Price Volatility and Residential Electricity Decisions: Experimental Evidence on the Convergence of Energy Generating Source

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Abstract

The recent trend in most developed countries has been toward greater reliance on renewable or "green" energy sources. This paper investigates how price volatility in residential electricity rates impacts consumers' preferences for green power. Using a choice-based experiment, we present respondents with choice scenarios that feature two electric utility plans: (i) a *conventional* plan where electricity is generated from either coal or natural gas, and (ii) a *green* plan where electricity is generated renewably from either wind or solar. We then systematically vary the monthly price volatility of each plan across choice scenarios. Our results suggest that price volatility in monthly rates significantly impacts respondents' plan choices and, specifically, their decision to adopt the green power plan. In particular, increased volatility in the green power plan reduces the likelihood of respondents choosing the green plan, while increased volatility in the conventional plan increases the likelihood of respondents choosing the green plan. Moreover, the documented effects of price volatility are robust across different price premiums for the green power plan.

Keywords: Renewable Energy, Green Power, Price Volatility, Choice-based Experiment

JEL Codes: Q40, Q20, Q50, Q01, C83, C90

Renewable power is good. More renewable power is not always better.
(The Economist, December 2015, p. 7)

1 Introduction

As an economy grows and develops, the mix of energy sources used to satisfy the demand for energy adapts. In the U.S., as well as in many other developed nations, the recent trend has been toward greater reliance on renewable or "green" energy sources. While the EIA (U.S. Energy Information Administration, http://www.eia.gov) reports that approximately 80% of current domestic energy production continues to be hydrocarbon based (e.g., coal, natural gas, and crude oil), there has also been a steady increase in production of renewable energy over the last decade from about 8% to upwards of 12%. This increase has likely been a result of the combination of shifts in energy policy aimed at stimulating renewable energy, as described by the American Wind Energy Association (http://www.awea.org/advocacy/), as well as increases in the demand for renewable energy stemming from its environmental benefits and sustainability. The convergence of the energy mix to an optimal or steady state depends on a number of factors, not the least of which is consumer demand.

The current study investigates how price volatility in residential electricity rates impacts consumers' preferences over how that electricity is generated; specifically, consumers' preferences for electric utility plans where the electric power is either generated from a conventional hydrocarbon-fossil fuel source or a renewable energy source. Conventionally, the bulk of residential electric power has been predominately generated from the combustion of coal or natural gas – the EIA reports that nearly half of the production in the electric power sector is coal based. However, in recent years residential consumers have been increasingly offered the option to purchase electric power that is, at least partially, generated from renewable and more "green" sources like solar and wind (Bird & Sumner, 2010). As a result, electric power generated from renewable sources accounted for 13.5% of the total generation in 2014, as reported by the EIA. While part of this increase in the provision of green power has been driven by regulatory reform and government policies, increasing consumer demand for green energy has also played an important role. In fact, there has been ample research documenting that residential consumers are willing to pay a premium, typically in the range of $5-$15 per month, to purchase electric power generated from green sources (see the survey by Sundt & Rehdanz, 2015 for a review).

Much of the prior research relating to residential demand for renewable electric power has focused on the impact of retail price differences between electricity generated by conventional sources (hydrocarbon or fossil fuel-based) and green sources on residential demand for green electric power.[1] Not surprisingly, the price premium associated with green power is an important determinant in consumers' decisions to purchase green power plans. In this paper, we take a complementary approach by considering how volatility in the price of plans for both conventional and green power impacts residential demand for green power. We view this as an important extension for several reasons. First, green power generation (especially wind and solar power) is susceptible to intermittency problems that can result in substantial variability in costs (Zeineldin et al. 2009; Denholm et al., 2010) and, ultimately, more volatility in green power prices. Second, uncertainty regarding future regulatory changes in subsidies and incentives for producers and consumers of green energy could lead to either lower or higher prices, thereby inducing substantial volatility in the retail price of green electric power (Kaplan, 2008). Third, technological innovation, which is inherently uncertain and unpredictable, could significantly increase the efficiency of green power generation and minimize the intermittency problems with green power; thus lowering the effective price of green power.[2] Fourth, variability in the price of fossil fuels used to generate electricity has been well documented (e.g., Ewing et al., 2002), which can induce substantial volatility in the current and future prices that consumers face regarding the retail price of electricity generated from conventional power sources (Kaplan, 2008).

Volatility in the price of retail electricity plans (assuming a constant expected price) would not be expected to directly impact plan choice of consumers under the assumption that consumers behaved in a risk-neutral manner. However, it is well known that price volatility, in general, can impact economic decision making; specifically, over the past several decades a plethora of research has documented decision making inconsistent with risk-neutrality.[3] Most notably, if consumers are risk-averse, then increases in price volatility of a given electric utility plan would

[1] We postpone our review of this literature and other related literature until Section 2.

[2] An example would be innovation in energy storage technologies that enable electric power grids that rely heavily on renewable energy power sources like wind and solar to operate more efficiently and mitigate problems of intermittency; we refer readers to a report by Denholm et al. (2010) for a more detailed discussion of topics relating to energy storage in renewable electricity generation.

[3] We will not attempt to cite all relevant studies in this extensive body of literature. Rather, we reference Cox & Harrison (2008), Dave et al. (2010), and Charness et al. (2013) who provide comprehensive, although not exhaustive, reviews of this extensive body of literature, especially in the domain of experimental evidence.

make that plan less attractive to consumers. In addition to risk preferences, other behavioral biases could influence how consumers respond to the increased price volatility of various plan offerings. For example, consumers may exhibit saliency bias (Bordalo et al., 2012; 2013), where either very low or very high possible prices are more salient to consumers when they are making their plan choice; thus, plans with more pricing volatility may either be more or less attractive to consumers depending on the strength of how salient these outlying prices may be. Consumers may also exhibit projection bias (Loewenstein et al., 2003) and, as a result, either overestimate or underestimate their future electricity usage.[4] Again, this could lead consumers to become more or less attracted to plans with greater price volatility. If consumers exhibit non risk-neutral behavior and/or various behavioral biases, which is likely to be true in the aggregate across residential consumers, then there is scope for price volatility to impact consumers' decisions regarding their preferred electric utility plan. Accordingly, we examine the specific case of price volatility in the context of electric utility plan choices.

The EIA reports that in 2014, the residential sector accounted for about 22% of U.S. energy consumption, and Brounen et al. (2013) note that about 20% of the global energy demand stems from residential energy demand. That being said, it is of great importance to better understand consumer preferences for residential power generated from green power, and the possible factors that influence consumers' adoption of green power. In this paper, we implement a choice-based experiment, administered via survey, to investigate how price volatility in residential electricity rates impacts consumers' preferences over how the electric power was generated. In the survey, individuals are presented information on two hypothetical electric power plans companies that they can choose to purchase. We systematically vary several attributes of these electric power plans including: (i) the source by which the electricity is generated – conventional or green, (ii) the expected price difference between the two plans (i.e., the price premium associated with the green plan), and (iii) the volatility of monthly prices of each plan. The information obtained from the survey allows us to examine the causal link between price volatility and consumers' demand for green power. We also investigate how price dispersion across both the green and conventional

[4] While not specifically in the context of electricity usage, several papers have documented empirical evidence of individuals exhibiting projection bias. Examples include DellaVigna & Malmendier (2006), Conlin et al. (2007), and Busse et al. (2015).

power plans impacts plan choice. Lastly, we consider how personal attitudes toward the environment and green energy, as well as other socio-demographic measures impact plan choice.

Based on results from 832 respondents and 9,108 plan choice scenarios, we find that price volatility significantly impacts plan choice. Specifically, as the monthly price volatility of the green energy plan increases (holding the expected monthly price constant), respondents are significantly less likely to choose the green energy plan. Similarly, as the price volatility of the conventional plan increases (holding the expected monthly price constant), respondents are much more likely to choose the green energy plan. Importantly, our main results regarding the impact of price volatility are robust across three different levels of monthly price premium for the green energy plan. Moreover, not only do we show that price volatility of monthly rates impacts plan choice, we also show that price dispersion matters; respondents are significantly more likely to choose the green plan the more dispersed the distribution of possible monthly prices (holding the level of variance constant). Lastly, in line with prior studies, we document that respondents with a greater overall concern for the environment are more likely to choose the green power plan.

The paper proceeds by briefly discussing the prior literature relating to the residential adoption of green electricity in Section 2. In Section 3 we introduce the choice-based experiment and describe the survey procedure. Section 4 describes the conceptual framework. Section 5 presents the empirical results, and Section 6 concludes with discussion of the possible implication of our main findings and areas of future research.

2 Review of Related Literature

As of late, there has been a growing trend toward renewable energy generation both in the U.S. and globally. For example, the U.S. Department of Energy reported that in 2014, renewable electricity in the U.S. grew to 15.5% of installed capacity and 13.5% of total generation, and these rates have been steadily increasing over the last decade; moreover, renewable electricity accounted for 52% of the new capacity additions in 2014. The increasing importance of renewable energy as a significant component of the overall energy mix has spurred substantial research relating to consumption of renewable energy. Most closely related to our study is the existing literature examining residential adoption of green power.

Not surprisingly, much of this prior research has focused on estimating residential consumers' willingness to pay (WTP) to purchase green power that is, at least in part, generated from renewable sources.[5] In general, these prior studies document a positive WTP, on average, for green power (see Sundt & Rehdanz, 2015 for a review of this literature). Specifically, Goett et al. (2000), Roe et al. (2001), Borchers et al. (2007), Longo et al. (2008), Scarpa & Willis (2010), Cicia et al. (2012), and Gracia et al. (2012) use choice-based experiments (CE) to document a positive WTP for green power, while Champ & Bishop (2001), Zarnikau (2003), Whitehead & Cherry (2007), Wiser (2007), Bollino (2009), Yoo & Kwak (2009), and Mozumder et al. (2011) use contingent valuation (CV) approaches to document a positive WTP. The WTP estimates tend to be clustered in the range of $5-$15 per month. While the motivation of our paper is not to estimate WTP for green power, our results are consistent with these prior studies; namely, we document that 36.6% of plan choices in our survey were for the green plan when the price premium ranged from $5-$15 per month. As such, our paper provides additional evidence of a positive WTP for green power.

Several prior studies have also documented other factors, besides the price premium, that can impact preferences toward green power. For example, Borchers et al. (2007) find that the specific type of generating source (e.g., wind, solar, biomass, hydro, etc.) can impact preferences for green power. Ek (2005) finds that individuals who are more environmentally conscience have a more positive attitude toward wind power, Clark et al. (2003) and Kotchen & Moore (2007) find that pro-environmental respondents were more likely to have enrolled in a green power program, while Mozumder et al. (2011), Cicia et al. (2012), and Garcia et al. (2012) find that more environmentally conscientious people have a higher WTP for green power. Bergmann et al. (2006) find that environmental impact, wildlife impact, pollution, and job creation all impact an individual's decision to adopt a green power plan. Bergmann et al. (2008) document differences in green power preferences between urban and rural households. Lastly, income has also been shown to be positively related to preferences for green energy adoption (Clark et al., 2003; Borchers et al., 2007; Kotchen & Moore, 2007; Bollino, 2009; Yoo & Kwak, 2009; Mozumder et al., 2011).

[5] There is also an extensive amount of survey and polling research aimed at eliciting individuals' opinions and attitudes toward different energy sources. In lieu of attempting to cite all such studies, we refer readers to Greenberg (2009) for a thorough review of the literature. In general, most of this research indicates that individuals support the increased reliance on renewable energy sources.

In the current study, we examine how price volatility in both the conventional and green power plans impact the decision to adopt the green power plan. In doing so, we complement the existing literature, highlighted above, aimed at deepening our understanding of possible factors that that can impact residential demand for renewable or green energy. Moreover, given the substantial variability in current and future prices that consumers face regarding retail electricity rates, we view our study as an important contribution to the existing literature. The results of our study can provide valuable insights regarding possible changes in energy consumption patterns in response to both regulatory and technological changes that are likely to impact price volatility of retail energy prices.

3 Survey Design

We designed a survey to ascertain how monthly price volatility impacts residential adoption of green power plans. Imbedded in the survey was a choice-based conjoint (CBC) analysis, or choice-based experiment, where respondents were asked to make a series of choices between a conventional electricity plan and a green energy alternative plan. Information about the price volatility of each plan was systematically varied across the different choice sets, allowing us to estimate the impact of price volatility (in both the conventional and green energy plan) on the take-up rate of the green energy plan. In what follows, we first describe the choice-based experiment and the attributes that were manipulated within the experiment. We then describe the general survey procedure and the demographic data that was collected. Lastly we describe the sampling procedure and the two distinct samples that were used in the study. In total, 832 respondents completed the survey in February of 2016. The experimental procedure and data collection methods were IRB approval by the Texas Tech University Human Research Protection Program.

3.1 Choice-Based Experiment

The experimental component of the survey involved respondents choosing between hypothetical electricity plans. Our overall design is similar in spirit to the choice-based experiments employed by Roe et al. (2001), Borchers et al. (2007), and Lungo et al. (2008), amongst others; this methodology has been demonstrated to produce results consistent with revealed preferences (Adamowicz et al., 1994; Adamowicz et al., 1997). Respondents were simultaneously presented with information on two hypothetical plans offered by a local electric utility, and were asked to

choose which of the two plans they would select to provide electricity for their residence. For each plan, respondents received information about the following attributes: (i) generating source of the electricity, (ii) the price volatility, and (iii) average expected monthly price. A sample of a choice set presented to respondents is presented in Figure 1.

Figure 1: Example Choice Scenario

PLAN A – CONVENTIONAL ELECTRICITY		PLAN B – GREEN ELECTRICITY	
Generating Source: Coal or Natural Gas		**Generating Source: Wind or Solar**	
Possible Monthly Price	**Chance of Price**	**Possible Monthly Price**	**Chance of Price**
$93	15%	$98	10%
$100	70%	$108	80%
$107	15%	$118	10%
Average Expected Monthly Price: $100		**Average Expected Monthly Price: $108**	

The generating source of electricity took one of two forms: (i) *conventional* – produced by either coal or natural gas, (ii) or *green* – produced by either wind or solar.[6] Each choice set always consisted of one conventional plan and one green plan. We varied the average expected monthly price for the green plan. Specifically, in all choice sets the average expected monthly price for the conventional plan was normalized to $100/month, while the average expected monthly price for the green plan took one of three possible values: (i) $105/month, (ii) $110/month, or (iii) $115/month. This manipulation of expected monthly prices for the green plan is equivalent to a manipulation of the monthly premium of the green plan of $5, $10, or $15, respectively; these specific values were chosen to be consistent with the general range of estimated willingness to pay for green energy from prior research (e.g., Roe et al., 2001; Zarnikau, 2003; Borchers et al., 2007; Wiser, 2007; and Mozumder et al., 2011), as well as actual observed and documented average price premiums of green power programs (Bird et al., 2002; and Bird & Sumner, 2010).

[6] We specifically chose wind and solar for the type of green electricity generation based on previous work by Ek (2005), Borchers et al. (2007) and Garcia et al. (2012) suggesting that consumers generally have a more positive attitude about these two source of green energy generation.

Table 1: Price Volatility Manipulations

Price Volatility Manipulation	Possible Monthly Price	Chance of Price	Variance	Range
Low Volatility (LV)	- $5 $0 + $5	5% 90% 5%	2.5	$10
Medium Volatility/Low Dispersion (MV-LD)	- $15 $0 + $15	20% 60% 20%	90	$30
Medium Volatility/High Dispersion (MV-HD)	- $30 $0 + $30	5% 90% 5%	90	$60
High Volatility/Low Dispersion (HV-LD)	- $15 $0 + $15	40% 20% 40%	180	$30
High Volatility/High Dispersion (HV-HD)	- $30 $0 + $30	10% 80% 10%	180	$60

The primary manipulation in the choice-based experiment was the monthly price volatility for each plan. In particular, the price volatility varied along two possible dimensions – the amount of volatility in the monthly price distribution and the dispersion of the price distribution – and took one of five forms: (i) low volatility (LV), (ii) medium volatility/low dispersion (MV-LD), (iii) medium volatility/high dispersion (MV-HD), (iv) high volatility/low dispersion (HV-LD), and (v) high volatility/high dispersion (HV-HD). Information about the monthly price volatility for each plan was presented to respondents in the form of a price distribution table that displayed the

possible monthly prices and the corresponding percent chance of each price occurring. Table 1 displays the five specific price volatility manipulations we used with the corresponding variance and range of each price distribution. All the prices displayed in Table 1 are depicted relative to the expected monthly price of each plan; therefore, changes in the premium of the green plan just shifted the entire price distribution by the amount of the price premium, which does not change the variance or range of the distribution.

Our main-effects, full factorial design consisted of $3 \times 5 \times 5 = 75$ choice sets. Because of the large number of choices in the full factorial deign, we implemented a blocked, orthogonal, fractional factorial design with 48 choice sets divided into 4 blocks, which we use to estimate the main effects. The FACTEX and OPTEX procedures in SAS v9.4 were used to generate the aforementioned design. In the experimental component of the survey, respondents were randomly assigned to one of the four blocks and presented with twelve choice sets.

3.2 Survey Procedure

We used a web-based survey that was developed and administered through Qualtrics. After following the link to the survey and consenting to participate in the study, all respondents were given some general information about the study. Namely, respondents were informed that they would be making a series of choices about which hypothetical electric utility plan they would choose from the offerings of the local electric utility, and in each scenario they would always be choosing between two plans:

Plan A: conventional plan where electricity is generated from coal or natural gas
Plan B: green plan where electricity is generated from renewable source like wind or solar

Respondents were further informed that the monthly price of each plan may differ across scenarios. Moreover, to motivate the possible volatility in prices of each plan, respondents were informed that the rates the utility company charges are subject to change because of variability in the cost of generating electricity; as such, there may be volatility in the price of each plan. To provide more context to the decision, respondents were advised to assume that they would be committed to their plan choice for a period of at least 12 months, that all pricing information provided for each plan is projected based on usage of a typical consumer, and that they should make their decision assuming they are a typical electricity consumer. Respondents were then

presented with a sample scenario. To ensure adequate understanding of the sample scenario, all respondents were required to correctly answer four comprehension check questions about plan options and prices before proceeding. After passing the comprehension check questions of the sample scenario, respondents then proceeded to the choice-based experiment component of the survey. Then, respondents made their preferred plan choice in each of the 12 choice scenarios.

After completing the choice scenarios, respondents were asked a series of questions relating to their current electric utility, their attitudes toward the environment, their risk tendencies, and other general demographic characteristics. Specifically, respondents were asked questions about whether they are currently responsible for paying their own electricity bill, whether their current utility offers any green energy plans, and whether they participate in a green energy plan. We elicited a risk preference measure for each respondent using a general risk question where they were asked to rate on a 7-point scale their general propensity to take risks (Dohmen et al., 2011; Charness et al., 2013). For elicitation of general environmental concerns, we used the 15-item New Ecological Paradigm instrument (Dunlap et al., 2000; Kotchen & Reiling, 2000). We also include a 5-point, Likert-scale question to specifically measure each respondents concerns for electricity being generated from a renewable source. Lastly, we gathered a standard set of demographic controls including: age, gender, education, and income.

3.3 Sample Selection

Our survey utilized two distinct samples, totaling 832 respondents. The first sample is a representative Qualtrics panel provided by Qualtrics Panels, LLC. For this panel, we screened respondents so that only individuals responsible for paying their electricity bill were eligible to participate. After the initial screening, this sample consisted of 408 respondents. About 60% of the sample was female, the age profile was essentially normally distributed with a mean range of 45-54 years of age, and over 400 distinct zip codes were reported. There was a response rate of 35%. All participants who completed the survey received points, as part of a more general point system used by Qualtrics, which could be later redeemed for gift cards, skymiles, online credit, etc.

The second sample consists of students enrolled in the Rawls College of Business at Texas Tech University. The Rawls College maintains a database of students who voluntarily enroll to participate in research studies. An email was sent to all participants in the database notifying them of the availability of the survey and the designated window of time they had to complete the survey.

In total 424 participants from this student database completed the survey; 56% of the sample was female. In return for their participation, students received research credits that counted toward class credit. Participants from this student sample were not required to be responsible for paying their own electricity bill; although, we did ask respondents and 63% indicated that they did pay their own electricity bill.

We feel there are compelling reasons to specifically consider the student sample, in addition to a more representative sample. Most notably, students represent the next generation of residential electricity consumers; thus, better understanding their tendencies toward green power adoption and the factors that can influence their energy choices is pivotal for predicting future energy consumption patterns and informing policy aimed at stimulating the adoption of green power alternatives. Moreover, Gossling et al. (2005) document evidence that university students generally have a positive attitude toward green power, which suggests that they may be the population most likely to consider green power alternatives and the most susceptible to impacts of price volatility. That said, only using a student sample may lead to an overestimate of stated preferences for green power and bias estimates of the impacts of price volatility on green power adoption. For that reason, we complement the student sample with the representative Qualtrics panel of adults who pay their own electricity bill. Together, using two distinct samples enables us to draw more robust inferences regarding the impact of price volatility on green power adoption.

4 Conceptual Framework

In what follows, we provide an outline of the random utility framework that characterizes our choice-based experiment. For a more thorough presentation of this model, as it applies to choice-based experiments, we refer the reader to Louviere et al. (2000). The individual respondent is assumed to choose the electric utility plan that maximizes their utility such that individual *i* chooses alternative *j* because $U_{ij} > U_{ik}\ \forall\ j \neq k$. The total utility for the decision maker is composed of both a deterministic portion (V_{ij}) and a stochastic portion (ϵ_{ij}), where ϵ_{ij} is unobservable to the researcher. The random utility model, as presented by Train (2009), is defined as:

$$U_{ij} = V_{ij} + \epsilon_{ij} \tag{1}$$

In general, the probability that the individual chooses alternative j is given by:

$$\Pr\{j\ is\ chosen\} = \Pr\{V_{ij} + \epsilon_{ij} \geq V_{ik} + \epsilon_{ik}\ \forall\ j \neq k\} \tag{2}$$

and assuming that the ϵ_{ij} are iid extreme value for all *i*, the probability that individual *i* chooses alternative *j* is:

$$\Pr\{j\ is\ chosen\} = \frac{e^{\beta' x_{ij}}}{\sum_k e^{\beta' x_{ik}}} \tag{3}$$

which may be estimated with logistic regression.

Each choice set in this study consisted of two alternatives; a conventionally-produced electricity plan (A) and a green-produced electricity plan (B). Following Hudson and Lusk (2004), we let $C_i = \{A, B\}$ be the choice set for individual *i*, then the probability of an individual choosing one of the alternatives is:

$$\Pr\{j\ is\ chosen\} = \Pr\{V_{ij} + \epsilon_{ij} \geq V_{ik} + \epsilon_{ik}\ \forall\ j \neq k, k \in C_i\} \tag{4}$$

Again, if we assume that the ϵ_{ij} are iid extreme value for all *i*, the probability that individual *i* chooses electricity plan *j* is:

$$\Pr\{j\ is\ chosen\} = \frac{e^{\beta' x_{ij}}}{\sum_{k \in C} e^{\beta' x_{ik}}} \tag{5}$$

Equation (5) is estimated using a conditional logit model.

5 Results

5.1 Description of the Data

A description of the plan attributes that were included as variables in the empirical estimation, as well as a description of socio-demographic variables that were collected and their corresponding summary statistics, are presented in Table 2. The plan attributes in each choice set in the analysis are characterized by the monthly price premium of each plan (which takes values of $5, $10, or $15), the price volatility of the conventional plan (low, medium, or high), the price volatility of the green plan (low, medium, or high), and the degree of price dispersion for each of the plans (low or high). Our main focus is on estimating how the price volatility and price dispersion of each plan impacts the respondent's choice of the green plan.

Table 2: Model Variable Descriptions

Panel A – Plan Attribute Variables

Variable Name:	Description:
Green price premium	Monthly price premium associated with green energy plan ($5, $10, or $15)
Low conv. price volatility	Indicator for low volatility of conv. plan
Medium conv. price volatility	Indicator for medium volatility of conv. plan
High conv .price volatility	Indicator for high volatility of conv. plan
Low conv. price dispersion	Indicator for low dispersion of conv. plan
High conv. price dispersion	Indicator for high dispersion of conv. plan
Low green price volatility	Indicator for low volatility of green plan
Medium green price volatility	Indicator for medium volatility of green plan
High green price volatility	Indicator for high volatility of green plan
Low green price dispersion	Indicator for low dispersion of green plan
High green price dispersion	Indicator for high dispersion of green plan

Panel B – Socio-Demographic Variables

Variable Name:	Description:	Mean Value:
Pay electricity utility bill	Indicator: respondent pays own electric bill	0.80
Age	Categorical: age of respondent (1=less than 18, 2=18-24, 3=25-34, 4=35-44, 5=45-54, 6=55-64, 7=65-74, 8=75-84, 9=over 85)	3.34
Male	Indicator: respondent was male	0.42
Children	Indicator: respondent has children	0.29
Education	Categorical: level of education of respondent (1=less than high school, 2=high school, 3=some college, 4=2 year degree, 5=4 year degree, 6=professional degree, 7=doctorate degree)	4.07
Income	Categorical: level of income of respondent (1=less than $30K, 2=$30K-$60K, 3=$61K-$90K, 4=$91K-$120K, 5=$121K-$150K, 6=$151K-$180K, 7=over $180K)	2.84
Risk Aversion	Self-reported Likert scale measure of propensity to take risks in general (1 = Not at all willing to take risks, …, 7 = very willing to take risks)	4.08
New Ecological Paradigm	Sum of 15, 5-point Likert scale questions to measure respondent's concern for the environment (15= not at all concerned, …, 75 = very concerned)	49.5
Green Electricity	Self-reported Likert scale measure of the importance that electricity be generated from renewable source (1=strongly disagree, …, 5=strongly agree)	3.84
RSRP	Indicator: respondent was in the RSRP sample	0.54

In terms of socio-demographic variables, Panel B of Table 2 shows that over 80% of our respondents were responsible for paying their own electricity bill. On average, respondents were between 25 and 44 years of age, 42% were male, 29% they have children, have graduated high school and have some college education, and report an annual income in the range of $30K-$90K. Respondents self-reported an average measure of general risk taking of 4.08 out of 7 (with 1 = not at all willing to take risks and 7 = very willing to take risks). In terms of environmental concerns, respondents in our sample displayed a moderate level of environmental concern with an average NEP score of 49.5 out of 75 (with 15 = not at all concerned for the environment and 75 = extremely concerned for the environment). Lastly, respondents expressed, on average, that they agree with the statement that it is important for energy to be generated in a renewable manner, with and average measure of 3.84 on a 5-point Likert scale (1 = strongly disagree and 5 = strongly agree).

Recall, our survey utilized two distinct samples. The first sample consists of 408 respondents from a representative Qualtrics panel. The second sample consists of 424 respondents from the RSRP student database at the Rawls College of Business at Texas Tech University. Before proceeding with our main empirical analysis of plan choice, we first compare response behavior across the two samples. Aggregated over all respondents and all plan attributes, respondents from the Qualtrics panel chose the green plan 37% of the time, while respondents from the RSRP student sample chose the green plan 36% of the time; this difference is not statistically different (Chi-squared test: $p = .150$). Moreover, if we stratify by the three different price premiums for the green plan, the three different price volatility levels of the green plan, or the three different price volatility levels of the conventional plan, then there is only a significant difference (at the 10% level) in the rate of green plan selection between the two samples on 3 of the 9 total comparisons. In our view, this is within an acceptable threshold to assume no concerning sample differences with regard to respondent behavior; consequently, we pool the data across the two samples in the remainder of the analysis to provide a larger sample size, additional power, and more robust inference of the results.[7]

[7] In our main empirical estimation we also include a dummy variable for those respondents in the RSRP sample, and this variable is not significant, which provides further evidence of no major sample differences in respondent behavior. In addition, all are main results are robust if we analyze the data from each sample separately.

5.2 Overall Effect of Plan Attributes on Plan Choice

In this section, we present the results from a conditional logit model, to estimate the effect of plan attributes on plan choice. In this model the dependent variable is the choice of plan, as each choice set is an observation. The parameter estimates, therefore, represent the relative importance of the attributes of each plan in the likelihood that the plan is chosen. Additionally, the analysis using this model is restricted to the plan attribute variables because there is no variation in respondent characteristics within the choice set. We explore the role of these characteristics later in this section. In total, we have 9,108 unique observations included in the analysis spanning 815 unique respondents (who made at least 1 plan choice decision); although, not all 815 respondents made the full set of 12 choices. However, because each choice made represented a unique data point, the analysis does not require each respondent to make the full set of 12 choice to be included.

Table 3: Conditional Logit Results with Electricity Plan Choice as Dependent Variable

Variable:	Odds Ratio	Parameter Estimate	Robust Standard Errors
*green****	1.987	0.687	0.116
*expected price****	0.878	-0.130	0.005
*medium price volatility****	0.694	-0.366	0.032
*high price volatility****	0.544	-0.610	0.027
*high price dispersion****	1.322	0.279	0.049

Wald $\chi^2 = 1124.7$, Prob > $\chi^2 < .001$, Pseudo $R^2 = .112$, N = 9108, Respondents = 815

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The attribute variables included in the conditional logit are the average expected monthly price of the electricity plan and dummy variables for the green plan, medium expected price volatility, high expected price volatility, and high expected price dispersion. Results for the conditional logit model are presented in Table 3. From Table 3 we see that each of the parameter estimates for the included plan attributes in the model are statistically significant ($p < 0.001$) with the signs and overall pattern of results being consistent with our hypotheses. In particular, the coefficient on the green plan is positive indicating that, all else equal, the likelihood of a particular electricity plan

being selected is greater if that plan represents a green source of electricity. The interpretation of the estimate is that the log of odds that a plan is selected is 0.687 greater if the plan is for green electricity than conventionally produced electricity. The odds ratio often provides an easier interpretation of the result, where the odds ratio for variable *i* is equal to e^{β_i}. In this case, the odds that a plan with green electricity is chosen is 98.7% greater than a plan with conventionally produced electricity, all else equal.

Importantly, the estimate on the variable for expected monthly price is negative and, therefore, consistent with economic theory. For every one dollar increase in the expected price the odds that the plan would be selected decreases by 12.2 percent. Additionally, we hypothesized that in addition to expected monthly price, the expected price volatility of the plan would impact plan choice. From Table 3 we see that, indeed, price volatility does significantly impact plan choice. Specifically, the parameter estimates for medium and high price volatility are both negative and significant. The parameter estimates for medium and high expected price volatility are to be compared to the excluded alternative of low expected price volatility, therefore a negative sign on those estimates is predicted as is an increasing magnitude when moving from medium volatility to high volatility. The odds of a medium price volatility plan being selected are 30.6% lower than that of a low volatility plan and the odds of a high price volatility plan being selected are 45.6% lower than a low volatility plan.

The final plan attribute of interest in this model is the dummy variable for high price dispersion. The estimated coefficient on high price dispersion is positive and significant, indicating that (holding the expected price and volatility constant) respondents prefer plans with more price dispersion (i.e., a larger range of possible monthly prices). With an odds ratio of 1.322, the odds that an electricity plan with a high degree of price dispersion (i.e. a larger, but less likely, range of possible prices) is selected is 32.2% greater than the odds that a plan with a low degree of price dispersion (a smaller, but more likely, range of possible prices). For the case of residential electricity plan choice households appear to favor, relatively strongly, the plan with a larger range of potential monthly prices (with the extreme prices being unlikely) over the plan with a lower range of prices that are more centered around the expected price (with the tails of the distribution being relatively more probable).

5.3 Effect of Price Volatility and Price Dispersion on Green Plan Choice

Given that we have empirically documented that price volatility impacts plan choice in general, we proceed by specifically investigating the effect of price volatility and price dispersion on the decision to adopt the green energy plan. To get a sense of the overall impact of increases in price volatility on adoption of the green energy plan, Figure 2 depicts the frequency of the green plan choice as the variance of the green plan increases (Panel A) and as the variance of the conventional plan increases (Panel B), stratified by the price premium.

Figure 2: Impact of Increases of Price Volatility on Adoption of Green Power Plan

From Panel A of Figure 2 we see that as the price volatility of the green plan increases from low volatility to medium volatility to high volatility, the adoption rate of the green plan monotonically decreases. Moreover, this negative relation between the price volatility of the green plan and the adoption rate of the green plan is present across all three price premium levels. In Panel B, we see the opposite relation emerge as the price volatility of the conventional plan increases; namely, as the price volatility increases from low to medium to high, the adoption rate of the green plan increases. Taken together, this suggests that respondents dislike increased price volatility in their electric utility plan, which is consistent with the results from the conditional logit

estimation in the previous section. As a result, increased price volatility of the green plan discourages adoption of the green plan, while increased price volatility in the conventional plan encourages adoption of the green plan

Table 4: Logistic Regression with Green Energy Choice as Dependent Variable

Variable:	Odds Ratio	Robust Std. Err.	Marginal Effect	Delta-method Std. Err.
*Green price premium****	0.870	0.006	-0.032	0.002
*Medium conv price volatility****	1.404	0.079	0.077	0.013
*High conv price volatility****	1.735	0.107	0.126	0.014
*High conv price dispersion****	0.799	0.037	-0.051	0.011
*Medium green price volatility****	0.625	0.034	-0.107	0.012
*High green price volatility****	0.501	0.031	-0.158	0.014
*High green price dispersion****	1.441	0.070	0.084	0.011
Pay electricity utility bill	1.233	0.168	0.048	0.031
Age	0.966	0.061	-0.008	0.014
Male	1.018	0.112	0.004	0.025
Children	0.990	0.166	-0.002	0.038
Education	0.996	0.045	-0.001	0.010
Income	1.044	0.034	0.010	0.007
*Risk attitudes****	1.148	0.046	0.032	0.009
*New Ecological Paradigm****	1.042	0.007	0.009	0.002
*Green Electricity****	1.581	0.098	0.103	0.014
RSRP	1.026	0.239	0.006	0.053
constant	0.125	0.072		

Wald $\chi^2 = 505.87$, Prob > $\chi^2 < 0.001$, Pseudo $R^2 = 0.0906$, N = 8938, Respondents = 815

Notes: Standard errors clustered at the respondent level. Possible block effects are controlled for with dummy variables for block.
*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

To more formally analyze the impact of price volatility on the decision to adopt the green energy plan we estimate a logistic regression model, with a binary dependent variable for green plan choice. The logistic regression of the decision to adopt the green plan enables us to directly estimate the impact of plan attributes, as well as socio-demographic variables, on the likelihood that the green plan is chosen in the choice set, which is not possible with the conditional logit

model analyzed in the prior section. A total of 8,938 choice observations are included in the sample after removing incomplete responses. To account for the fact that each respondent made multiple plan choices in the survey, which could lead to serial correlation in the error terms, we clustered standard errors at the respondent level. Table 4 presents the results for the logistic regression with selection of the green energy plan as the dependent variable.[8] Included are both the odds ratios and marginal effects for the model, where marginal effects are evaluated at the means of each variable. Possible subject pool effects are controlled for with a variable RSRP=1 for respondents in the RSRP student sample and RSRP=0 for respondents in the Qualtrics panel sample. As seen in Table 4, the RSRP dummay variable is insignificant indicating that there are no substantial subject pool differences and the pattern of responses from the college student sample does not differ significantly from the general population sample.

Similar to the results from the conditional logit, the expected price premium for the green plan is important in determining the likelihood of selecting the green plan. Specifically, as seen in Table 4, *green price premium* enters negatively and is statistically significant ($p < 0.001$). The variable reflects the expected average price difference, in dollars, between the green electricity plan and conventional electricity plan within a particular choice set. Looking at the marginal effects from the logit regression reported in Table 4, moving from a green price premium of $10/month to $15/month would decreases the likelihood that the green plan is selected by 16 percentage points, holding everything else constant. Alternatively, at any particular price premium a $1 increase in premium reduces the odds that the green option is selected by 13%.

While price differences are clearly important (as economic theory would dictate) in explaining the selection of the green plan over the conventional plan, the expected volatility of prices in both plans are also important explanatory factors. Looking first at the effect of increases in the volatility of the green plan, we see from Table 4 that the dummy variables *medium green price volatility* and *high green price volatility* enter negatively and are both statistically significant ($p < 0.001$). These two variables are to be compared to the excluded variable for *low green price volatility*. They can be interpreted as representing an increase in the likelihood of selecting the green plan as the price

[8] We present the results from a logit model with clustered standard errors at the respondent level as our preferred specification, as it allows us to include socio-demographic variables as controls (which do not vary over choices at the individual level). However, or main results regarding the impact of price volatility and price dispersion are robust to alternative specifications including a probit model and linear probability model. Our main results are also robust and stable to the inclusion of respondent fixed effects.

volatility of the green plan increases. Looking at the reported marginal effects, moving from the low green price volatility plan to the medium green price volatility plan and the high green price volatility plan would reduce the likelihood of selecting the green plan by about 10.7 percentage points and 15.8 percentage points, respectively. To put this in perspective, the magnitude of the effect of moving from low to high price volatility of the green plan is roughly proportional to a $5/month change in the price premium of the green plan.

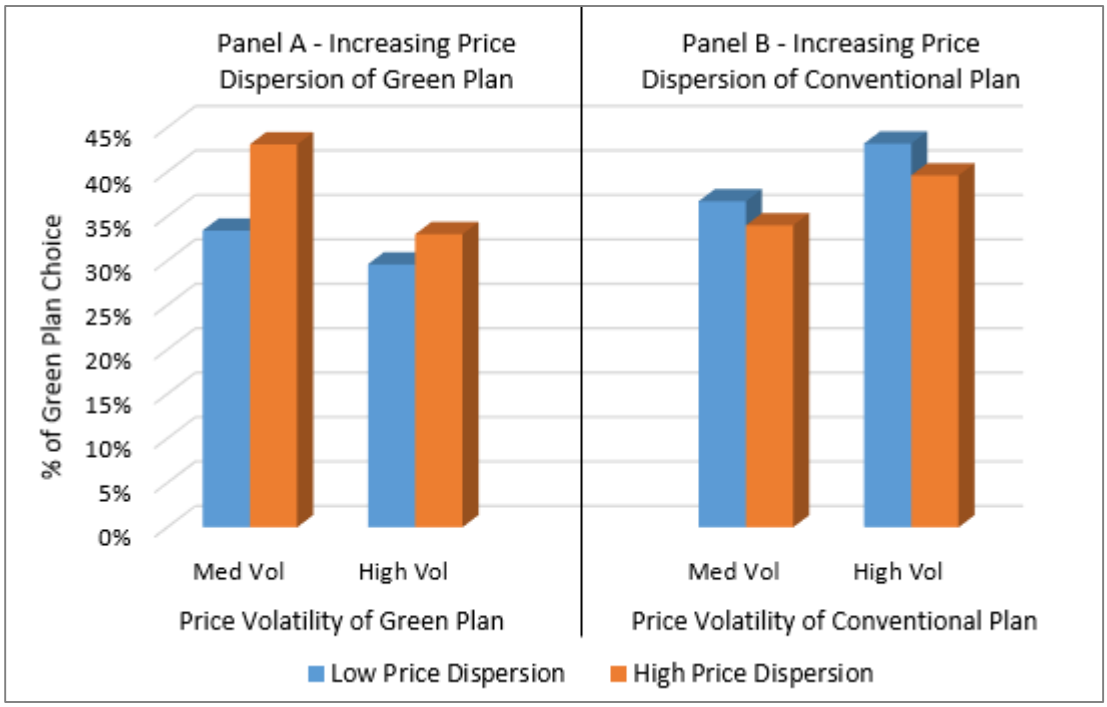
The price volatility of the conventional plan similarly impacts the decision to choose the green plan, but in the opposite direction and to a lesser extent. Namely, both *medium conv price volatility* and *high conv price volatility* enter in positively and are statistically significant ($p < 0.001$). Again, these two variables are in comparison to the excluded variable for *low conv price volatility*, and they can be interpreted as representing an increase in the likelihood of selecting the green plan as the price volatility of the conventional plan increases. From the reported marginal effects, moving from the low conventional price volatility plan to the medium and high conventional price volatility plans would increase the likelihood of selecting the green plan by about 7.7 percentage points and 12.6 percentage points, respectively. Of note is the fact that these effects of changes in the price volatility of the conventional plan are not as strong, in magnitude, as the more direct effect of equivalent changes in the price volatility of the green plan.

Next we look at how the degree of price dispersion for each of the plans impacts the decision to choose the green plan (holding the degree of volatility constant). Figure 3 compares the frequency of the green plan choice between the low and high green price dispersion plans (Panel A) and the low and high conventional price dispersion plans (Panel B), aggregated over the three different price premiums. Consistent with the results from the conditional logit in the previous section, we see that respondents generally prefer a plan with more price dispersion to less. Conditional on the level of volatility, respondents are more likely to choose the green plan when the green plan has high price dispersion compared to low price dispersion; correspondingly, respondents are less likely to choose the green plan (i.e., more likely to choose the conventional plan) when the conventional plan has high price dispersion compared to low price dispersion.

The effect of price dispersion is made further evident in Table 4. Both the *high green price dispersion* and *high conv price dispersion* variables in the logit regression are statistically significant ($p < 0.001$); the former enters in positively and the latter enters in negatively. In terms

of marginal effects, the likelihood of selecting the green plan is about 8.4 percentage points higher for the *high green price dispersion* plan compared to the *low green price dispersion* plan. Similarly, the likelihood of selecting the green plan is about 5.1 percentage points lower for the *high conv price dispersion* plan compared to the *low conv price dispersion* plan. These results suggest that respondents prefer plans with larger, but less likely, price swings (in both directions) over smaller, but more likely, price swings from the expected price.

Figure 3: Impact of Increases in Price Dispersion on Adoption of Green Power Plan



Lastly, we briefly report on the results from the socio-demographic variables included in Table 4. In general, the included demographic variables do not appear to have a large influence on the likelihood of choosing the green electricity plan. The variables for age, gender, children, education, and income do not significantly impact the choice of green plan. Consistent with prior studies mentioned in Section 2, we do find that more pro-environmental attitudes positively relate to choosing the green energy plan. As a measure to capture pro-environmental attitudes, we include the score for the *New Ecological Paradigm* scale, and this measure enters positively and is statistically significant ($p < 0.001$). An increase from a NEP score of 45 (low pro-environmental attitude) to 52 (entering the top tercile of the sample) increases the likelihood of selecting the green

option by 6.3 percentage points, ceteris paribus. We also find that the self-reported measure of the importance that electricity be generated in a renewable manner, *green electricity*, enters in positively and significantly ($p < 0.001$), as we would expect; respondents who think renewable electricity is important are more likely to choose the green plan, all else equal. The other demographic measure that enters significantly is the variable *risk attitude* ($p < 0.001$), which is a self-reported, Likert scale measure of the respondents general willingness to take risks (1=not at all willing and 7=very willing). The *risk attitude* variable enters in positively, indicating that more risk-averse respondents are less likely, on average, to select the green plan.

6 Discussion and Conclusions

It is estimated that upwards of 20% of the overall energy demand stems from demand in the residential sector. As such, increasing our understanding of the possible factors that can influence consumers' attitudes and choices regarding residential electricity usage is critically important in the analysis of energy convergence and the evolution of energy production and consumption across generating sources. The aim of this paper is to contribute to this understanding by investigating how price volatility in residential electricity rates impacts consumers' preferences for green power. In particular, we report the results from a choice-based experimental survey where respondents are asked to choose between a *conventional* electricity plan (e.g., coal or natural gas generating source) and a green electricity plan (e.g., wind or solar generating source). We systematically vary the price volatility in the monthly rate of each plan, as well as the price premium associated with the green plan, which allows us to identify how increases in the price volatility of both the conventional and green plans impact reported adoption rates of the green plan.

The results from our study suggest that price volatility impacts plan choice. Specifically, we find that as the price volatility of the green power plan increases, respondents are statistically significantly less likely to choose the green plan over the conventional plan (holding the expected monthly price of the plans constant). In the same way, we find that as the volatility of the conventional plan increases, respondents are significantly more likely to choose the green plan. Although, the documented effects of increases in price volatility of the green and conventional plans are not symmetric; increases in the price volatility of the green plan have a relatively larger impact compared to increases in the price volatility of the conventional plan. Importantly, not only are impacts of price volatility statistically significant, but they are also economically meaningful;

for example, moving from the lowest level of price volatility for the green plan to the highest level of price volatility is estimated to reduce adoption of the green plan by about 15 percentage points, which roughly equates in magnitude to the estimated decrease in the adoption rate of the green plan corresponding to a $5/month increase in the price premium of the green plan. Not only does the degree of price volatility impact plan choice, but we also find that the degree of price dispersion matters; namely, respondents are significantly more likely to choose the green plan the more dispersed or spread-out the distribution of possible monthly prices (holding both the expected monthly price and the level of variance constant).

We view this study as an important contribution in increasing our understanding of consumer demand for green energy. There is likely to be inherent volatility in residential electricity rates generated from both conventional fossil fuel sources as well as renewable green energy sources. Volatility in fossil fuel prices can induce volatility in electricity rates of conventional electricity plans, while intermittency and the uncertainty regarding technological innovation can induce volatility in green energy plans. Moreover, uncertainty regarding future regulation of both conventional and green energy sources can induce further price volatility in residential electricity rates. That said, much of the prior literature has focused on how the price premium of green power impacts consumers' choices to adopt the green power plan (either directly or indirectly by estimating a willingness to pay). However, given the substantial price volatility associated with residential electricity plans, only considering how the expected price impacts green energy demand delivers an incomplete view. Our results suggests that, in addition to expected monthly price, the volatility of possible prices associated with each plan can significantly impact the choice to adopt the green plan; thus providing a more complete view of the impact of price on green energy adoption. Overall, we view our study as contributing to and extending the extant literature that uses choice-based, experimental survey methodology to better understand factors that influence consumers' choice to adopt a green energy plan.

The results from our study provide useful information on how price volatility in residential electricity rates impacts the demand for electricity generated from green sources, which can have important implications across several different domains. From a descriptive perspective, our results can be informative for better understanding the possible factors that can impact growth of renewable energy and the overall electricity generation mix within a country moving forward;

specifically, increases in the volatility in the price of green electric power (possibly though the elimination of subsidies) would likely decrease the residential demand for green electric power, while increased volatility in conventional hydrocarbon and fossil fuel-based electric power would increase the demand for green power. From a green power marketing perspective, our results suggest that a possible avenue by which electric utilities could increase the take-up rate of green power plans would be to make the price of such plans more stable, and then market this price stability to potential customers. From a prescriptive perspective, our study can be informative for energy policy aimed at promoting more green energy. Sustaining continued growth in the green energy production infrastructure hinges on increased and/or sufficient consumer demand for energy produced from green sources. Our results suggest that policies aimed at providing more stability in the price of green electric power would increase the overall demand for green electric power and, thus, stimulate overall growth in the renewable energy sector; examples of such policies include the subsidization of green power generation, the subsidization of green power consumption, or alternatively, stimulus programs aimed at promoting research and development of energy storage technology that enable green power sources to operate more stably and efficiently. Overall, our results suggest that price volatility in residential electricity plans can significantly impact plan choice of consumers; given that residential energy demand accounts for a sizable portion of overall energy demand, our results further suggest that changes in price volatility across conventional and green electric power can play an important role in the convergence of an optimal energy mix between conventional and green power.

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