all households is just 1.0% but the change in means is insignificant.

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1. INTRODUCTION

The rate of adoption of solar photovoltaic (PV) technology has increased dramatically in the residential electricity sector. In 2013, a record year for solar PV, installations increased by over 60% from the prior year (GTM 2014). Approximately 66% of electricity consumed in the U.S. is currently produced using carbon intensive fossil fuels such as coal and natural gas (EIA 2014). Residential solar PV generation displaces electricity produced from these fuel sources and can reduce carbon emissions in the electricity sector (Drury, Denholm et al 2009; Perez, Richard et al 2011, Sivaraman and Keoleian 2010). In addition, since such systems generate electricity during times of peak grid use, widespread diffusion could reduce the need for 'peaking' generation units that are typically less efficient and produce higher amounts of carbon emissions per unit of generation (Ong, Denholm, et al 2010; Sivaraman and Keoleian 2010). However, the environmental benefits of solar PV are influenced by consumer behavior. The benefits may increase or decrease if consumers modify their behavior to conserve energy post-adoption or increase consumption that offsets the incremental benefits of solar PV.

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 energy-efficient 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).

Past studies have investigated how consumers change energy-use patterns after adopting efficient technologies (Keirstead 2007; Bahaj and James 2007; Ueno et al. 2006; Grønhøj and Thøgersen 2011). The "rebound effect" arises when a switch to more efficient technology creates monetary savings on a per-unit basis, resulting in increased energy consumption compared to the expected level of consumption with the efficient technology (Greening et al. o 2000; Moniz et al. 2012; Borenstein 2014). This effect is estimated at 12-55%, depending on the study and methods (Druckman et al. 2011; Sorrell, Dimitropoulos, and Sommerville 2009; Nässén and Holmberg 2009). Under the "ripple effect," however, adoption of more efficient technology leads to greater conservation through load-shifting, abatement, or further efficiency measures (Sreedharan et al. 2012; Hertwich 2005).

The rebound and ripple effect have been extensively studied under rational choice theory and behavioral economics. Rational choice theory assumes that consumers have ordered, known, consistent, and invariant preferences and the information needed to make calculated utility-maximizing decisions (Simon 1955; Tversky and Kahneman 1986; Smith 1991 Frederick et al 2002; Wilson and Dowlatabadi 2007). Under rational choice theory, PV adopters would exhibit behavior that maximizes the value obtained from their PV systems, which might include load shifting and information searching to select the optimal electricity rate plan. During the information search process, consumers must consider the cost of conducting research (Gabaix et al. 2006; Rai and Robinson 2013) and account for uncertainty in rate prices over the system's lifetime, which limits the value of the information search process (Borenstein 2007; Rai and Sigrin 2013).

In contrast to rational choice theory, behavioral economics contends that consumer decisions are impacted by factors beyond price, including social norms (Elster 1989; Other REFs), default options (Kahneman 2003), framing (Levin, Schneider, and Gaeth 1998), decision heuristics, and biased information channels (Wilson and Dowlatabadi 2007). Salient to PV is the concept of 'green consumers' who prioritize the environmental impact of their consumption choices to maintain identities as 'socially responsible' consumers (Brekke, Kverndokk, and Nyborg 2003; Young et al. 2009; Nyborg, Howarth, and Brekke 2006). Such consumers are willing to pay a premium for electricity generated from renewable and efficient sources (Roe et al. 2001; Zarnikau 2003; Hartmann and Apaolaza-Ibáñez 2012; Rowlands et al. 2002).

Whether consumers employ utility-maximizing decisions or other factors to inform their energy consumption choices, research indicates that the presence and frequent use of feedback and electricity monitoring systems can effectively encourage consumers to conserve energy and load-shift (Becker 1978; Keirstead 2007; Van Houwelingen and Van Raaij 1989; Petersen et al. 2007; Abrahamse et al. 2005). Studies find that automated technology (e.g., programmable two-way thermostats) promote conservation and reduce the need for information collection efforts (Faruqui and Sergici

2010; Rocky Mountain Institute 2006; Violette, Erickson, and Klos 2007). Through load-shifting, a demand-side management technique, consumers would ideally move energy consumption to times of day when electricity prices are low – typically nights and mornings – such that they save the most on their electricity bills (Denholm and Margolis 2007). Load-shifting may be facilitated by dynamic pricing such as time-of-use (TOU) or critical peak pricing, which unlike flat rates, produces signals to encourage customers to conserve energy and or shift consumption to certain times of the day, though the magnitude of this shift differs across empirical studies (Orans et al. 2010; Matsukawa, Asano, and Kakimoto 2000; Bartusch et al. 2011; Torriti 2012; Newsham and Bowker 2010).

In this thesis I evaluate how PV adoption might catalyze behavioral change in the way PV adopters consume electricity, such as load-shifting or the 'ripple effect', whereby increased awareness of electricity consumption triggers additional electricity conservation (Henryson et al, 2000; van Houwelingen and van Raaij 1989). I use quantitative and qualitative data on PV adopters in the Texas residential sector to determine whether they exhibit significantly different post-adoption electricity consumption behavior. I utilize data on how consumer efforts to obtain knowledge on household electricity choices and habits, and the related information searching costs, affect the total amount and timing of electricity use. I compare post-adoption consumer behavior to pre-adoption patterns and investigate effects on the environmental benefits of their PV systems. Finally, given that the decision to install a solar PV system is a financial investment for many households, I evaluate how the selection and availability of rate plans affect the value of the system.

1.1 The Rebound Effect Literature Review

A rebound effect following the installation of energy efficiency measures has been widely analyzed in the existing literature due to its effect on the environmental benefits associated with energy conservation; However, little research has been conducted on the effect of consumer behavior post PV-adoption. One of the most widely referenced papers on the energy efficiency rebound effect (Greening et al. 2000) surveys over 75 studies in the residential sector. Greening et al. reports potential rebound effects from these studies of 10-30% for space heating, 0-50% for space cooling and 5-12% for residential lighting. The wide range in the rebound effects is problematic and arises out of a lack of consistency in how the rebound effect is defined within these studies. Four types of rebound effects can be used to determine both microeconomic and macroeconomic effects: (1) direct rebound effects, (2) secondary fuel use effects, (3) economy-wide effects and (4) transformational effects (Greening et al. 2000).

The direct rebound effect is a pure price effect. It assumes that when the price of a good or service declines, consumers will increase their demand for this good or service. Under this theory, when a consumer's energy expenditures decrease, consumers are likely to increase their use of the same energy-consuming service. However, this theory ignores consumer utility of energy services where consumers may not demand more of the same energy service but rather prefer other, potentially energy-consuming, goods or services – also called the secondary fuel use effects. This income effect can lead to economic growth due to the increased demand for other goods and services, producing economy-wide effects. One of the most recent studies on this matter (Thomas and Azevedo 2013) found that while the indirect rebound effect of a single household may be large, the economy-wide effects will be less significant as not all households are able or willing to make energy efficiency improvements. Finally, the transformational effects, most often ignored in the literature, occur when a consumer's preferences change in response to technology shifts.

While much of the literature suggests a positive rebound effect, a new study released by the Energy Institute at Haas, considers the possibility of a negative rebound effect. The magnitude of secondary rebound effects is based on the energy intensity of the goods bought with an additional dollar of income (Borenstein 2014). According to Borenstein, if the energy intensity of the substituted goods and services is lower than the current consumed goods and services, the rebound effect will be negative. Another example of a negative rebound effect occurs when the net savings of the energy efficiency measure is also negative. This occurs when the consumer, knowingly or unknowingly invests in energy efficiency retrofits that are not cost effective.

One of the few studies that evaluated consumption behavior after the installation of solar PV focused on nine households in an urban community housing for low- and middle-income families (Bahaj and James 2007). This study found that when the electricity generation of a PV system was visible and the consumer was aware of the association between the intensity of the system generation and their electricity use, this higher awareness resulted in more effective planning of daily energy use. All tenants of the housing development studied were given home PV user guides post-installation to enable them to take financial advantage. Monthly data on system performance was published on a web site to show users' consumption and export to the grid, and meters showing cumulative generation totals were installed in each unit. The results showed wide variation in consumption and export levels between households; 8 households exported between 40 and 70 percent of generated electricity despite having some of the highest demand. Overall, they found an increase in consumption levels over a year (+3 percent for 3 high-energy households and +34 percent for six lower-energy households) and considerable room for load shifting, as consumers' peak usage occurred early and late in the day and did not correspond with peak generation. It appears that consumers adopted the rebound effect, using more high-energy electronic devices on constant power and switching to less efficient lighting. Consumers failed to efficiently match their loads to PV system generation. Bahaj and James suggest more sophisticated household systems for load management control that can enhance consumers' load shifting to optimal generation times.

1.2 The Ripple Effect Literature Review

In contrast to the rebound effect, the ripple effect emerges when energy efficiency improvements trigger additional benefits such as increased conservation. While the rebound effect largely attributes increases in energy consumption to the income effect, the literature credits the ripple effect to increased awareness of energy use. Several factors have exhibited the potential to reduce residential energy consumption. Metering and tariff arrangements for residential generation offer different incentives for consumers to alter energy consumption (Keirstead 2007). Monitoring systems and on-grid vs. off-grid systems also influence consumption behavior. Keirstead's study on 118 households, which comprised of a questionnaire with a 77 percent response rate and 63 follow-up interviews found a ripple effect among respondents, with a reported reduction in electricity use of roughly 6 percent from pre-installation levels. Respondents were more aware of their usage and showed preference for efficient lighting. The presence of monitoring devices in the home (61 percent of devices were in a visible area and a majority of respondents checked at least daily) had an effect on the timing of consumption as respondents reported that they shifted use to more closely reflect PV generation (43 percent reported load shifting).

In their study of increasing consumer awareness of energy use trends and behavioral impact, Ueno et al. (2006) provided consumers with information on energy use from various appliances. They monitored usage in 19 households (all occupied by married couples with 1-3 children), measuring end-use electric power and room temperature at 30-minute intervals. They developed an online energy information system and implemented information terminals in 10 of the 19 monitored households to provide feedback directly to consumers, and to offer an estimate of financial expenditures for the equivalent energy use. Tips on energy savings were included, to which households could respond by clicking a button. Responses were high initially, subsequently declined but then rose again about 8 months later. Consumers took particular interest in usage graphs comparing their patterns to other households, as it induced their “competitive spirit”. Feedback on electricity consumption, but not total house-wide energy, was displayed to consumers. Energy use was reduced by 12 percent across the 10 households that had an information system, with power consumption throughout the entire house decreasing by 17.8 percent for these same households. Energy expenditure in major appliances (especially space heating) decreased in the feedback group as well. Ueno et al. concluded that increased awareness of consumption habits spurred users to make lifestyle changes.

A similar study implemented feedback mechanisms by way of a small LCD screen in twenty Danish households to inform consumers of their electricity usage in real time to determine what effects, if any, this new development had (Grønhøj and Thøgersen 2011). The LCD setups also gave current on/off status of various appliances and historic consumption data for the household. Grønhøj and Thøgersen monitored behavior for five months and found that households who took part in the study achieved a reduction of 8.1 percent in their usage. This was compared to a control group (163 households) that did not receive similar feedback, who saved only 0.8 percent, presumably because they were not as highly aware of their consumption levels and patterns and thus did not find reason to reevaluate their energy-consuming activities. The participant households were each comprehensively interviewed at the end of the study to gauge their true understanding of the feedback system and its impact on perceptions of energy use. While participants were generally predisposed to conserving electricity beforehand, the authors argue that detailed feedback allows consumers to actually determine the most effective ways to save electricity. The importance of consumption/generation monitoring and feedback has thus been a major factor in studies of energy use behavior and is cause for further investigation. They further differentiate between direct (real-time) feedback effects, such as via smart meter, and indirect (time-delayed) feedback, such as information on monthly electricity bills. Direct feedback creates a "better connection between behavior an effect", thus stimulating people to alter their behavior as they see the energy savings add up in real time (Grønhøj and Thøgersen 2011).

1.3 Rate Structure and PV Value

The rebound effect theory is underpinned by the savings achieved through the introduction of new technologies. Thus, the size of the rebound effect is directly related to the level of additional income attained. The financial attractiveness of an investment in solar PV is an important consideration for many would-be solar adopters. An electronic survey (the *"Solar PV Survey"*) conducted during August-November 2011 in Texas, sought to understand the reasons and experiences of PV adopters in selecting and installing a residential solar PV system (Rai and McAndrews 2012). Respondents were asked the importance of five factors in their decision to install PV: (1) General interest in energy and electricity generation, (2) evaluation that solar PV is a good financial investment, (3) reducing impact on the environment by using a renewable energy source;

(4) influence of others in the neighborhood with PV systems; and (5) influence of a close acquaintance not from the neighborhood. Respondents found the first three of the five factors equally important.

Consumer investment decisions involve the consideration of the costs and benefits of solar PV ownership. Consumers use several tools to analyze the financial attractiveness of a solar PV system such as a payback period, a net present value calculation or an internal rate of return. The *Solar PV Survey* found that 87 percent of respondents used a payback period calculation, 36 percent used an internal rate of return and nearly 12 percent used a net present value calculation to analyze the financial attractiveness of a solar PV system (Rai and McAndrews 2012).

Rate design is fundamental to the economics of commercial and residential solar PV and can alter the economic value of solar PV by 25 percent to 75 percent, depending on the size of the system relative to building load (Wiser et al. 2007). Differences in rates ultimately reflect differences in the revenue requirements of the various utilities, the size of the PV system relative to building load, and customer load shapes.

Intertemporal variation in PV generation and the consumer consumption patterns create opportunities for value creation apart from traditional rate structures. For example, Wiser et al. (2007) found time-of-use (TOU) based energy charges with a large price spread between peak and off-peak prices offered as much as a 20 percent greater energy charge savings compared to seasonal or flat energy charges. While TOU and other novel rate structures can create additional value, their complexity creates consumer uncertainty as to which plan is optimal for their consumption patterns. Indeed, some in the utility industry have argued that the TOU (and other plans) have discouraged PV adoption because of this uncertainty (Borenstein 2007).

Consumers face risk and uncertainty in their investment decision regarding: (1) interannual solar variability and weather trends; (2) PV technical performance and maintenance costs; and (3) market uncertainty including future electricity rate escalations and net-metering policies (Drury, et al. 2014). Calculations of the financial return of solar PV will depend very much on how retail rates will change over the system's lifetime (20-30 years), a very difficult path to predict (Borenstein 2007). Drury et al. found that risk and uncertainty differs by region. For example, market factors have a higher impact in California and Massachusetts while the PV technical performance risk is higher in Missouri and Florida.

1.3.1 Time of use rate structure

Time-of-use rate can provide substantial value to many PV customers as these structures levy high tariffs during 'peak' periods of grid use (when production from PV arrays is highest) and compensating lower tariffs during 'off-peak' periods, when production is lowest (Wiser et al. 2007). Assuming these structures exclude demand-based charges, a TOU generally provides the greatest value to PV users across a wide variety of circumstances. Therefore, expanding the availability of such rates would increase the value of many PV systems.

Borenstein (2007) examined data from 274 residential PV customers in California to determine the financial attractiveness of then-mandated time-of-use (TOU) rate structures as compared to standard rate plans. Among PG&E customers, whose structure is non-tiered, he does indeed find that a large majority would be better off on a TOU plan. However, the picture is inverted for Southern California Edison where standard non-PV plans are tiered, but TOU plans are not. That is, even though solar PV production is greatest during TOU peak periods, many SCE customers' value from the system is maximized on a flat-rate tariff. Overall, his results suggest that a TOU mandate is unlikely to be a significant cause of declining demand for solar PV installations.

1.3.2 NET ENERGY METERING

Important factors in the solar value proposition are the policies regulating credits for any moment-to-moment excesses of PV generation over consumption exported to the grid as "outflows". These policies vary widely based on local regulations. For example, in California PV owners benefit from net energy metering (NEM) policies which credit outflows at the retail rate. Conversely, the Public Utility Commission of Texas does not regulate credits for these 'outflows' (PUCT 2012). Texas retail electric providers' current practice is to credit outflows at a rate below the marginal price of electricity. An emerging alternative to NEM is the Value of Solar Tariff (VOST), which is designed to pay residential solar generation based on a more nuanced benefit-cost analysis to determine the actual value of residential solar to utility operations. Unlike NEM, VOST-compensated solar generation is not counted against consumption. Rather, generation and consumption are treated as two separate functions.

Wiser et al. (2010) found that eliminating NEM altogether could result in more than a 25 percent loss in the rate-reduction value of commercial PV for commercial systems that serve a large percentage of building load. In contrast, elimination of NEM rarely results in a financial loss of greater than 5 percent of the rate-reduction value of PV when annual solar output is less than 25 percent of customer load-- and excess PV production can be sold to the local utility at a rate above $0.05/kWh.

A study that analyzed the bill savings for 215 residential PV customers of California's two largest electric utilities, Pacific Gas and Electric (PG&E) and Southern California Edison (SCE) in order to understand the influence that net metering policies and rates had on PV value (Darghouth et al. 2010). Not surprisingly, bill savings under NEM were significantly greater for high-usage customers than for those with low levels of use. In total, the median bill savings per kWh of PV generation ranged from $0.19-$0.25/kWh. Furthermore, bill savings declined with PV system size—since at larger capacities the customer faces a progressively lower marginal price for its net consumption when moving along tiers. Additional value for residential consumers can also be created when NEM is combined with TOU rates, especially as the size of the PV system increases (Darghouth et al. 2010).

The continued existence of NEM policies is threatened by calls for repeal by utilities across the U.S. Residential solar PV precipitates reduced customer demand for energy from a utility and, consequently, lower revenues. In response to the difficulties posed by NEM-backed solar PV to utility revenues, efforts to reduce or eliminate NEM have been or are currently underway in Colorado, Virginia, California, Texas, Arizona, Louisiana and Idaho, among others (Cardwell, 2013; Copley, 2013; Tracy, 2013). Minnesota is the first state to issue a statute requiring the department of commerce to develop a methodology for valuing solar electricity generation (Minnesota 2014). Minnesota utilities will have an opportunity to use this methodology in lieu of net energy metering. According to a proceeding filed before the Minnesota Public Utilities Commission, "the methodology values distributed solar PV by considering each utility's solar PV fleet in the aggregate; determining the fleet's value to the utility, customers, and society; and establishing a bill credit for solar PV customers based on that value. A Value of Solar tariff, if approved, would apply to future solar PV interconnections." The elimination or down phasing of NEM policies will have a material effect on the economic value of solar PV systems.

1.4 Rate Structure and Consumer Behavior

Households in competitive markets such as Texas have a choice in their energy service provider and rate plan. Sub-optimal rate selection by customers generally leads to a reduction in bill savings of less than 10 percent, but can have a much greater impact for some customers at a low PV-to-load ratio (Darghouth et al 2010). Despite this loss, several reasons exist why a consumer may elect for a sub-optimal plan. First, electricity comprises only 4 percent of the average household expenditure (EIA 2013). Consumers may actively search for an electricity provider only when they move to a new residence (Watson et al. 2011). Therefore, unless consumers have a strong motivation to seek new suppliers, it is unlikely that they will actively search for information and thus will remain loyal to their existing supplier. Second, consumers may use a satisficing heuristic, rather than a profit maximizing objective. In other words, they only seek information if unsatisfied-- even if there is a possibility that there may be an alternative that would derive them greater utility. Complacency may also be a reaction to information overload when a large number of options for suppliers and rates exist (Watson et al. 2011).

Pollitt and Shaorshadze (2011) have explored this issue from a behavioral economics perspective. They highlight several factors that influence rate structure selection. The endowment effect means that consumers are insulated from variable rates during the day; furthermore, individuals are attached to their routines and daily habits and may be inflexible to modify them, or demand high compensation to do so. Status-quo bias means that consumers prefer to retain the same rate structure over time, even when savings are available through switching. Under time-varying discount rates, new structures could create initial “rate shock”, whereby bills dramatically increase in the near term before behavioral adjustments kick in that reduce consumption (either overall or from the grid). Because individuals tend to have higher discount rates, they might undervalue the benefits, especially if the savings are initially small or there is no change.

1.5 Load-Shifting

Load-shifting is a demand-side management technique use by consumers to transfer energy consumption to times of day when electricity prices are low to reduce energy costs (Denholm and Margolis 2007). The cost effectiveness of load-shifting is dependent on site-specific characteristics such as location, installation costs and performance (Sreedharan et al. 2012). Targeted approaches to demand response design and implementation are a necessity. As applied to solar PV users, this would mean that consumers should be encouraged to shift their highest demand to midday hours, when PV arrays will be generating at their peak rate. This can lead to decreased use of power from the grid and further cost savings as well.

In their investigation of load shifting under certain pricing schema, Spees and Lave (2008) incorporated real data from Pennsylvania, Maryland, and New Jersey to ascertain consumer and producer savings from both real-time pricing and time-of-use rate structures based on load-shifting behavior. They discovered that peak savings were 7 times larger under real-time pricing and that half of all customer savings from load shifting were obtained by shifting just 1.7 percent of all MWh electricity used to another time of day. Larger customers with greater demands need to be responsive and shift a sizable amount of their energy use to get most of the short-run savings.

Individuals have a tendency to underestimate energy consumption caused by various activities, especially when approximating the expenditure level for high-energy products and activities (Attari et al. 2010). There is a related tendency to overestimate the amount of energy saved by cutting back on low-intensity activities, so consumer self-reporting of consumption behavior may not accurate. Furthermore, consumers choose to change behavior in relation to the less intensive options, not realizing the increased impact they could make by focusing on other high-intensity activities. Consumers also tend to favor abatement options over energy efficiency options (i.e., using less electricity in general rather than taking proactive effort to install more efficient appliances and redesigning their homes to use less energy). Their results suggest that programs intended to improve consumers' understanding of actual impacts of various activities on energy use could pay large dividends (Attari et al. 2010).

2. DATA AND METHODOLOGY

I use three intersecting data sets that form a comprehensive picture of consumer behavior after adopting PV (fig 1). The primary data set uses electricity consumption profiles for residential households in the Austin, Texas metro area to analyze actual consumption patterns. I supplement this data with results from a Solar PV survey completed by 858 residential PV adopters in Texas in 2011-2012 (Rai and McAndrews 2012) and 21 follow-up interviews to reveal behavioral effects. While there is coincidence of respondents within each data set, each set is intended to sample from the broader population of residential PV adopters in Texas.

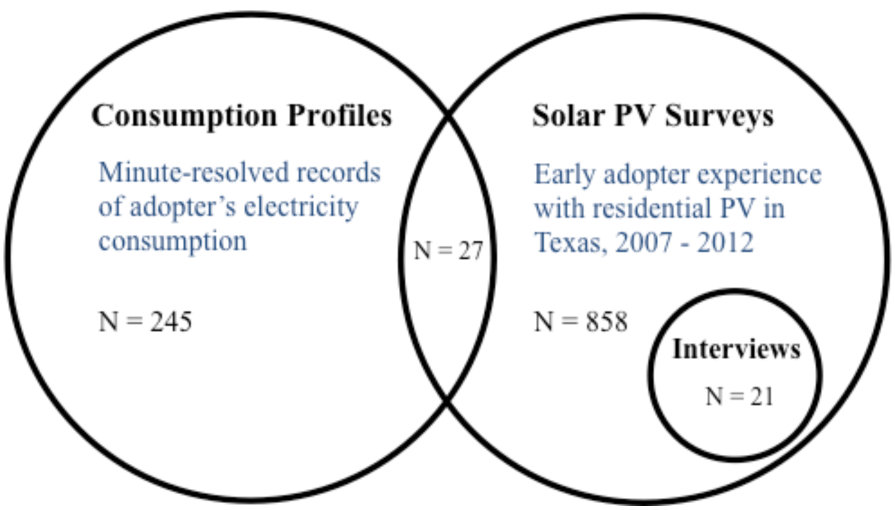

Figure 1: Description of data sets

2.1 Consumption Profiles

2.1.1 Electricity Consumption Data

Consumption profiles were obtained for 245 households in the Austin, Texas metro area and are organized into two electricity-consumption time-series data. Of the 245 profiles, 22 profiles were excluded because of insufficient or irregular data. Consequently, only 223 profiles are utilized. The first time series ("dataset 1" or "DS1") records minute-resolved household patterns of electricity use for the households post PV-adoption from January 2011 to June 2013. This includes total levels of consumption and grid inflows (in kWh) as well as PV system generation levels. Profiles vary in length, with a mean length of 16.9 months and interquartile range of 8.1 – 21.0 months, reflecting new PV adopters over the period studied. As described below, I was able to accurately control for the difference in data lengths in this dataset. The second time series ("dataset 2" or "DS2") records electrical consumption for a sub-set of the same households for the 12 months prior to PV adoption. Pre-adoption data is only available for 84 households. For this sub-set, I use observed month-resolved consumption patterns for a year prior to PV adoption and the minute-resolved consumption patterns for 6 – 31 months after adoption as contained in DS1.

2.1.2 Descriptive system details and demographics

The 223 households in the analysis are typically more affluent than the average Austin metro household. The median home value for the data set as of January 2014 is $418,159 compared to $224,000 for all Austin homes (Zillow 2014). The average home square footage is 2,313 with an average home age of 13 years and median of 5 years. The average system size is 5.64 kW. Additional demographic data on the households could not be obtained for this dataset; however, the *Solar PV Survey*, which collected information on households in the Austin and Dallas area provide insight on the characteristics of households in DS1. In the *Solar PV Survey*, the mean size of the PV systems installed by the respondents is 5.85 kW. The median household income in 2011 is between $85,000 and $115,000 compared to the median household income in 2012 in Texas of $51,563. The average home value is $410,287 and the median home value is $318,000. Respondents of the *Solar PV Survey* are also more highly educated and older than the average Texas resident. Over 80 percent of PV adopters have a bachelor's degree or higher, compared to just 25.4 percent reported in the 2010 Census report. The mean age of all respondents is 52 years.

2.1.3 DATA PROCESSING

This analysis uses MATLAB to process the consumption profiles, aggregate the data and conduct statistical analysis. Consumption profiles were collected for the 245 households in DS1 in fifteen minute-resolved values from the first date of available data for each profile through June 30, 2013. Consumption profile data was processed to correct for some known errors in the data logging process. These can include unreasonably large 'spikes' in consumption (>100 kWh in a 15-minute period), periods of inactivity in the profile, and negative or near-zero consumption. Inactivity can occur when the monitoring system is turned off or network connectivity is not available to transmit data to the web-based electric energy and power data aggregation device used for logging the data. To correct these errors I exclude any outlier data points (>3σ from mean) from each profile, and also exclude the profile *entirely* if more than 5% of the profile length is inactive. Consequently, 22 of the 245 profiles were excluded from the analysis following the data processing. Finally, profiles were aggregated from minute-to-minute to hourly periods of analysis and cropped to include only whole months of analysis. Profiles with less than one full month of consumption data were also excluded.

2.1.4 CONSUMPTION PATTERNS ANALYSIS

I compare PV-adopter consumption patterns to those of non-PV adopting households by generating back-casted profiles. Back-casted profiles were obtained from the ERCOT website for each year. I use a load profile for the average consumption of electricity by single-unit residences within the south-central region of the ERCOT grid from January 2011- June 2013 (ERCOT 2013). Back-casted load profiles are available on a quarterly basis and, therefore, June 2013 was most current profile at the time of this analysis. Since the ERCOT and PV adopters' profiles are similarly time-stamped, this allows control for annual and seasonal variations in grid-wide electricity use and to compare historic patterns of consumption along hourly and seasonal factors. The strategy here is two-fold: first, a "within" analysis to compare changes in gross household energy consumption pre and post PV-adoption; second, to determine if, post PV-adoption, adopters' hourly and seasonal consumption patterns differ significantly from non-adopters'.

2.1.4.1 Pre/Post-Adoption Within Analysis

To compare changes in total household consumption pre and post adoption *for each adopting household* separately, let c_{ijk} be the gross household consumption for a given household occurring in hour *i,* day in month *j* (1-31), and month of year *k.* Then

$$c_k = \sum_i \sum_j c_{ijk}\,, \tag{1}$$

where c_k is the gross electricity consumed for that household in month *k*. Let e_k be the gross electricity consumed in the ERCOT back-casted profile for that same month *k*. For *each adopting household,* the mean percentage difference (p_k) between c_k and e_k is determined for month *k*:

$$p_k = \frac{c_k - e_k}{e_k}. \tag{2}$$

Next, sets *pre* and *post* are defined as the sets of months *k* (unique to each adopter) occurring prior and post-system adoption, respectively. Last, the median of p_{pre} and p_{post} are calculated, where $\tilde{p}_{pre,m}$ and $\tilde{p}_{post,m}$ are the medians of p_{pre} and p_{post} for the specific adopter m. That is, $\tilde{p}_{pre,m}$ represents the median percentage difference in gross monthly consumption of the adopting consumer m prior to adoption and the average consumption of ERCOT households in the same months and geographic area. Therefore, Δ ($\tilde{p}_{post} - \tilde{p}_{pre}$), the difference of $\tilde{p}_{pre}$ and $\tilde{p}_{post}$, represents the change in gross monthly consumption after system adoption after controlling for seasonal factors. I determine Δ for each consumer in the study (DS2, the 84 PV adopters that allow these metrics to be computed), the distribution of Δ, and its summary statistics.

2.1.4.2 Hourly/Seasonal Variation

Next, I determine seasonal and hourly variations between the adopter and the average ERCOT consumption profiles, but only using the post-adoption data (the monthly granularity in the pre-adoption data limits this analysis only to the post-adoption period). Because there are many factors that can produce seasonal and hourly variation such as the building envelope and incentives that reward consumers for load-shifting, this analysis alone cannot explain post-adoption behavior and must be combined with qualitative information provided in the *Solar PV Survey* and interviews. First, the difference of an individual adopter and average ERCOT consumption occurring in the same time periods is determined:

$$d_{ijk}{}^{m} = c_{ijk}{}^{m} - e_{ijk}. \quad (3)$$

For hourly pattern analysis I calculate both the mean and median of the set of d_{ijk}, where *i* = 1,2,...,24. That is, $d_i{}^m$ is the set of all differences in consumption for the adopter and equivalent ERCOT consumption occurring in hour *i,* and $\bar{d}_i{}^m$ is the mean or median of the set of d_i differences. Finally, $\bar{d}_i$ is determined for each consumer in the study (in DS1) and the distribution of $\bar{d}_i$ and its summary statistics are determined.

For monthly pattern analysis the process is similar, whereby the difference (d_k) between the adopter's consumption in month k (c_k) and the equivalent ERCOT consumption in the same month (e_k) is determined for all months; then the mean $(\bar{d}_k)$ or median $(\tilde{d}_k)$ is taken of all monthly consumption differences. Lastly the distribution of $\bar{d}_k$ and $\tilde{d}_k$ for all consumers and its summary statistics are determined. In contrast to the hourly pattern analysis, I use monthly consumption from October 2011 through June 2013 for this analysis due to the small number of profiles with consumption data for the 9 months prior. Furthermore, to ensure that the seasonal analysis largely includes the same households, I include only profiles with an inception date of at least June 2011.

2.2 Solar PV Survey

To bring additional contextual data to bear upon the analysis, I use specific portions of the *Solar PV Survey* (see the opening paragraph of Section 2) – namely, reported changes in awareness of electricity consumption, total amount of consumption, and frequency and timing of energy-intensive activities post-adoption. I also use survey data relating to adopters' use of information that enable post-adoption monitoring/evaluation of PV system value, such as the prevalence and use of consumption-monitoring devices, and home upgrades made concurrently with system installation.

2.3 Structured Interviews

Follow-up interviews were held with 21 households who completed the *Solar PV Survey* to elaborate on issues not easily captured within the survey format. Each interviewee took part in either the 2011 or 2012 *Solar PV Survey*, in which they answered a range of questions on the motivation for installing PV and electricity consumption habits. However, the survey questions that specifically asked about consumption habits post-installation were limited in scope, and allowed little opportunity for participants to elaborate on their overall approach to electricity use. To cover that gap to some extent, the interview topics included: (i) respondents' motivations for adopting PV; (ii) their research (info search) on rate structures available post-adoption, and rebates/subsidies available for a system installation; (iii) methods used to monitor their PV system generation and electricity consumption trends; and (iv) an explanation of time-of-day or seasonal electricity consumption patterns post-adoption.

2.3.1 Interview Design

The goal was to speak with a small subset of the *Solar PV Survey* participants, from which I had contact information for 181 households located in the Dallas-Fort Worth and Austin metro areas. These households specifically consented within the survey form to be contacted for additional information. Twelve Round Rock, Texas area residents were contacted via email to inquire interest in participating in a telephone interview. Eleven responded and agreed to participate in the interview. Furthermore, 20

Austin area households were contacted from the *Solar PV Survey* list by email and 10 interviews were completed.

2.3.2 GOALS AND HYPOTHESES

By interviewing Austin and Round Rock consumers, a comparison of consumption and information searching behavior could be made between a deregulated market and a regulated market. The city of Austin is served by Austin Energy, a municipal utility that is the sole electric provider for households within its service territory. Conversely, Round Rock is in a competitive deregulated market where consumers can choose their retail electric provider (REP). REPs such as TXU, Green Mountain and Reliant each offer different rate plans for PV generation. By comparing the responses between consumers in a regulated and deregulated market, I could make inferences about how the choice of provider affects the information searching process and how different rate plan structures might influence consumption behavior. Given the deregulated nature of the market, I hypothesized that Round Rock consumers spend considerably more time researching rates and providers and would be more aware of their ideal rate plan than those in Austin, who presumably have no incentive to investigate different plans to see which one best fits their electric needs.

Although households residing within Austin Energy's service territory have no choice in electric provider, the utility's recent adoption of a value of solar tariff (VOST) in place of net energy metering would provide insightful information on its potential influence on the rebound/ripple effect given its generous rate. Beginning October 2012, Austin Energy offered 12.8 cents per kWh to its solar PV customers, higher than its top residential tier rate (Clean Power Research, 2013). (In comparison, as of September 2013 Austin Energy charged a maximum of 9.6 cents per kWh during the non-summer months, and 11.4 cents per kWh during the summer months.) However, the solar credit may be adjusted annually as utility costs fluctuate. For example, the re-evaluated VOST for Austin Energy in 2014 has been set at 10.7 cents per kWh (Clean Power Research, 2013) and took effect in January 2014. One interview question focused on whether this change encouraged a change in consumption behavior.

All interviews followed a prescribed list of questions with accompanying audio recording. Interviewees were purposefully chosen to provide perspectives on access to both a competitive retail electricity market (11 from Austin/Round Rock, TX and Dallas-Fort Worth metro areas) and a regulated non-competitive retail market (10 from Austin Energy territory). Each interview was 15-20 minutes long. Some participants provided documentation of their electricity usage over time, and a majority claimed to keep spreadsheets based on monthly bills detailing their post-installation consumption.

Interviews covered five topics: (i) changes in household electricity consumption after installing PV; (ii) monitoring and feedback mechanisms consumers use to track their electricity usage and generation; (iii) energy efficiency or additional investments consumers made to reduce their overall consumption; (iv) effect of living in retail choice areas on consumer's awareness of energy issues; and (v) information-searching for a rate plan and/or a retail electricity provider (REP) that would be better suited to meet the interviewee's needs post PV-adoption (refer to the Appendix for the list of questions). Responses were coded as affirmative/non-affirmative statements based on twenty specific research questions; this allows determining the percentage of sample expressing each opinion. For questions that could not easily be coded as a binary response, such as monitoring mechanisms, clusters of responses within the sample were determined, and then individual responses were coded categorically based on these clusters.

3. RESULTS OF CONSUMPTION PATTERN ANALYSIS

As noted before, existing literature suggests that the purchase of energy-saving technologies, PV included, could trigger behavioral shifts among consumers such as changes in overall electricity consumption and load-shifting to times of peak PV generation (Keirstead 2007; Bahaj and James 2007; Ueno et al. 2006; Grønhøj and Thøgersen 2011). While on aggregate, the results do not support these hypotheses, at the individual level there appears to be some level of ripple and rebound effect (see fig 2). In addition, PV adoption appears to have triggered increases in awareness of electricity use and relatively low levels of shifting of hourly patterns of consumption. However, there is some evidence of additional behavioral changes to support the "ripple effect" hypothesis: while in the survey and interviews the vast majority of adopters reported either decreases or no change in household electricity consumption post-adoption, examination of actual consumption records shows that PV adopters, on the aggregate, do not significantly change the gross amount of electricity consumed. However, on the individual level, I estimate both increases and decreases in net consumption after PV adoption (see section 3.1.1) .

3.1 Post-Adoption Behavior

3.1.1 Changes in Net Consumption

Gross levels of household electricity consumption[1] are compared before and after PV adoption. By referencing pre and post-consumption levels to the ERCOT profile, annual variances such as weather differences, improving economic outlook, as well as seasonal variances are controlled for (see Section 2.1.2.2). Using this method, the aggregate household mean consumption for the 84 profiles in DS2 increases by just 1.0% and median consumption by 1.9% (fig 2). However, the change in means at the aggregate level is insignificant using a paired Student's t-test ($p = 0.6793$).

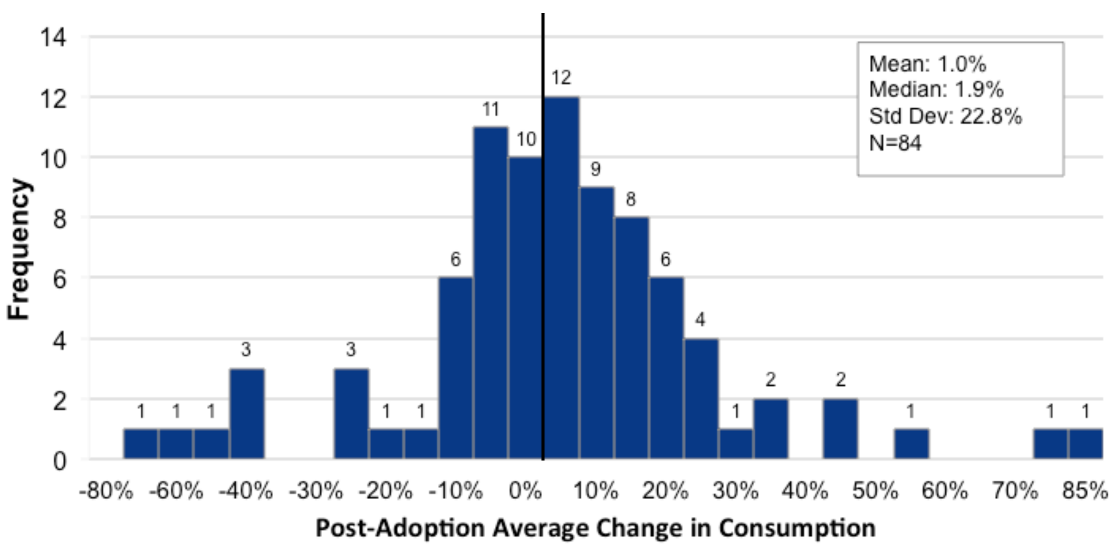

Figure 2: Comparison of changes in monthly electricity consumption post-PV adoption

[1] Total consumption refers to all electricity consumed by the household. This is not net consumption, as I include electricity the household consumes that is generated by the PV system.

In general, the quantitative findings are consistent with the interview results, where I find little evidence of changes to total electricity consumption at the aggregate level. However, approximately 20 percent of the sample has decreased consumption by 10 percent or more while approximately 32 percent of the sample has increased consumption by 10 percent or more. Although the analysis appears to support both a rebound and ripple effect for some portion of the sample, I cannot directly attribute the observed increases and decreases to a behavioral change. The dataset does not provide characteristics of the household that would allow me to eliminate the possibility of exogenous factors such as changes in household size, the purchase and at-home charging of an electric vehicle or the installation of other energy efficient equipment or upgrades. Given the minimal overlap between the households in the *Solar PV Survey* and DS2 (only 23 profiles could be matched to a survey response), it is not possible to isolate external causes for the perceived changes in post-PV adoption consumption.

These results, however, are inconsistent with changes in overall consumption self-reported in the *Solar PV Survey*, in which a large portion of the respondents (48 percent) reported a 'much lower' or 'lower' change in the total amount of electricity used after PV adoption (table 2). Further, in both the survey and interview datasets, respondents underreport actual increases in post-adoption consumption when 'more consumption' is defined as an increase of 10 percent or more in mean monthly consumption.

The findings at the individual level appear to support, in part, prior studies which report significant changes in consumption behavior in response to increased energy use awareness. One study (Ueno et al. 2006) found that the use of a monitoring device triggered energy conservation behavior over a 9-month period while a second study (Bahaj and James 2007) found that the most high-energy users reduced energy consumption following an educational discussion; however, in this study, reductions in energy use were not sustained.

	Solar PV Survey n = 717	Interviews n = 21	Consumption Profiles n = 84
'Much Lower' or 'Lower	48.0%	10%	20.00% decrease consumption by 10%
'No Change'	47.4%	76%	54.12% no change
'More' or 'Much More'	4.6%	14%	31.76% increase consumption by 10%

Table 1: Comparison of reported changes in monthly electricity consumption with actual consumption changes

For those interviewed, exogenous factors, rather than behavioral shifts, explain the majority of consumption changes. For example, purchase of electric vehicles charged at home or installation of energy efficient equipment or home upgrades often coincided with PV adoption. I learned from the interviews that PV adoption arose from environmental attitudes among interviewees that motivated increases in energy efficiency. As such, for most interviewees, PV installation was one of several actions taken toward reducing their environmental footprint. Thus, adopting a PV system does not prompt adopters to implement further energy efficiency measures post adoption.

Austin Energy, the only available electric utility for the majority of households in the dataset due to a lack of retail choice, requires homeowners to complete a series of energy efficiency home improvements for homes older than 10 years of age in order to qualify for solar PV incentives (Austin Energy 2014). Therefore, most homes in the dataset are more energy efficient than the average home in the Austin metro area.

3.1.2 NET CONSUMPTION COMPARISON TO AVERAGE HOUSEHOLD

While in the aggregate PV adopters do slightly (and statistically insignificantly) increase their monthly consumption post-adoption, they still use significantly less electricity (mean: -4.7%, median: -13.4%) than the average central Texas household (figure 3). The method for this comparison uses equations 1 and 2 and the approach is similar to the pre and post comparison made in Section 3.1.1 (figure 2), which controls for weather and other time-based effects and thereby isolates differences in overall levels and patterns of consumption between the PV adopter and the average Texas household. Note, however, that this calculation is based on only post-adoption data and uses all records available (n=223, DS2), unlike the analysis shown in figure 2, which only includes consumption profiles where both pre and post adoption records are available (n=84).

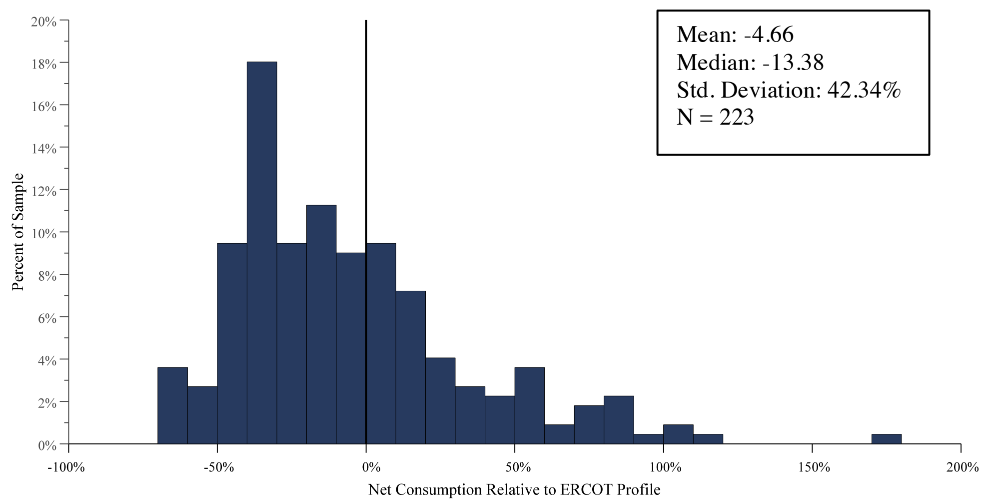

Figure 3: Comparison of net monthly consumption compared to ERCOT

As the distribution of net consumption differences changes is non-normal, a Wilcoxon signed-ranks test is used to determine if the median of the sample is significantly greater than zero ($Z = -4.76$, $p < 0.001$), which it is. This confirms responses from the survey and interviews that PV adopters already had taken several steps to reduce their household's electricity consumption prior to adopting PV whether through energy efficiency upgrades to satisfy Austin Energy requirements or as part of a campaign to reduce household electricity use.

The following figures display the net consumption relative to ERCOT by home characteristics such as square footage, home value and home age. Using the same methodology as in figure 3, figures 4 and 5 plot each household. First, I compare consumption against home square footage. Larger homes require greater amounts of energy for cooling and heating and thus would be expected to consume more energy than the average home; however there appears to be a weak correlation between the size of the home and the amount of energy consumed by the household relative to the average home. This may be due to the differing levels of energy efficiency upgrades undertaken by each household.

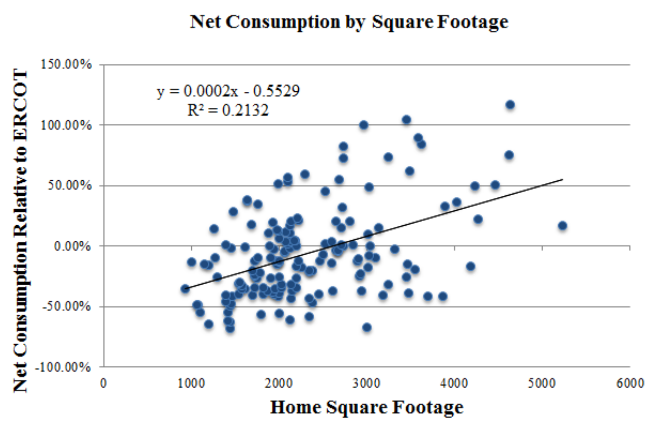

Figure 4: Comparison of net monthly consumption compared to ERCOT by square footage.

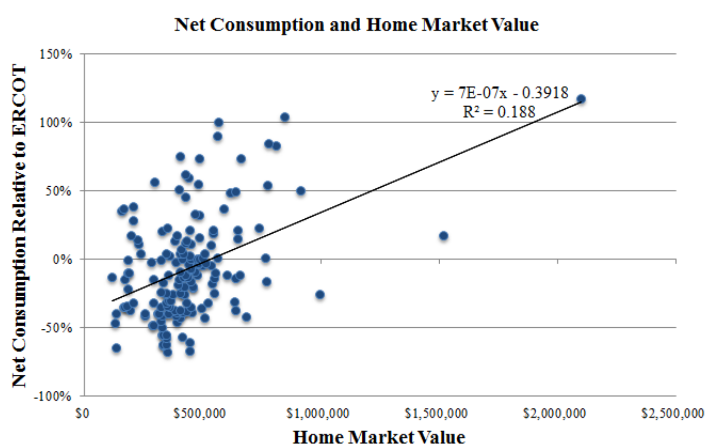

Figure 5: Comparison of net monthly consumption compared to ERCOT by home market value.

3.1.3 CHANGES IN AWARENESS AND TIMING OF ENERGY-INTENSIVE ACTIVITIES

Respondents (n=624) in the *Solar PV Survey* experienced a strong increase in their awareness of the amount of electricity they use, their monthly bill, and how they use electricity at home (64.4 percent, 62.4 percent, and 71.8 percent 'higher' or 'much higher' awareness, respectively) as a result of adopting PV. I assume that households in the consumption profile dataset (DS1 and DS2) are similarly aware. However, based on the survey results, increases in awareness do not appear to produce behavioral changes as defined by the timing and quantity of energy-intensive activities. A large majority (76.5 percent) of surveyed consumers reported not changing the frequency or quantity of electricity-consuming activities, whereas 18.2 percent reported a 'small' or 'large' decrease, and 5.3 percent reported a 'small' or 'large' increase in these activities. However, there is little incentive for customers within the Austin Energy service territory to shift load to other times of the day, as the residential rate structure does not reward the shifting of activity to off-peak hours.

The structured interviews provide detail on specific behavioral changes. Although 48 percent (n=10) of interview respondents listed the air conditioner as their highest-consuming appliance, they did not report changing its use. Pool owners changed their pool pumps more often than other appliances. Some consumers reported changes in the timing of laundry loads, and vehicle charging for those who own an electric vehicle.

I note that, although large increases in awareness are reported, interviews and other survey responses suggested that these households were already energy-conscious prior to PV adoption, which could limit the additional benefits of increased awareness.

3.1.4 Seasonal Consumption Patterns

Seasonal patterns already exist in household consumption of electricity, resulting mainly from weather, but variation in system production and in prices of electricity could accentuate seasonal variations for PV adopters. The results suggest seasonal variation in adopters' consumption, as there is a consistent inter-monthly pattern of differences between the average ERCOT profile and the median adopter's consumption (figure 6). That is, while on the average, adopters do consume less electricity than the average ERCOT household, they consume *relatively* more than the sample average across all months from November 2011 to January 2012 and, critically, *relatively* less during the summer months of May 2012 to September 2012 and May 2013 to June 2013 (11.2 percent). I determine these differences by taking the percentage difference between adopter and ERCOT consumption as detailed earlier. Because of data limitations I am unable to exactly determine if such differences in seasonal patterns of consumption existed prior to system adoption or, in fact, are triggered by technology adoption. However, given that I noted above that PV adoption does not appear to trigger significant consumption pattern changes *and* that energy efficiency measures were completed (or already in place) for nearly all of the PV-adopting homes, it is likely that these seasonal differences are a reflection of the pre-existing building characteristics. This is explained further next.

I determine that the seasonal variation is likely due to the high energy efficient nature of the homes in the dataset. As previously noted, Austin Energy requires homes under 10 years old to comply with energy efficiency standards in order to qualify for a rebate. Furthermore, the age of the homes in the dataset (average of 13 years) is considerably less than the average home in the Austin metro area (29 years). Older homes tend to be less energy efficient than newer homes, particularly during the summer months due to leakage from air conditioning systems (Rhodes et al. 2011). The amount of energy consumption savings from energy efficiency measures is significant. A study by the National Renewable Energy Laboratory and a study conducted by GDS Associates on behalf of Austin Energy found that energy savings resulting from energy efficiency measures can result in summertime energy consumption savings of between 27.6 percent and 29.2 percent (Belzer et al 2007; GDS Associates 2012), which is consistent with our results. For example, from June through August 2012, the median household consumption for the dataset is between 22 percent and 23 percent less than the average household in the ERCOT profile. In May 2013 and June 2013, the median household consumption is between 19 percent and 25 percent, respectively, less than the average household.

Nevertheless, below average consumption during the summer months has significant environmental benefits in the form of peak load reduction. In Texas, electricity demand is at its highest during the months of June through September and can be substantially higher than the shoulder months. In 2012, average demand in August was 25 percent higher than the average demand across the entire year (ERCOT Demand and Energy Report). Due to the high energy demand during the summer months, inefficient peaking generation units are heavily utilized (FERC Market Oversight 2013). According to the Federal Energy Regulatory Commission, the implied heat rate, which refers to the inverse of the overall efficiency of power plants, are more than double the average heat rate during the winter months (FERC Market Oversight 2013). This translates into significantly higher carbon emissions during the summer months as compared with other seasons. However, I note that the potential for emission reductions is dependent on the fuels being displaced. While I cannot directly assign the adoption of PV as the cause for lower electricity consumption of PV adopters during the summer months as compared with their average household, I do find that the "collection" of activities, including efficiency upgrades and other hardware changes concurrently with a PV installation has a significant impact on lowering overall consumption during the summer peak periods.

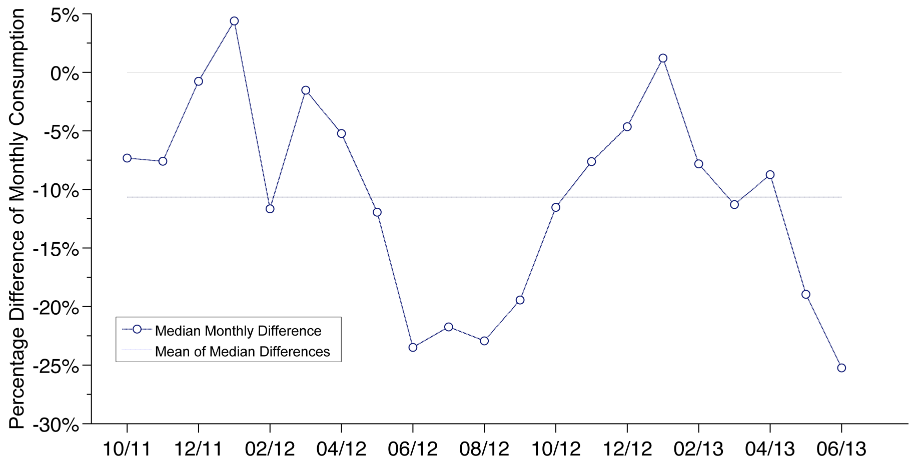

Figure 6: Net monthly consumption for consumer and ERCOT profile

3.1.5. Hourly Consumption Patterns

Electricity consumers traditionally have little economic reason to moderate their consumption based on hourly factors other than to maximize bill savings or suit convenience. Two factors could explain why PV adopters would actively seek to alter their inter-hourly consumption patterns. First, to maximize the economic value of PV system generation, particularly if consumers have time-of-use rate plans (Denholm and Margolis 2007). Secondly, a greater awareness of electricity issues, specifically, peak load issues and the environmental impact of peak generation, which may have catalyzed PV adoption (Orans et al. 2010; Matsukawa, Asano, and Kakimoto 2000; Bartusch et al. 2011; Torriti 2012; Newsham and Bowker 2010).

To explore this hypothesis, I aggregate hourly differences in adopter and ERCOT consumption into a 24-column matrix corresponding to the 24-hour day (equation 1

Section 2.1.2). Thus, the first column is the collection of all consumption differences occurring from 0:00 – 1:00, for all adopters simultaneously; and so on. In other words, following the convention developed in Section 2.1.2, for a particular hour i all d_i for every adopter form the i^{th} column of this difference matrix. The central tendencies of each of the columns is plotted in figure 7. Note that this process does not consider seasonal variations (all months are collated) and that all hourly analysis uses only post-adoption data, as the pre-adoption data is aggregated at the monthly level. That is, within the dataset there are no means of determining whether inter-hour patterns existed prior to PV system adoption.

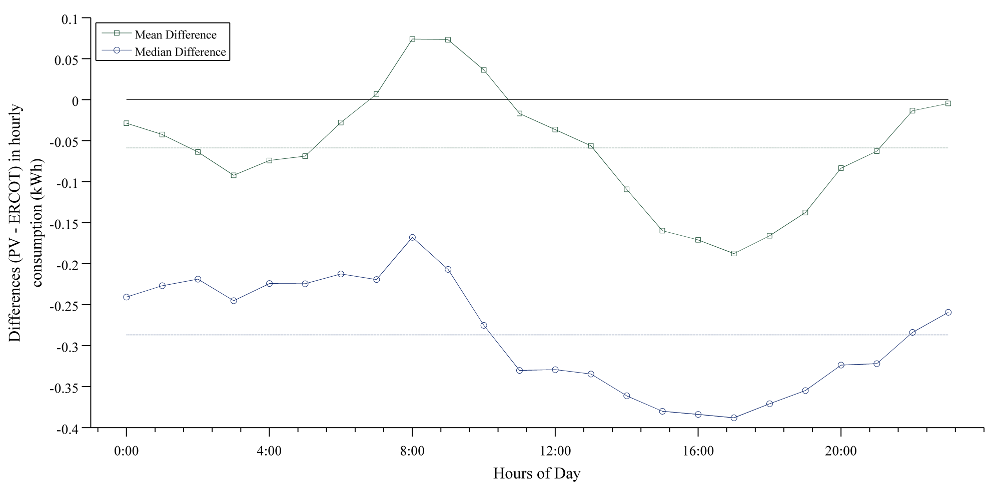

Figure 7: Mean Hourly Difference in Consumption

PV consumers do demonstrate evidence of different patterns of consumption than ERCOT, specifically they have lower consumption from 11:00 – 22:00 *relative* to the

ERCOT profile and have higher consumption for other times. Because of the large sample size, results are highly significant for each hour (and thus confidence are not shown), but are small overall—on the order of 0.06 kW shifts per hour. While these shifts are small on an hourly basis, when combined for all hours and days in a month, the magnitude of the shift is significant at the monthly level.

While the hourly consumption analysis above shows some evidence of load shifting, a majority of interviewees (71 percent) said they do not actively shift usage to different times of day. Furthermore, 75 percent reported that they did not actively shift consumption to match peak system generation, and thus were indifferent to any value this behavior would create. Many interview participants cited a lack of a TOU rate in Austin Energy's service territory as a reason for not actively shifting energy intensive activities. However, a TOU rate plan option was implemented by Austin Energy after the interviews were held.

3.2 The Role of Information in PV Consumerism

Past studies have addressed heuristics and processes consumers use to search for data to inform decision-making (Conlisk 1996; Gigerenzer & Todd 1999; Todd & Gigerenzer 2003; Tversky & Kahneman 1974). In this study, this refers to consumers' search for information about PV systems, installers, and feedback mechanisms, which shape the financial attractiveness of PV investment. The non-monetary cost of this information-searching significantly influences the path chosen (Wilson & Dowlatabadi 2007; Rai & Robinson 2013). Therefore, I study consumer use of monitoring and feedback mechanisms to track post-adoption consumption and generation habits to evaluate the potential influence on consumption behavior.

3.2.1 Monitoring and Feedback for Electricity Habits

Exposure to monitoring devices and feedback from behavior has consistently been shown to induce behavioral change (Henryson et al, 2000; van Houwelingen and van Raaij 1989; Alahmad et al 2012; Grønhøj et al. 2011). I determine, first, how many PV adopters have access to monitoring or feedback devices, such as smart meters or web monitors; next I determine if access to such devices does catalyze changes in consumption behavior and through which channels.

Through the survey, I determined that 86 percent (n=18) of adopters interviewed have access to some monitoring device that provides feedback on their electrical consumption and system generation. These devices are primarily online monitoring tools (62 percent, n=13), in-house displays (5 percent, n=1), and smartphone apps (19 percent, n=4), though outdoor meters and inverter displays were also common. High cost and lack of interest were the most commonly stated reasons for those without monitoring devices.

In contrast to the previous studies noted above, the monitoring devices were used infrequently and did not appear to significantly influence energy consumption patterns. Save for a post-adoption "honeymoon" period—in which adopters are highly attentive to their monitoring device, adopters appear to rarely utilize monitors and did not prioritize tracking their system's performance. A large majority (78 percent, n=14) of those with a monitor check it infrequently (once every 1-2 months or less) or have stopped entirely. Only 17 percent check regularly (once a month or greater). Most respondents indicate that monitoring devices were used initially to monitor the performance of their PV system and not to track energy consumption. While monitoring devices are largely left alone once consumers are comfortable with PV, most do track their consumption through monthly bill statements – which all consumers review prior to submitting payment to their utility. These statements report excess generation credits, consumption and generation levels – a crude monitoring device. The interviews showed that consumers scrutinize bills more closely than monitoring devices. 90 percent of interviewees assess bills to some degree, looking at savings and amount of net metering credits accumulated.

4. RATE STRUCTURES ANALYSIS

The rate structure analysis seeks to examine two fundamental questions: First, how do rate structures provide value to solar consumers? Second, how can competing rate structures influence consumption behavior? The existing body of literature has extensively analyzed how rate structures provide value to solar consumers but offers very little coverage on the latter. According to Wiser et al (2007), rate design is fundamental to the economics of commercial and residential PV and can alter the value of PV by 25 percent to 75 percent, depending on the size of the PV system relative to building load. I test this assumption by calculating the range of savings that can be achieved under competing rate structures in the ERCOT deregulated retail electricity market and within the regulated, monopolistic Austin Energy market.

4.1 Rate Structure Data

The rate structure analysis uses two sources of data. First, I use a database of leading electricity rate structures in the ERCOT market and those available to Austin Energy consumers. Secondly, I use the consumption profiles in DS1 to evaluate the value provided by the electricity rate structures available to PV adopters.

The rate structures used in the analysis comprise six rate plans offered by TXU Energy, Reliant Energy, Green Mountain Energy and Austin Energy. The rate plans vary in terms of price tiers, customer base charge and the solar price credited for customer's solar PV generation. All rate plans offer a solar credit for the excess generation that is supplied to the grid with the exception of Austin Energy, which credits customers for the entire amount of solar PV generated from its customer's systems. The solar credit is billed against the customer's monthly charge which bills customers for all energy consumption including energy delivered by Austin Energy and energy consumed from the customer's own solar PV system.

Rate Plan	Rate Price Tiers ¢/kWh	Customer Base Charge $/Month	Solar Credit $/kWh
Green Mountain Renewable Rewards Buy-Back Program	10.8¢/kWh at all times	$0.00	0-500 kWh: 10.8¢ >500 kWh: 5.4¢ for excess generation supplied to grid
Reliant e-Sense Sell-Back 12	9am – 4pm: 7.2¢ 4pm – 9am: 5.4¢	$9.95	0-500 kWh: 7.5¢ >500 kWh: 5.0¢ for excess generation supplied to grid
TXU Energy e-Saver 12	7.5¢/kWh at all times	$6.95	7.5¢ for excess generation supplied to grid
TXU Energy Free Nights 18	10pm – 6am: 0.0¢ 6am – 10pm: 12.0¢	$4.95	7.5¢ for excess generation supplied to grid
TXU Energy SureStart	Month(s) Usage (kWh) ¢/kWh Oct-Jun 0-1400 8.9¢ Oct-Jun 1401-2000 8.8¢ Oct-Jun > 2000 10.0¢ Jul-Sep 0-1400 8.8¢ Jul-Sep 1401-2000 7.0¢ Jul-Sept >2000 10.0¢	$4.95	7.5¢ for excess generation supplied to grid

Table 2: continued, next page.

Rate Plan	Rate Price Tiers ¢/kWh			Customer Base Charge $/Month	Solar Credit $/kWh
Austin Energy Residential Rate	Month(s)	Usage (kWh)	¢/kWh	$10.00	12.8¢ for all generation whether supplied to grid or consumed on site (as of December 2013)
	Oct-May	0-500	1.8¢		
	Oct-May	501-1000	5.6¢		
	Oct-May	1001-1,500	7.2¢		
	Oct-May	1501-2,500	8.4¢		
	Oct-May	>2,500	9.6¢		
	Jun-Sep	0-500	3.3¢		
	Jun-Sep	501-1000	8.0¢		
	Jun-Sep	1001-1,500	9.1¢		
	Jun-Sep	1501-2,500	11.0¢		
	Jun-Sep	>2,500	11.4¢		

Table 2: Rate structures terms for six competitive rate plans and one regulated rate plan.

I calculate the cost of consumption for every 15-minute interval across all 223 consumer profiles and six rate plans by applying the rate plan tier criteria and corresponding price. By aggregating the 15-minute intervals into one month blocks, I calculate a monthly consumption cost for each consumer. Using a similar methodology, I calculate the related solar credit for each consumer under each rate plan. I subtract the monthly solar credit from the monthly consumption cost to obtain a monthly bill for each consumer. For each month, I compute the average monthly bill under each rate plan. Finally, I calculate the average monthly bills to obtain an average bill under each rate plan using the equation

$$C_{pr} = \frac{\sum_{i_n} c_{i_n k} - \sum_{i_n k} c_{i_n kg}}{\sum_i c_i - \sum_i c_{ig}} \quad (4)$$

where p is the monthly bill , r is the rate plan, i is the set of periods for which data exists, for each consumer, k is the price for a particular rate plan, n is the month, c is the consumer's profile data and g is the amount of solar PV generation.

4.2 Impact of Rate Structure on Behavior and Value of Solar

Competing rate plans can produce significantly different economic value for a PV system. If PV adopters are aware of this phenomena, I would expect to see an influence on the information searching process and consumption behavior. To explore this hypothesis I utilize results from the qualitative interviews as well as our analysis on the range of savings that can be achieved under various rate plans. The contrast of Austin Energy—a non-competitive market, and the ERCOT deregulated market acts a control variable to evaluate whether consumers in competitive markets are more aware of their consumption behavior than consumers in regulated markets and how rate structures influence consumption behavior. Because the households in the dataset are largely located in Austin Energy service territory, a direct analysis of the impact of rate structure on consumption behavior cannot be made. Instead, this analysis attempts to evaluate the total economic value of the PV systems under different rate structures and compare these savings to the observed consumption behavior described above.

4.2.1. RANGE OF SAVINGS UNDER COMPETING RATE STRUCTURES

The results show a wide range in the expected monthly bill under the six rate plans analyzed. Notably, Austin Energy customers would expect an average bill of just over $17 compared to the highest average bill of over $66 for TXU's SureStart rate plan. Austin Energy's value of solar plan, which credits customers for the entire amount of electricity produced by a consumer's solar PV provides an attractive value proposition for consumers. The solar credit of 12.8 cents per kWh (in place at the time of this analysis) is greater than the highest energy price tier resulting in immediate savings to solar PV consumers. Among the options available in competitive markets, consumers can achieve 30% savings from switching from the highest cost rate plan to the lowest cost plan to reduce their monthly bill from over $66 to approximately $46.

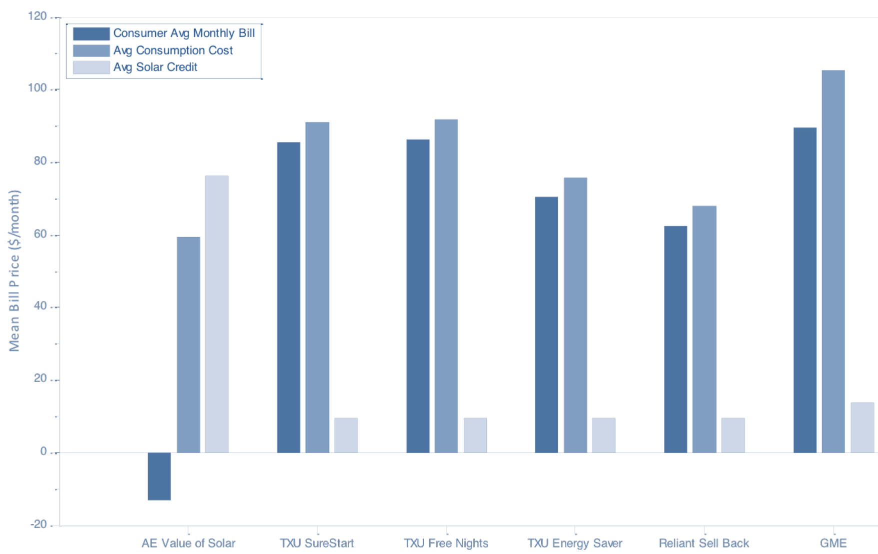

Figure 8: Comparison of average monthly bill under different rate plans.

4.2.2. Consumer Average Cost Compared to ERCOT

Comparing the consumption cost excluding credits for solar generation for the consumers in the dataset against the average consumption cost for the ERCOT profile, I find that consumers in our data set should expect an average savings of approximately \$30 or 32 percent over the average ERCOT monthly bill. Savings are a result of the lower energy consumption of households in the dataset as compared to the average household. While the savings is relatively small when compared to other household expenditures, the inclusion of a generation credit, particularly Austin Energy's value of solar tariff, increases the value significantly. Austin Energy households should expect to save approximately \$82 per month over non-solar PV adopters.

4.3 Rate Searching

The interviews, surveys, and rate plan analysis each studied the impact of rate structures on PV adopter decision making. Given a selection of flat and time-of-use rates, would consumers recognize which option is most beneficial financially? This leads to an assessment of whether consumers' choice of provider depends more on the rate paid for grid electricity or the rate received for exported PV electricity.

Interview responses suggest that the rate received for excess generation weighs most heavily in the adopter's choice of provider. When asked whether they switched providers, 36 percent of deregulated customers listed their provider's favorable generation credits as the main reason they stayed or switched, while only 9 percent mentioned a better retail rate. Only 25% of those who spent time researching providers actually switched-- in part because they found their current provider offered the most favorable excess generation credit.

The *Solar PV Survey* responses support this notion that consumers prioritize generation credits when selecting providers. Out of 113 adopters from deregulated markets, 87 percent of responders reported that excess generation credits were either ‘extremely’ or ‘very’ important to their decision. Comparatively, only 65 percent reported that provider retail rates were ‘extremely’ or ‘very’ important. Half of respondents switched providers, a much higher frequency than those interviewed. Both interviews and surveys appear to indicate that PV adopters seriously consider the financial worth of system outflow credits separately from the retail rate paid when choosing a plan. However it appears that consumers primarily seek value through selling excess PV generation, as opposed to lowering inflow rates, and look to maximize this benefit when researching providers.

5. CONCLUSION

The adoption of PV represents a major investment of time and resources for consumers. Past literature has suggested that owning a PV system could impact electricity consumption decisions through behavioral effects of PV technology and related electricity monitoring systems.

My analysis found that while awareness of patterns and level of electricity was significantly enhanced, gross levels of electricity consumption on an aggregate level did not significantly change among PV adopters after installation; However, some significant increases (as well as decreases) are observed at the individual household level. This contrasted with the survey and interview responses among a majority of adopters, who reported decreased or unchanged consumption after installation. I explain this discrepancy by noting that consumers took several efforts to reduce their environmental impact and implement efficiency upgrades to reduce consumption prior to installing PV, leaving few options to further reduce consumption after adoption. Further, consumers who increase electricity use tend to underreport the amount of increase, which I explain as a behavioral cognitive dissonance. Adopters' disinterest in monitoring their long-term electricity use could also contribute to underestimating how much PV system generation they use.

Moreover, the electricity rate structures studied provide widely varying financial value to PV adopters, affected by interaction between pricing, excess generation credits, and consumption levels. Both survey and interview responses indicate that consumers understand the particular significance of solar credits to the value received from PV, and apply this knowledge in their rate plan choices.

These findings provide informative lessons for future research and solar-policy design. Policymakers should not expect substantial ‘ripple’ effects from PV adopters. Rather, they should direct conservation policy efforts that targets households with low levels of awareness of electricity use, and have the most room for ‘low hanging’ gains in conservation habits. Furthermore, compelling solar PV adopters to implement energy efficiency measures as a pre-requisite to financial incentives produces real benefits in the form of reduced energy consumption during the critical peak load periods.

Appendix A

List of Structured Interview Questions

Questions posed to deregulated customers only:

1. How much time did you spend researching different electricity providers and rate plans?
2. Did you stay with the same provider when you installed your PV system, and if you switched what was the reason?
3. What type of rate plan do you have?
4. What were the most important factors in choosing a provider?
5. What is your overall satisfaction with your net metering plan and provider services?
6. If you leased your system, what are the advantages you gain from leasing as opposed to purchasing a PV system?

Questions posed to Austin Energy customers only:

1. How aware are you of the details of the Value of Solar plan, and what are your thoughts on the rate change?
2. What is your overall satisfaction with Austin Energy services, and would you switch providers if able?

Questions posed to all customers:

1. How much time did you invest in researching the installation process for your PV system, and did you prioritize calculating a payback period?

2. What were your main incentives for installing a PV system, and which was the primary influence?
3. How did your overall electricity consumption change after installing a PV system?
4. Were there any changes in the timing of your electricity use after installing your PV system?
5. Which household appliances or activities consume the most electricity, and which were most affected by changes in consumption post-installation?
6. What other energy efficiency measures did you implement, and how were these actions timed in relation to the PV system installation?
7. Apart from your monthly bills, what types of monitoring devices do you have to track your electricity use habits?
8. How often do check these devices, and has this changed since you first installed a PV system?
9. How closely do you check monthly bills, and what particular items do you evaluate?
10. How closely do you match your electricity consumption to what your PV system generates?
11. What effect do your monthly savings have on electricity consumption decisions?

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