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Consumer willingness-to-pay for a resilient electrical grid

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ABSTRACT

The research objective is to estimate consumer willingness to pay (WTP) for electricity grid fortification. Data are from a representative survey of Oklahoma citizens. Extreme weather events, aging utility infrastructure, increased demand for affordable energy, and terrorism threaten the safety and security of the way most citizens access electricity. This study is a first look at public willingness to support energy grid security measures in the United States Southern Great Plains. Findings suggest that consumers would pay an additional $14.69 in monthly utility bills for a fortified grid. This WTP estimate is close to a recent energy bill hike of $14 initiated by local electricity providers. The findings provide policymakers and energy providers with information on consumer willingness to support efforts to modernize the current grid.

1. Introduction

Electrical grid security and resiliency are topics of concern for citizens, energy providers, and elected officials. The grid's aging infrastructure is increasingly prone to failures and outages (United States [U.S.] Government Accountability Office, 2021). The 2020 Inflation Reduction Act (IRA) (H.R. 5376) aims to address this issue by legislating funds to upgrade and modernize the grid. The objective of the IRA is to reduce the frequency and impact of outages on the domestic electrical grid and to ensure that the grid continues to meet the energy needs of communities. The Act recognized the need to diversify the U.S. energy portfolio by investing in advanced technologies such as smart grids and distributed energy resources, which can better withstand extreme weather events and other disruptions (Government Accountability Office [GAO], 2021). The IRA earmarked $760 million in grants to upgrade interstate electricity transmission lines, $100 million for wind electricity transmission planning, and an additional $2 billion for transmission facility financing, all managed by the U.S. Department of Energy (The White House, 2022). Public investment in grid improvements also depends on how much customers value resiliency and reliability and how much they are willing to support such investments over the long term.

This research aims to estimate consumer willingness to pay (WTP) for grid fortifications that mitigate the risk of experiencing power outages or other disruptions. Panteli and Mancarella (2015) define electrical grid resiliency as "the ability of anticipating extraordinary and high-impact low probability events, rapidly recovering from these disruptive events, and absorbing lessons for adopting its operation and structure for preventing or mitigating the impact of similar events in the future." Conjoint or contingent valuation (CV) studies on WTP for improvements in grid resiliency are more frequent. There is ample literature on WTP for enhanced energy technologies related to climate change mitigation, which Streimikiene et al. (2019) summarized. Morrissey et al. (2018) found that residents in northwest England were willing to pay US$37.94 to avoid power disruptions during winter months. In their analysis of 15 European Union countries, Cohen et al. (2016) found a range of WTP estimates to avoid a power outage (US$0.38 to $4.25). Kim et al. (2021) found that South Korean residents living in apartments were WTP US$32.12 m^{-2} for reliable energy provision.

Fewer studies have analyzed WTP for grid resiliency in the U.S. A study by Baik et al. (2020) elicited consumer WTP for grid resilience. Their research found that residential customers in the northeastern U.S. would pay U.S. $1.7 per 2.3 kWh for private demands. In their conjoint analysis of WTP for microgrid resilience, Hotaling et al. (2021) estimated that households in New York State were willing to pay an additional $14 $month^{-1}$. Respondent age, gender, political ideology, and energy profile significantly influenced WTP estimates in these studies.

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The state of Oklahoma is an interesting case study of WTP for improving and modernizing the electrical grid. Oklahoma is worth studying for both technical and policy reasons. First, numerous features of Oklahoma's electrical grid (*e.g.*, transmission lines) are almost 100 years old (Everett, 2007). There have been campaigns to improve the grid, but much of it still needs modernization (OG&E, 2008). Electrical grid modernization may also be more pressing in Oklahoma, given the frequency of severe weather events, for example, extreme heat and cold, ice storms, tornadoes, and flooding. These events stress the current grid system. Rural areas are also more likely to experience prolonged power outages (Bohman, 2020).

Second, from a policy perspective, Oklahoma is an example of regulatory capture by utilities. Market imperfections are common in electricity and natural gas markets, and local utility companies tend to behave like natural monopolies (Davies et al., 2021). Utilities are also often governed by the rate of return from regulation (Pindyck, 2001). Regulators have used price setting over the past fifty years to attain this goal. Most of this regulation occurs at the state level (Joskow and Schmalensee, 1986). Despite efforts to balance the public interest with utility profits, however, regulators and legislators are prone to "capture" (Stigler, 1971). Regulators may tend to curry favor with the industries they are supposed to regulate instead of protecting the public from monopoly pricing (Levine and Forrence, 1990). Consumers might pay higher utility prices, and regulation of utilities may become less effective, but this outcome is not always assured. While prone to regulatory capture, utility pricing is complex and nuanced and depends on, among other things, existing energy technologies and infrastructure, changes in energy demand, and the effectiveness of local and state institutions.

During the winter freeze of 2021, cold temperatures froze critical equipment. Oklahoma utilities passed repair and provision costs onto consumers. The state's largest gas company paid prices 600 times higher than usual (Monies and Green, 2022). Oklahoma utilities also paid out billions in fuel to out-of-state energy companies. According to the American Association of Retired Persons (AARP), some Oklahoma utility providers were unprepared for the winter storm Uri and did not inform customers of the storm's impact on their bill of an impending $800 million rate hike (Oklahoma AARP, 2022). Other utilities and entities also incurred supra-normal costs, such as Oklahoma Natural Gas ($1.45 billion), the American Electric Power-Public Service Company of Oklahoma (AEP-PSO) ($725 million), and Summit Utilities of Oklahoma ($95 million).

Oklahoma energy prices are rising faster than most other states, which is another reason why it presents an interesting case to examine in light of the expected costs of creating grids that are resilient to the effects of climate change on weather. A US Energy Information Administration (USEIA) report indicates that Oklahoma's electricity prices are climbing at the fastest rate in the nation (USEIA, 2022). Electricity prices in Oklahoma increased from 7.3 cents per Kilowatt Hour in June 2021 to 10.87 cents per Kilowatt Hour, June 2022 (USEIA, 2022). Energy prices in Oklahoma increased 49% year over year from 2021 to 2022. By contrast, the rest of the country only saw a 14% increase in the cost of energy (Rael, 2022).

Oklahoma participates with 14 other states in the Southwest Power Pool (SPP). The SPP manages the electric grid and wholesale power market for the central United States. As a regional transmission organization, the nonprofit corporation is mandated by the Federal Energy Regulatory Commission (FERC) to ensure reliable power supplies, adequate transmission infrastructure, and competitive wholesale electricity prices. Contrary to a widespread misconception, problems with natural gas fuel supply caused the vast majority of energy outages during February 2021 (FERC, 2021).

In the aftermath of Winter Storm Uri, FERC recommended that Congress, state legislatures, and regulatory agencies, such as OCC, require those natural gas facilities to implement and maintain cold weather preparedness plans and that natural gas infrastructure facilities undertake voluntary measures to prepare for cold weather spells (FERC, 2021, 2021). In November 2022, the Public Service Company of Oklahoma (PSO) increased monthly electricity payments by $14 (Killman, 2023)—the service provider aimed to increase grid security, reliability, and resilience and support economic growth. The $14 increase is a reference point for this research. This 10% increase over the previous rate was the third hike since December 2021, affecting nearly 500,000 customers. Under Oklahoma law, the Oklahoma Corporation Commission (OCC) regulates utility pricing by companies like PSO. In 2023, the OCC stated that most of the increase is due to higher natural gas prices and not rates (Clark, 2023). Furthermore, the OCC stated that:

"*Under Oklahoma law, the utility can pass on its fuel costs to the customer, but at no profit. The OCC audits fuel costs from the utility to ensure no profit is made and that the contracts for purchase meet other legal requirements. Barring any problem in those areas, the pass-through of fuel costs must be allowed. The OCC has no pricing jurisdiction over the entities that sell fuel to the utilities*" (Clark, 2023).

Utilities use natural gas markets for baseload generation, which is always available, unlike solar or wind. Any regulation of natural gas markets is under the jurisdiction of federal agencies, not Oklahoma (*ibid*). Utilities, therefore, can pass on fuel costs to customers, but not at a profit.

The idea of fortifying the grid to achieve resiliency targets is laudable. Nevertheless, proposed increases must be seen in light of Oklahoma utilities' price increases on consumers. The enormous disruption caused by the ice storms in 2021 and the usual likelihood of tornadoes in spring and early summer likely increased public acceptance of these hikes. However, some organizations opposed the $14 increase of November 2022. For example, the American Association of Retired Persons of Oklahoma noted that older Oklahomans on fixed incomes struggle to afford higher food costs, health care, and prescription drugs (AARP Bulletin, 2023).

This study uses data from a representative survey of Oklahoma citizens, the Meso-Scale Integrated Sociogeographic Network (M-SISNet). The M-SISNet survey provides an in-depth perspective on consumer attitudes and beliefs about a changing climate, ideological positions on politics, society, and nature, and other detailed socioeconomic data. These factors are hypothesized to affect WTP for grid enhancements in various ways. The survey included a contingent valuation (CV) section, which asked respondents if they were willing to accept an increase in monthly utility bills for robust grid enhancements. The methodological contribution of the study is the use of a novel modeling procedure to estimate WTP and the marginal contributions of respondent characteristics to WTP. A bivariate ordered regression is used to estimate WTP, with unobserved preference heterogeneity modeled as random parameters. We use this procedure because a screening question was used to isolate respondents who would most likely support a referendum to improve Oklahoma's grid resilience. Thus, the sample we use to estimate WTP is a nonrandom sample with self-selection into a group that would support a grid price hike to improve resilience. The implication is that the WTP distribution is truncated since it is unobserved for respondents who self-selected out of the sample. Findings suggest that, on average, consumers are WTP an extra $14.69 per month for enhanced grid improvements. Demand for grid improvements in rural areas is more robust than in urban and suburban communities.

2. Data

Data are from the Oklahoma M-SISNet survey.[1] M-SISNet surveys collect biannual data on household perceptions and responses to climate and extreme weather events (Jenkins-Smith et al., 2017). Additional questions focus on citizens' views toward government and policies,

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[1] OU-NC IRB Number: 10323 Approval Date: 2/14/2019. Survey documentation and data are available at http://crcm.ou.edu/epscordata/ and https://crcm.shinyapps.io/s3ok/.

societal issues, and how viewpoints and opinions influence citizens' perceptions of energy and water use. The panel survey began in 2014. Since M-SISNet's inception, contingent valuation questions have been included three times: 2015 (wave 7), 2020 (wave 22), and 2021/22 (wave 24). This study uses data from wave 24, conducted from November 22, 2021, to January 7, 2022; 2180 individuals responded to the survey (response rate, 36%). This timing means that the survey was implemented roughly nine months after the historic cold wave in February 2021 that significantly impacted the electrical grid in Oklahoma. There were 1826 observations used in the analysis after eliminating records with missing values. A critical research caveat is that the data and findings may not be generalizable to other states or regions, given the survey's target population used in the analysis.

2.1. Screening question: The likelihood of supporting grid fortification

A screening question appeared before the CV section. Pre-screening identifies individuals who stated they would vote for an enhanced grid at no cost. Pre-screening before the CV helps minimize yea-saying bias (Blamey et al., 1999; Jensen et al., 2015) and identifies which individuals define the potential financial supporters of energy grid improvements.

First, half of the participants viewed an information screen with a definition of an electrical grid:

> *An electric grid is a complex network of generation, transmission, and distribution systems that carry electricity from power plants to people and businesses. In most places, electric grids are shared resources that everyone in the community relies on for electricity. Most people get electricity from an electric grid.*

This description was randomized across respondents to assess the possibility of a recall effect (Whitehead and Hoban, 1999). A dummy variable was included in the statistical model to control for this possibility. A figure accompanied the definition, depicting where electricity is generated and how energy is delivered to residences (Fig. 1).

Next, respondents answered questions related to their perceived risks of experiencing power outages, dependence on the electrical grid, grid reliability, perceptions of the causes of outages, and characteristics of their utility provider.

The screening question followed. The grid improvement program was introduced with the following statement:

> *Officials in private companies and government organizations are considering a program that will reduce the risks of severe electric outages. The program is expensive, but estimates suggest that it will reduce the risk of severe electricity outages by [**randomized**: 10%, 40%, 70%] in Oklahoma.*

The risk reduction levels were chosen based on informal conversations with opinion leaders and officials in Oklahoma (*e.g.*, regulatory officials, policymakers, and industry representatives). The group agreed that these values represented a realistic variety of policy scenarios that range in cost and effectiveness. Respondents who answered "yes, I would vote for the program" continued to the CV question (74%, or 1352 respondents). The distribution of respondents answering "yes" across the risk reduction categories was 411 (10% reduction), 249 (40% reduction), and 691 (70% reduction). The risk reduction amounts of '10', '40', and '70' were included in the statistical model.

Next, all respondents answered the following hypothetical question:

> *Imagine that government officials were asking you to vote on the program. If it would not cost you anything, would you vote for or against the program to improve the electric grid in Oklahoma?*

1 – *Vote for the program*
2 – *Vote against the program*
3 – *Not sure*

Respondents who answered 'vote for the program' (1352) continued to the CV question (discussed below).[2]

We modeled the likelihood of an individual elected to support grid fortification (at no cost) using probit regression (discussed below).

2.2. Hypothetical referendum on energy grid fortification

The CV section followed the screening question. The CV format was a one-shot single binary, discrete choice referendum format. The single-bound format was used to minimize strain on participants responding to an otherwise long and complex survey. Additionally, past work suggests that this format is less likely to encourage strategic behavior than double-bound choice formats or open elicitation formats because it does not signal uncertainty concerning the increases in utility costs (Arrow et al., 1993; Carson et al., 2001). In addition to reducing strategic behavior, the referendum format is more realistic than other formats, reducing the hypothetical bias in CV estimates (Murphy et al., 2005). The CV question followed:

> *Would you vote for the grid improvement program if it were to increase your electricity bill by [**randomize bid**: $1 to $30] each month for the next 120 months (10 years)?*

The bid range is based on conversations with Oklahoma opinion leaders and officials (*e.g.*, regulatory officials, policymakers, and industry representatives). Respondents could answer "no," "yes," or "unsure." Including the "unsure" option is a strategy to address "warm glow" effects that could bias WTP estimates (Kahneman and Knetsch, 1992). Table 1 summarizes the distributions of responses across the levels of risk reduction. Interestingly, the distribution of response frequencies is similar across the risk reduction categories, indicating that respondents who supported the program were willing to do so even at modest levels of grid improvement. Another possible interpretation could be that respondents could not distinguish clearly among the 10%, 40%, and 70% levels.

2.3. Variables hypothesized to influence enhancement support and WTP

We hypothesized that WTP for enhanced grid reliability, as well as the likelihood a respondent would vote for grid fortification, would be influenced by respondent characteristics, residential location, respondent beliefs about risks to grid reliability, respondent viewpoints and opinions on the quality of current service providers, and the cost of the program (increase in a monthly utility bill).

Previous studies found that gender influences WTP for improvements in grid resilience. In their study of WTP for reliable electricity in Senegal, Deutschmann et al. (2021) reported a negative relationship between females and WTP. Wang et al. (2020) found a positive relationship between females and their willingness to participate in demand-saving energy programs. Given this inconsistency, we had no *a priori* expectation on the relationship between gender and WTP for grid enhancements. Fifty-eight percent of the respondents were female (*female*, Table 2).

The statistical model includes a proxy for educational attainment as a covariate. We hypothesized that individuals with a college degree are more likely to be familiar with the structure and functioning of electrical grids and, therefore, more likely to support grid fortification. Twenty-nine percent of the respondents had a college degree (*college*, Table 2).

Political ideology may influence public willingness to support infrastructure projects (Fogg et al., 2020). We hypothesized that a

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[2] A more effective screening question might have been only to include the household bill-payer or other person who affects decisions on financial payments in the household. As one reviewer suggested, including individuals who were not the primary bill payer in the WTP question may inflate the average WTP value. We can only surmise that including other demographic controls, such as respondent age, offset this potential for upward bias of WTP.

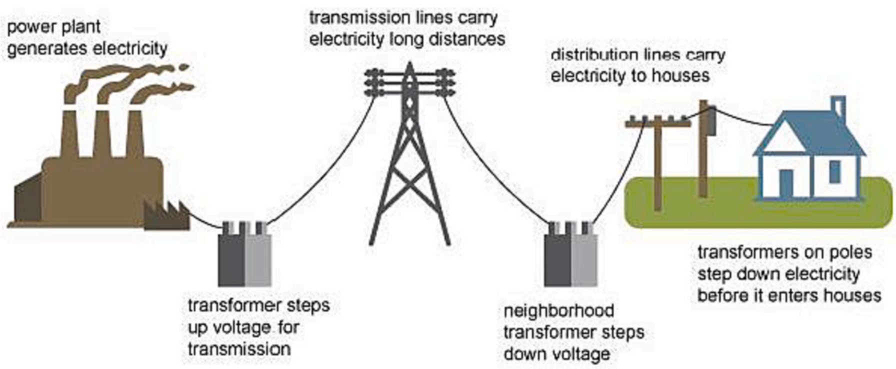

Fig. 1. Definition of an electrical grid.

Table 1
Distribution of responses to the contingent valuation question on a grid resilience program.

Response	10%	40%	70%
No	99	46	157
(proportion)	(0.24)	(0.19)	(0.22)
Yes	192	127	319
(proportion)	(0.46)	(0.52)	(0.47)
Not sure	120	76	215
(proportion)	(0.30)	(0.29)	(0.31)
Total	411	249	691

respondent who self-aligns with conservative values would be less likely to support a program managed through a quasi-government institution that levies an increase in monthly utility bills. The variable *ideology* was measured on a Likert scale; 1 (“strong liberal”) to 7 (“strong conservative”). Ideology is self-reported. The mean of *ideology* is 4.44.

Voting behavior may also be associated with WTP for, and the propensity to support, grid fortification. Two dummy variables were included in the statistical model to control for this source of heterogeneity. The first, *votenatl*, equals ‘1’ if the respondent voted in the 2020 national election (‘0’ otherwise). The second, *votelocal*, equals ‘1’ if the respondent voted in local elections (‘0’ otherwise). The location of a respondent’s residence, the years a respondent lived in Oklahoma, and a respondent’s dependency on the grid for electricity were hypothesized to influence WTP for enhanced grid services. Respondents living in more densely populated communities may perceive the benefits of grid enhancements differently from households living in less densely populated areas. We maintained no *a priori* hypotheses on the relationship between respondents living in urban (*urban*, 19% of respondents, Table 2) or suburban (*suburban*, 43% of respondents, Table 2) communities. The reference group is rural communities (38% of respondents).

Respondents reported their years of living in Oklahoma (*okhome*, 40 years, Table 2). Presumably, the longer a person lived in Oklahoma, the more familiar they would be with energy grid issues. We hypothesized that individuals who lived longer in Oklahoma would be more likely to support a grid enhancement program. We also included respondent age in the regression. We expect that older respondents would be more likely to support improvements.

Some respondents relied heavily on the electric grid. In contrast, others were less reliant because they had access to off-grid electricity sources. We included a Likert variable, *dependgrid* (1 = “not at all dependent,”…5 = “extremely dependent”), to control for this source of heterogeneity (mean, 4.24, Table 2). We expected this variable to contribute positively to WTP. Respondents were provided a short definition of power outages and examples of their causes. Following a prompt, respondents were asked to self-report the frequency of outage occurrences at their household (Likert scale, 1 = “not at all frequent”, 5 = “extremely frequent”). The mean of the variable *outage* was 1.68 (Table 2). We expected that perceived outage frequency would

Table 2
Summary statistics.

Variable	Label	Units	N	Mean	Std. dev.	Min	Max
Female	*female*	(= 1)	2256	0.58		0	1
College degree	*college*	(= 1)	2256	0.29		0	1
Political ideology	*ideol*	Likert	2117	4.44	1.70	1	7
Years living in Oklahoma	*okhome*	Years	2180	39.93	20.05	1	91
Age	*age*	Years	2180	54.20	15.95	18	92
Urban residence	*urban*	(= 1)	2256	0.19		0	1
Suburban residence	*suburban*	(= 1)	2256	0.43		0	1
Dependence on grid	*dependgrid*	Likert	2116	4.24	0.97	1	5
Outage	*outage*	Likert	2118	1.68	0.88	1	5
Belief in grid reliability	*reliability*	Likert	2117	3.15	1.01	1	5
Risk of outage, home	*riskego*	Likert	2116	2.78	0.87	1	5
Risk of outage, economy	*riskecon*	Likert	2117	3.09	0.88	1	5
Risk of outage, safety	*risksafe*	Likert	2114	3.13	0.89	1	5
Coop provision	*ecoop*	(= 1)	2256	0.23		0	1
Govt. provision	*egovt*	(= 1)	2256	0.11		0	1
Private co. provision	*epriv*	(= 1)	2256	0.56		0	1
Trust in utility co.	*trustutil*	Likert	2114	3.41	0.86	1	5
Voted: national election	*votenatl*	(= 1)	2116	0.90		0	1
Voted: local election	*voteloc*	(= 1)	2118	0.76		0	1
Rank: e-grid needs attention	*elecrank*	Likert	2179	3.26	1.85	1	7
Infrastructure concern	*elecinfra*	Likert	2167	3.26	1.32	1	5
Increase in monthly utility bill	*bid-cost*	$	2124	15.69	8.70	1	30
Income ($1000 s)	*income*	$	1883	64.77	36.35	10	150

positively influence WTP for grid enhancements. Respondents rated grid reliability on a Likert scale, with a ranking of 1 “not at all reliable” and 5 “extremely reliable” (*reliability* mean, 3.15, Table 2). The relationship between perceptions of reliability and WTP was also expected to be positive.

Electric grids face risks from accidents, natural disasters, and deliberate physical and cyber-attacks (GAO, 2019). These disruptions can cause severe, long-lasting electricity outages that impact large portions of the population. In addition to harming the quality of life, outages can significantly affect economic well-being and public safety. Respondent perceptions on the degree of risk posed by a *status quo* electricity grid system could influence WTP for a grid enhancement program. Respondents were asked to rate the risk of severe electricity outages to their household on a 1 (“no risk) to 5 (“extreme risk”) Likert scale to account for this source of preference heterogeneity (*riskego*, mean 2.78, Table 2). Respondents were also asked to rate the risk of severe outages to the state’s economy (*riskecon*, mean 3.09, Table 2) and public safety (*risksafe*, mean 3.13, Table 2). We hypothesized that there would be a positive relationship between these variables, support for the grid enhancement, and WTP.

Respondents were asked if they knew where their electricity was generated and who provided the service to assess familiarity and trust with the grid services. Options included a private utility provider (*epriv*, 56%, Table 2), an electric cooperative (*ecoop*, 23%, Table 2), and a quasi-government provider (*egovt*, mean 11%, Table 2). We had no *a priori* beliefs about these variables’ influence on WTP. However, we considered it important to control for these sources of heterogeneity in the statistical model. A follow-up question asked respondents to rate their trust in electricity service providers on a Likert scale (*trustutil*, 1 = “no trust”, 5 = “complete trust”, mean 3.41, Table 2). We expected respondents who trusted their current service provider would be more likely to support a program that advances grid improvements.

Respondents were asked to imagine they could advise scientists and policymakers on which topics should receive the most attention to evaluate the relative salience of grid infrastructure in comparison to other issues in the state, including water availability, water quality, water cost, wildlife habitat, soil quality, electricity infrastructure, and transportation infrastructure. We constructed a variable from this list, *elecrank*, which ranked the electricity grid as ‘1’ (highest priority) to ‘7’ (lowest priority). We hypothesized that the higher a respondent ranked the electrical grid as a priority concern, the more likely the respondent would support the grid enhancement program. The mean of *elecrank* was 3.26 (Table 2). Lastly, respondents were asked to rate their concern about electricity infrastructure on a 1 (“definitely no” concerns) to 5 (“definitely yes” concerns) Likert scale. The mean of *elecinfra* was 3.26 (Table 2). We hypothesized that respondents concerned about their region’s electricity infrastructure status would be more willing to support a program that improved grid resiliency.

3. Methods and procedures

An energy consumer’s WTP to reduce outage risk with grid improvements is the maximum amount of income (m) individual $i = 1\cdots n$ would forgo to pay for enhancements. Let $v_0(\mathbf{x}_i, m_i, u_{0i})$ denote an individual’s indirect utility, absent grid enhancements. Individual characteristics, including age, education, and other demographic variables, enter $\mathbf{x}_i$ and were discussed above. The variable u_{0i} is a random error with an expected value of zero and a constant variance. The indirect utility of an individual supporting grid enhancement is $v_1(\mathbf{x}_i, m_i - t, u_{1i})$, where t is the monthly increase (dollars) in a utility bill and u_{1i} is similarly defined above. An individual is willing to pay for grid enhancement when $v_1 > v_0$. The consumer is indifferent between the *status quo* and innovation when these terms are equal.

McFadden (1974)’s random utility model (RUM) is applied to parameterize these utilities as linear-additive functions of systematic and random components. We included individual-specific effects (a_i) to allow for preference heterogeneity across the sample of respondents (Train, 2009). Absent grid enhancements, a consumer’s indirect utility is:

$$v_{0i} = \mathbf{x}_i\boldsymbol{\alpha}_0 + \alpha_m \cdot m_i + a_{0i} + u_{0i} \tag{1}$$

with u_{i0} a stochastic error term; $\alpha_m > 0$ the marginal utility of income; and $\boldsymbol{\alpha}_0$ are parameters. Consumer characteristics and other demographic variables were included in the $1 \times k$ vector $\mathbf{x}_i$ and were discussed above.

The indirect utility of a consumer who unequivocally supports energy grid enhancements is:

$$v_{1i} = \mathbf{x}_i\boldsymbol{\alpha}_1 + \alpha_m \cdot (m_i - t) + a_{1i} + u_{1i} \tag{2}$$

where t is the monthly dollar amount the individual pays to support grid enhancements, the $\boldsymbol{\alpha}$’s are utility weights, and the other variables and parameters were previously defined.

Since only differences in utility are important, and the level of utility is irrelevant (Train, 2009), we chose the “no” option (eq. 1) as the normalizing reference category. At the point of indifference, utility with and without improvement is equal. Subtracting eq. 1 from 2:

$$v_i^* = \mathbf{x}_i\boldsymbol{\beta} - \alpha_m \cdot t + a_i + u_i \tag{3}$$

where v_i^* is the latent, unobserved change in utility; $\boldsymbol{\beta} = \boldsymbol{\alpha}_1 - \boldsymbol{\alpha}_0$; a_i are differences in individual preferences between states, and $u_i = u_{i1} - u_{i0}$, which has an expected value of zero and a constant variance. The stochastic terms are unobserved, and the inequality favoring the referendum is only observable as a yes/no outcome (Hanemann, 1984) (discussed below).

WTP is the amount of money that makes a consumer indifferent between the *status quo* state (eq. 1) and the case where grid enhancements are preferred (eq. 2) (Habb and McConnel, 2002). At the point of indifference, $v_i^* = 0$ (eq. 3), and WTP equals the grid enhancement bid, t. Setting the change in utility to zero and solving for WTP:

$$wtp_i = \frac{\mathbf{x}_i\boldsymbol{\beta} + a_i}{\alpha_m} + \frac{u_i}{\alpha_m} \tag{4}$$

The marginal contribution of an individual’s attributes on WTP was found by differentiating eq. 4 with respect to the variables in $\mathbf{x}$; $wtp_k = \frac{\partial wtp_i}{\partial x_{ik}} = \frac{\beta_k}{\alpha_m}$.

The literature on willingness to pay (WTP) for a public good (such as a secure electrical grid) suggests that stated WTP methods may underestimate an individual’s true willingness to pay for a robust energy grid. The gap between stated and actual WTP is called hypothetical bias. Hypothetical bias happens when people state a lower WTP in conjectural scenarios compared to their true WTP, which is observed in actual market situations (Mitchell and Carson, 1989; List and Gallet, 2001; Hanley et al., 2001; Becker et al., 2017). Thus, our estimates of WTP for grid fortification in Oklahoma may be a lower bound for what residents would pay. The potential for underestimating WTP is an important caveat of this research. The divergence between stated and actual WTP has implications for policy decisions. It suggests that alternative approaches, such as revealed preference methods, may produce more accurate estimates of peoples’ true valuation of public goods. For the present study, conducting a revealed preference survey was infeasible. Nevertheless, underestimating WTP may provide a lower bound on what consumers are WTP, a feature that may be desirable for some policymakers as they balance fiscal concerns with spending to upgrade an energy grid.

3.1. Ordered regression with sample selection

Single-equation probit or logistic regression is usually used to estimate WTP using eq. 3. Including the “not sure” option compels us to consider an alternative modeling strategy. One might consider using multinomial probit regression to estimate jointly the three choice options. However, this would cause conceptual and methodological problems. Assuming that the "no" category is the base outcome, it is unclear then what form the linear utility for the "not sure" outcome would be, given that α_m must be restricted to be the same for "not sure" and "yes" responses. An *ad hoc* fix would include a slope shifter on the bid variable for the "not sure" version of eq. 3. This extra parameter would then represent a proportional shift in the marginal utility of income for the "not sure" responders. A methodological issue arises because said parameter would be either unidentified or only identified through nonlinearities of the system.

Instead, we assume that response categories proceed in order from "no" to "not sure" to "yes," with the "not sure" category a grey area of hesitancy. This response pattern suggests using an ordered outcome regression. This modeling choice bypasses having to impose *ad hoc* restrictions on the marginal utility of income parameter. For the ordered-categorical model, responses to the CV question are observed as:

$$y_i = \begin{cases} \text{"no"} & \text{if} \quad \kappa_0 = -\infty \le v_i^* < \kappa_1 \\ \text{"not sure"} & \text{if} \quad \kappa_1 \le v_i^* < \kappa_2 \\ \text{"yes"} & \text{if} \quad \kappa_2 \le v_i^* < \kappa_3 = \infty \end{cases} \tag{5}$$

where $j =$ "no" ($y = 1$), "not sure" ($y = 2$), or "yes" ($y = 3$); and $\kappa_1, \dots \kappa_{J-1}$ are real numbers (or "thresholds") ordered as $\kappa_j < \kappa_m$ when $j < m$ (De Luca and Perotti, 2011). The observed category changes when the latent variable v_i^* crosses a threshold (Long and Freese, 2014). The ambivalence of "not sure" responders is captured when $\kappa_1 < v_i^* \le \kappa_2$. For "yes" responders, $\kappa_2 \le v_i^*$.

Another issue complicating WTP estimation is that respondents answering "yes" to the screening question are a nonrandom sample because they self-select into the CV experiment (Cameron and Trivedi, 2005).[3] Self-selection out of the CV sample truncates the WTP distribution since this portion of the sample's willingness is unobserved. The implication is that WTP estimates are biased if the selection mechanism is ignored (Maddala, 1983).

We estimated WTP using ordered probit regression adjusted for self-selectivity (Fig. 2). Estimation requires specifying a joint distribution for the error terms of v_i^* and the random errors of a selection equation. The selection equation is:

$$vote_i = 1(\mathbf{z}_i\boldsymbol{\gamma} + \varepsilon_i) \tag{6}$$

where $vote_i = 1$ for "yes" answers to the screening question ("0" otherwise); ε_i is a random error term; $\boldsymbol{\gamma}$ are parameters; and $\mathbf{z}_i$ includes most of the same covariates in $\mathbf{x}_i$. Keane (1992), Cameron and Trivedi (2005), and Wooldridge (2010) discuss the role of exclusion restrictions in sample selection models. The bid price is naturally omitted from $\mathbf{z}_i$, but income is included $\mathbf{z}_i$.

3.2. Estimation

Bivariate sample selection models have been discussed at length (Amemiya, 1985; Wooldridge, 2010; Cameron and Trivedi, 2005). De Luca and Perotti (2011) provide additional details on estimating bivariate ordered probit models. The joint distribution for the error terms of eqs. 5 and 6 is bivariate normal (BVN):

$$\begin{bmatrix} u_i \\ \varepsilon_i \end{bmatrix} \sim BVN\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right) \tag{7}$$

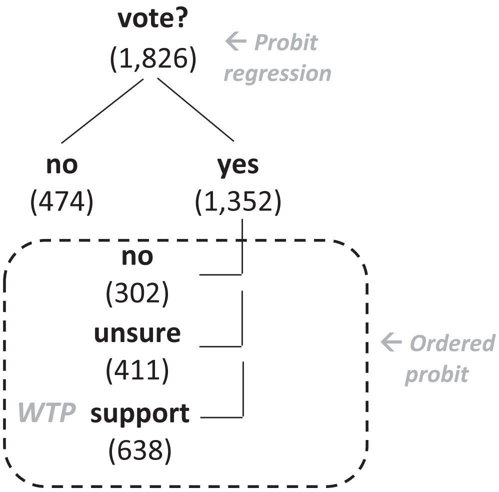

Fig. 2. Response patterns and models.

where ρ is a correlation coefficient. Define $f(\mathbf{x}_i, t, a_i)$ as the deterministic part of eq. 3, including the preference heterogeneity parameters, a_i. The log-likelihood function is:

$$\begin{aligned} lnL_i = {} & \sum\nolimits_{i \notin S} ln\Phi(-\mathbf{z}_i\boldsymbol{\gamma}) + \sum\nolimits_{i \in S} ln\Phi_2(\mathbf{z}_i\boldsymbol{\gamma}, f(\mathbf{x}_i, t, a_i) - \kappa_1, -\rho) \\ & + \sum\nolimits_{i \in S} ln[\Phi_2(\mathbf{z}_i\boldsymbol{\gamma}, f(\mathbf{x}_i, t, a_i) - \kappa_2, -\rho) - \Phi_2(\mathbf{z}_i\boldsymbol{\gamma}, f(\mathbf{x}_i, t, a_i) - \kappa_1, -\rho)] \\ & + \sum\nolimits_{i \in S} ln[1 - \Phi_2(\mathbf{z}_i\boldsymbol{\gamma}, f(\mathbf{x}_i, t, a_i) - \kappa_2, -\rho)] \end{aligned} \tag{8}$$

with Φ and Φ_2 the standard normal and bivariate standard normal cumulative density functions (CDF), respectively, and "S" includes respondents who self-selected into the CV section by answering "I vote yes" during the screening question. The distribution of the preference parameters is also normal, with an expected value of zero and variance σ_a^2.

The terms inside the CDF are used to estimate the probability that a respondent self-selects into the CV sample and the change in the probability of answering "no," "not sure," or "yes" for the CV question. Differentiating each CDF component above with respect to its covariates gives the marginal change in the likelihood of "yes, I would vote for it" and the marginal change in probabilities for "no," "not sure," and "yes," given self-selection into the CV section (Long and Freese, 2014).

The third term of eq. 8 was used to estimate WTP. Habb and McConnel (2002) discuss several approaches for estimating WTP. The parametric procedure used here evaluates WTP at the median of the error distribution for u_i. The error distribution is symmetric about zero, so the error term is zero at the median. This feature simplifies the WTP formula. The ordered outcome WTP estimator is:

$$wtp_i = \frac{\mathbf{x}_i\boldsymbol{\beta} - \kappa_2}{\alpha_m} \tag{9}$$

We used Roodman (2011)'s multi-equation, multi-level, conditional mixed-process procedure (*cmp*) to maximize the likelihood function and solve for the model parameters. The *cmp* procedure implements full information maximum likelihood (FIML) to estimate the model parameters. FIML estimates are more efficient than a two-step procedure since the error distributions of both outcomes are jointly modeled (Greene, 2018). The *cmp* procedure runs in STATA (StataCorp, 2021). We used *cmp* because the preference heterogeneity parameters enter the model as random effects. The *cmp* procedure allows us to model self-selectivity into the sample with unobserved preference heterogeneity simultaneously. Train (2009)'s simulation procedure was used to compute the integrals required to estimate the probability density for these unobserved random effects. One hundred draws were completed per

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[3] The screening question offered no price, so we do not know if WTP $= 0$. If WTP $= 0$, we would use something like Cragg (1971)'s hurdle model. Instead, WTP is unobserved. Since WTP is unobserved in the screening question, we use a Heckman-type model to address the issue of individuals' self-selecting into the pool of respondents most likely to vote for enhancements (Heckman, 1979).

observation on each maximum likelihood iteration. Antithetic draws were also included. Including antithetic draws effectively doubles the number of draws per observation and reduces the variability of simulated densities (Gates, 2006).

Given the multitude and likely overlap between the covariates described above, variance inflation factors (VIF, Kutner et al., 2004) and collinearity diagnostics (Belsley et al., 1980) were used to detect potential problems that could arise from multicollinearity. No definitive criteria indicate what VIF or collinearity diagnostic values are acceptable. A general rule-of-thumb for VIF scores is <10, with those values suggesting that the standard errors are not inflated due to collinearity (Chatterjee and Price, 1991). The collinearity diagnostic of Belsley, Kuh, and Welch is an omnibus statistic. Generally, values <30 suggest that estimates of standard errors are not compromised by collinearity.

Two-tailed z-tests were used to determine variable significance. The discussion focuses on the variables statistically related to the outcomes at the 10% significance level (two-tailed tests). A Wald statistic was used to test the joint significance of the variables in both model tiers. This joint test has 46 degrees of freedom. The critical value is 26.67 at the 1% level of significance.

Robust standard errors were calculated with a Huber-White covariance estimator (Cameron and Trivedi, 2005). Standard errors for the marginal effects, marginal WTP, and WTP are estimated using the delta method (Greene, 2018) and robust standard errors.

4. Results

Belsley, Kuh, and Welch's collinearity condition index was 44, but the average of the VIFs was 1.97. After removing the intercept, the condition index fell to 6.58 (Table 3). We concluded that collinearity was not a serious issue in compromising the estimation of standard errors or inferences.

A Wald statistic was used to test the null hypothesis that the covariates had no statistical relationship with the outcome variables. The hypothesis was rejected at the 1% significance level (Table 3). This result suggests that a subset of the variables in both parts of the model adequately predicted the outcomes.

The variable "grid track," included in the regression models to control for recall bias, was unimportant at any conventional significance level (Table 4). Recall bias did not influence willingness to vote for grid fortification measures. The risk reduction variable was not a significant predictor of voting or WTP. Thus, the degree to which grid fortification would reduce the likelihood of a power outage was unassociated with the decision to support grid fortification efforts or WTP.

4.1. Likelihood of voting "yes" to support a cost-free upgrade

The marginal effects of the "first stage" probit regressions (upper tier, Fig. 2) are reported in Table 4. Three variables were negatively associated with the likelihood of answering the screening question for "I vote yes." Female respondents were 0.06 less likely than males to "vote yes" to support grid fortification measures and continue to the CV section. Political ideology was negatively associated with a respondent's likelihood of supporting grid enhancement. A 1-unit increase toward more conservative values was associated with a 0.045 decrease in the probability that a respondent supported efforts to reduce outage risk. The higher the electricity grid was ranked in terms of infrastructure that needed to be addressed (the higher the rank, the less important the concern), the lower the likelihood a respondent would vote for grid enhancements and advance to the CV section (−0.011) (Table 4).

Table 3
Model statistics.

Variable	Estimate	z-score
κ_1 (threshold 1)	−1.87	−3.43
κ_2 (threshold 2)	−0.93	−1.52
ρ (vote/WTP error correlation)	−0.46	−0.92
σ_a (standard deviation, preference heterogeneity)	0.002	2.22
Wald test, H_0: $\boldsymbol{\beta} = \boldsymbol{\gamma} = \rho = \mathbf{0}$ (46 degrees of freedom) $^{(1)}$	370	
Collinearity condition index	6.58	
Minimum variance inflation factor (VIF)	1.01	
Maximum VIF	6.13	
VIF average	1.93	
Sample size	1826	
Log-likelihood	−2183	

Notes: (1) critical value, 1% significance level, is 26.66.

Respondent dependence on the grid for electricity, respondent perceptions of outage risk on home life, the risk of electricity outage on safety, trust in local utility providers, and if the respondent voted in the 2020 national election were significantly related to the likelihood that a respondent would "vote yes" to support grid enhancements (Table 4). Respondents were 0.06 more likely to vote "yes" for grid enhancements if they reported more dependence on the grid for electricity. Respondents concerned about the effects of outages on their home lives were 0.041 more likely to vote for grid enhancements. Respondents concerned about the impact of electrical outages on safety were 0.031 more likely to support grid fortification measures. Respondents who trusted their electricity providers were 0.033 more likely to support measures to improve grid resiliency.

The variable *votenatl* was a strong predictor of the likelihood of supporting grid enhancements. Respondents who voted in the 2020 election were 0.155 more likely to "vote yes" for a more reliable grid. The literature offers several explanations for this finding, suggesting that citizen support of referendums can be instrumental; they believe they will achieve a desired policy outcome.

For example, Werner (2019) suggested that citizens who favor a proposed policy or believe they hold a majority opinion are likely to express more support for referendums. Landwehr and Harms (2020) found that correspondence between a citizen's opinion and the expected majority opinion is correlated with support for a referendum.

Conversely, respondents who voted in the 2020 local elections were 0.051 less likely to vote "yes" to support a cost-free grid fortification. A possible explanation for these contrasting results could be that individuals more likely to vote in local elections are more suspicious of government state-sponsored referendums supporting public infrastructure and potentially higher taxes (Horton and Thompson., 1962). The screening question clearly stated that the upgrade would cost nothing to them. However, respondents may not have carefully read the statement.

4.2. Likelihood of accepting a utility bill increase for grid fortification

The marginal effects of the ordered probit regression (Fig. 2, bottom tier) are reported in Table 4. Respondents who leaned conservative on the ideology scale were less likely to support an increase in monthly electricity payments once a bid was observed. A 1-unit increase in the ideology variable corresponded with a 0.033 decrease in the probability of accepting the offered bid.

Urban and suburban residents were less likely to support a higher utility bill than rural respondents. Respondents living in urban (suburban) neighborhoods were 0.72 (0.85) less likely to accept an increase in the monthly utility bill to enhance grid resiliency than rural residents. Respondents who ranked electricity grid infrastructure as 'low priority' were less likely to accept a monthly increase in their utility bill to address the problem. A 1-unit decrease in the ranking scale for electricity infrastructure improvements corresponded with a 0.014 decrease in the likelihood of accepting the offered bid.

Variables positively associated with acceptance of higher monthly utility bills included respondent trust in a utility provider and the propensity of a respondent to vote in local elections (Table 4). Respondents who trusted their electricity provider were 0.037 more likely to accept the bid offer. Individuals who voted in local elections were 0.052 more

Table 4
Bivariate ordered probit marginal effects ($n = 1826$).

	Pr(vote = 1)		Pr(wtp = "no")		Pr(wtp = "undecided")		Pr(wtp = "yes")	
Variable	Marginal effect	*z*-score	Marginal effect	*z*-score	Marginal effect	*z*-score	Marginal effect	*z*-score
Female	−0.055	−2.72	0.018	0.85	0.008	1.04	−0.026	−0.91
College degree	−0.003	−0.12	−0.010	−0.59	−0.005	−0.61	0.014	0.60
Political ideology	−0.045	−7.18	0.023	1.74	0.011	3.78	−0.033	−2.15
Age	0.003	3.32	−0.001	−1.43	−0.001	−2.14	0.002	1.64
Year living in Oklahoma	−0.001	−1.52	5E-04	0.96	2E-04	1.10	−0.001	−1.01
Urban residence	0.034	1.11	0.049	2.11	0.023	1.91	−0.072	−2.19
Suburban residence	0.024	1.05	0.058	2.86	0.027	2.52	−0.085	−3.13
Dependence on grid	0.060	6.32	0.000	−0.02	-2E-04	−0.02	0.001	0.02
Outage	−0.017	−1.34	−0.008	−0.78	−0.004	−0.71	0.012	0.76
Belief in grid reliability	−0.009	−0.72	0.006	0.61	0.003	0.64	−0.009	−0.62
Risk of outage, home	0.041	2.58	−0.008	−0.54	−0.004	−0.60	0.012	0.56
Risk of outage, economy	−0.005	−0.28	−0.004	−0.31	−0.002	−0.31	0.006	0.31
Risk of outage, safety	0.031	1.84	−0.025	−1.56	−0.012	−1.93	0.036	1.73
Coop provision	−0.059	−1.10	0.054	1.13	0.025	1.23	−0.080	−1.18
Govt. provision	−0.034	−0.58	0.002	0.04	0.001	0.04	−0.003	−0.04
Private co. provision	−0.006	−0.11	0.069	1.59	0.032	1.54	−0.101	−1.64
Trust in utility co.	0.033	2.22	−0.025	−1.65	−0.012	−2.13	0.037	1.87
Voted: national election	0.155	4.30	0.045	1.20	0.021	0.91	−0.066	−1.10
Voted: local election	−0.051	−1.70	−0.035	−1.78	−0.017	−1.50	0.052	1.75
Rank: e-grid needs attention	−0.011	−2.07	0.009	1.60	0.004	2.18	−0.014	−1.82
Infrastructure concern	−0.001	−0.13	0.003	0.44	0.001	0.44	−0.004	−0.44
Grid track	−0.010	−0.43	−0.012	−0.68	−0.006	−0.69	0.017	0.69
Bid			−0.013	−4.65	−0.006	−5.50	0.019	9.78
Risk reduction	−3.4E-04	−0.91	-2E-04	−0.69	-9E-05	−0.65	3E-04	0.68
Income (1000 s)	5.0E-04	1.12						

Notes: bid enters statistical models as "$-t$". The signs are consistent with expectations.

likely to accept higher monthly utility payments.

4.3. Demand for a fortified grid

Table 5 reports the marginal WTP and WTP estimates for grid enhancements. Respondents were willing to pay $14.69 more in monthly utility bills to increase electricity grid reliability. This amount is not significantly different from a recent $14 increase in electricity bills implemented by a public utility provider in Oklahoma (Killman, 2023).

Given a unit change in the demographic variables, the marginal change in WTP provides additional insight into the components of WTP (Table 5). Demographic variables negatively associated with WTP included political ideology, urban and suburban residence status, and infrastructure concerns for the current state of the electrical grid. WTP decreased by $1.73 less for each incremental increase toward political conservatism. WTP for respondents living in urban (suburban) areas was $3.73 ($4.44) less than for rural residents. A 1-unit decrease in the electricity grid's rank as a critical infrastructure concern corresponded with a $0.71 decrease in WTP to support grid enhancements.

Table 5
Willingness to pay (WTP) estimates (dollars).

Variable	Marginal WTP	*z*-score
Female	−1.36	−0.95
College degree	0.75	0.60
Political ideology	−1.73	−2.54
Years living in Oklahoma	−0.04	−1.04
Age	0.10	1.79
Urban residence	−3.73	−2.12
Suburban residence	−4.44	−3.01
Dependence on grid	0.03	0.02
Outage	0.63	0.75
Belief in grid reliability	−0.48	−0.63
Risk of outage, home	0.63	0.58
Risk of outage, economy	0.32	0.31
Risk of outage, safety	1.89	1.83
Coop provision	−4.15	−1.20
Govt. provision	−0.16	−0.04
Private co. provision	−5.28	−1.62
Trust in utility co.	1.93	1.98
Voted: national election	−3.46	−1.03
Voted: local election	2.71	1.68
Rank: e-grid needs attention	−0.71	−1.95
Infrastructure concern	−0.22	−0.44
WTP	14.69	6.04

Demographic variables positively associated with WTP include concern over the effects of outages on public safety, trust in a utility company, and voting in local elections (Table 5). Respondents were WTP $1.89 more in their monthly electricity bill when the effects of an outage on safety was a concern. Individuals who trusted their utility company would pay an additional $1.93 monthly. Individuals who voted in local elections were WTP an additional $2.71 in monthly utility bills.

Residential status and political ideology were strong predictors of WTP. This finding encouraged us to examine differences in demand for these variables. Demand curves were estimated separately for urban, suburban, and rural respondents by incrementally changing the bid from '0' to '30' (Fig. 3). Fig. 3 includes the 90% confidence intervals for the predicted probabilities of accepting the bid for the rural group. The difference in the likelihood of accepting the offered bid between urban and suburban residents was nearly indistinguishable. At the lower end of the bid scale ('0' to '10' dollars), demand for grid enchantments for rural respondents is significantly greater than for urban or suburban households. Notably, the dispersion around the probability point estimate increases as the bid increases and the rural/urban-suburban divide disappears. This finding suggests that respondents were less certain about supporting grid fortification at the higher ends of the bid.

The second panel of Fig. 3 displays demand curves estimated at each end of the political spectrum ('strong liberal' and 'strong conservative') and for the 'middle-of-the-road' respondents. Demand for a fortified grid is not different between 'strong conservative' and 'middle-of-the-road' voters. However, demand significantly differs between the political ideology spectrum's left and right endpoints.

Fig. 4 compares the WTP estimates by political ideology and urban-suburban-rural status. These point estimates are not statistically

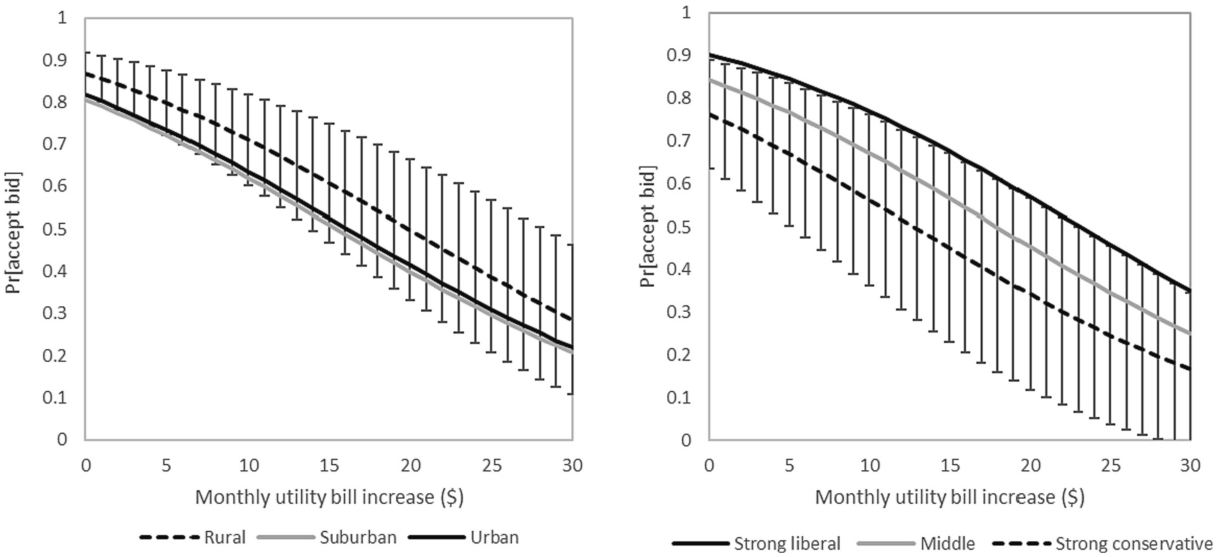

Fig. 3. Demand curves: urban-rural status and political ideology. Note: bars are 90% confidence intervals.

different, as evidenced by the variability around the WTP estimates. The range of WTP across all comparisons was $3.48. The WTP point estimate for rural residents consistently exceeds those of suburban and urban residents at all levels of the political ideology variable. There is a significant difference in demand for grid resiliency between rural and urban-suburban respondents at lower bids. However, there is no evidence that WTP differs between rural and urban-suburban respondents when compared across the political spectrum.

5. Conclusion

This research examined Oklahoma citizens' willingness to pay (WTP) for grid fortification to mitigate the risk of power outages or other disruptions. The study used a representative survey of Oklahoma citizens, the Meso-Scale Integrated Sociogeographic Network (M-SISNet) survey. The survey included a contingent valuation section that focused on consumer WTP for electricity grid enhancements. A bivariate ordered regression model was used to estimate WTP and the marginal contributions of respondent characteristics to WTP.

The study found that dependence on the grid for electricity and voting in the 2020 national election was significantly related to the likelihood of supporting grid enhancements at all levels of risk reduction. The WTP results suggest that, on average, consumers are willing to pay an extra $14.69 per month for enhanced grid improvements. This amount is close to the monthly bill increase of $14 recently initiated by electricity providers. Demand for grid fortification is significantly stronger in rural areas when the utility bill increase is less than $10 per month. Differences were less evident at higher bids. Public support for grid enhancements is weaker for conservative individuals, as is the WTP for these responders. Together, these findings provide insight for policymakers and utility companies about consumer willingness to support these investments to meet energy needs, reduce the frequency and impact of outages, and ensure grid resilience and reliability.

A fundamental limitation of this research suggests a path for looking further into the types of infrastructure improvements that could enhance grid resiliency. Proponents of grid resiliency agree that a robust grid will require the development of wind, solar, and nuclear capacity and their integration into current grid infrastructure. Consumer willingness to support the advancement of these technologies will likely vary across demographic factors, including ideological divisions, residential location, income and affordability, and other attributes. Future assessments of consumer willingness to support efforts to increase grid resiliency by researchers and policy-makers should focus on these novel technologies and their integration into existing grid infrastructure.

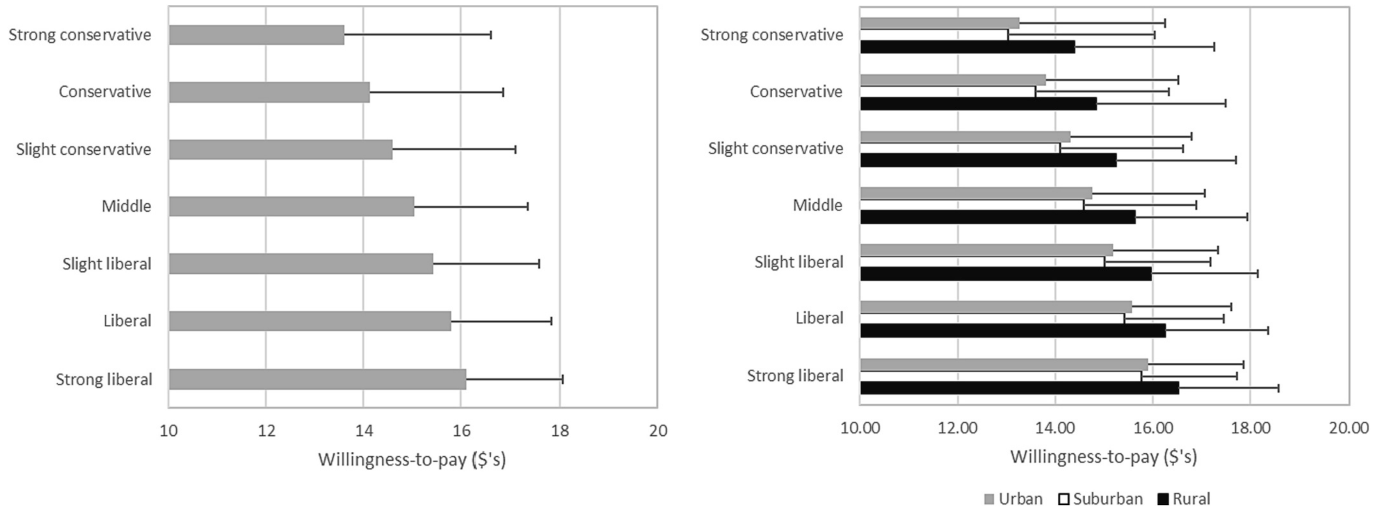

Fig. 4. Willingness to pay for grid fortification: ideology and urban-suburban-rural. Note: bars are standard errors of the estimate.

Lastly, another limitation was the regional scope of the study. Oklahoma is more vulnerable than other regions regarding the average age of utility infrastructure and the likelihood of experiencing severe winter storms and tornadoes. In addition, energy grids typically extend beyond state lines. The results reported here may not be generalizable to other states or regions. Nor do they address the interconnectedness of energy grids. Similar surveys could be replicated in other states or national levels.

CRediT authorship contribution statement

Dayton M. Lambert: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Joseph T. Ripberger:** Supervision, Investigation, Data curation. **Hank Jenkins-Smith:** Funding acquisition. **Carol L. Silva:** Funding acquisition. **Warigia Bowman:** Writing – review & editing, Writing – original draft, Conceptualization. **Michael A. Long:** Conceptualization. **Kuhika Gupta:** Data curation. **Andrew Fox:** Data curation.

Declaration of competing interest

The authors declare no competing interests.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107345.

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