What drives battery electric vehicle adoption? Willingness to pay to reduce emissions through vehicle choice

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Abstract

Battery electric vehicles (BEVs) are widely viewed as an effective option for vehicle owners to reduce carbon dioxide emissions, but the amount of emissions reduction that is achieved depends on the mix of energy sources used to produce the electricity for charging the BEV. Since the emissions in question are indirect, it is currently unclear whether differences in energy production mix affect vehicle purchasing behavior. This paper investigates how the emissions associated with charging a BEV influence choices between three different fuel types and how much individuals are willing to pay to offset their carbon dioxide emissions through vehicle choice. I use a mixed multinomial logit model that is estimated with data from a discrete choice experiment with 1,658 individuals in five US metropolitan areas who intended to purchase a new car within the next 5 years of the survey date. The results indicate that individuals' vehicle choices are significantly impacted by the indirect emissions from charging a BEV and by the regional mix of energy sources used for power generation.The results across multiple emissions scenarios indicate that individuals are willing to pay approximately 225 dollars per year for each metric ton of carbon dioxide emissions the electric vehicle offsets compared to a conventional vehicle. Thus, when purchasing a BEV, an individual is willing to pay about $7,000 more than for a conventional vehicle due to the emissions reduction. This willingness to pay is highly heterogeneous across individuals.

1 Introduction

The United Nations Intergovernmental Panel on Climate Change has repeatedly stressed the need to keep the average global temperature from rising more than 1.5°C above pre-industrial levels (e.g., IPCC, 2018). To ensure that the global economy meets this goal, the report urges reductions in carbon dioxide (CO_2) emissions of 45% between 2019 and 2030, and a goal of zero emissions by 2050. Meeting these goals will require the reduction and elimination of emissions across many facets of human activity. In 2018, the transportation sector accounted for 28% of all CO_2 emissions in the United States, and approximately half of those emissions were from passenger vehicles and light-duty trucks (EPA, 2018).

A promising approach to significantly reduce emissions from passenger vehicles is to invest in the further development and widespread adoption of battery electric vehicles (BEVs). A BEV can only operate on electricity drawn from its battery, requires being plugged into an outlet to charge, and has a set range that depends on the battery capacity. This sets it apart from a hybrid electric vehicle, which contains an electric motor and a battery that is recharged while operating the vehicle in order to obtain better gas mileage than a conventional vehicle. The hybrid electric vehicle cannot be plugged into an outlet to recharge the battery from the grid.

While a BEV does not produce tailpipe emissions, the production of electricity with which it is charged is an indirect source of CO_2 emissions caused by driving a BEV (Karplus et al., 2010). Thus, the overall impact of adopting a BEV on greenhouse gas emissions is highly dependent on the energy production mix used to charge the BEV. The energy production mix refers to the mix of energy sources and production methods that are used to generate electricity, which may include the burning of fossil fuels in coal or gas power plants, the use of renewable sources such as wind and solar power, and nuclear power. In fact, operating a BEV using electricity generated predominantly by burning coal produces more greenhouse gas emissions per mile than the tailpipe emissions of a modern hybrid vehicle with a high fuel economy, so in some regions where coal is the primary source of power production, a BEV is not be the lowest-emissions option (DOE, 2019).

At present, average purchase prices for BEVs remain higher than those of comparable hybrid and conventional vehicles. In the United States, without federal and state subsidies, the additional cost to purchase a BEV would outweigh the savings in fuel costs for an average driver over the lifetime of the BEV (Breetz and Salon, 2018). Since the total cost of ownership of a BEV is not usually lower than that of a comparable non-BEV, past literature has investigated a number of other variables and behavioral factors that may drive BEV adoption. It is clear that a concern for the environment is one of the factors that can drive a consumer to adopt a BEV, but at present, it may be difficult for consumers to obtain the full picture of the environmental impacts. Sales materials and media reports often focus exclusively on tailpipe emissions, and as a result, it is unclear to what extent consumers consider the overall emissions caused by driving a BEV when making a vehicle purchase decision. Developing a better understanding of the relationship between the energy production mix, and thus indirect emissions caused by driving a BEV, and willingness to adopt a BEV is critical.

This paper seeks to answer the following research questions: (1) How is the decision to adopt a BEV affected by regional differences in energy production mix? (2) How much are individuals willing to pay to reduce their carbon emissions? To answer these questions, I collected survey data that included a discrete choice experiment in which individuals were asked to indicate what vehicle they would purchase under different hypothetical settings. In all choice situations, respondents were asked to choose between a conventional vehicle, a hybrid vehicle, and a BEV, but the vehicles differed in their purchase prices, annual fuel (or fuel-equivalent) costs, and emissions levels. In the case of the BEV, the emissions levels represented the indirect emissions from power production. Each participant answered a total of eight stated preference questions that were divided into two blocks of four questions each. In the first block, the emissions levels of the vehicles corresponded to the national average emissions levels, but the purchase price and annual fuel-equivalent cost attributes varied. In the following block, each individual was randomly assigned to one of two different scenarios characterized by a change in the energy mix. One scenario involved a greener energy mix, where the emissions of the BEV decreased, and the other scenario involved an increase in the share of fossil fuels for energy production, with a corresponding increase in BEV emissions. The data were used to estimate a mixed multinomial logit model in order to quantify the effect of BEV-related greenhouse gas emissions on vehicle fuel type choices.

I quantify the average premium that individuals are willing to pay for a BEV and a hybrid vehicle and show that the premium is a function of the emissions scenario. The results indicate that indirect emissions of driving a BEV have a significant effect on stated vehicle purchase decisions. I find that individuals are willing to pay 225 dollars per ton of CO_2 avoided. In contrast, the current social cost of a metric ton of carbon used by the US federal government is \$51. At this point, it is unclear why people are willing to pay four times more than the official social cost of carbon to offset their emissions from driving. One possible explanation is that individuals' willingness to pay for emissions reductions depends heavily on the context in which the emissions reduction is achieved. Within the context of vehicle choice, selecting a hybrid vehicle or BEV can reduce emissions with minimal impact on the driver's life, so individuals may be willing to pay more to reduce their vehicle emissions than they would be in other contexts that lack nearly perfect substitutes.

The significance of this research is threefold. First, it uncovers a previously unrecognized factor that may be affecting BEV adoption rates in the US and dampening demand for BEVs in various states despite financial and tax incentives offered to prospective BEV owners. Understanding how consumers preferences for BEVs depends on indirect emissions is vitally important for policy makers and predictions of regional BEV adoption rates. Second, as indirect emissions are found to impact consumer decisions, it indicates that investing in greener energy production technologies can increase BEV adoption rates. Therefore, in the interest of better capturing the true costs and benefits of investments in various power generation technologies, it would be advisable to include such dynamic effects in the environmental benefits of renewable energy investments that are quantified in cost/benefit analyses.Third, it shows that in the context of vehicle choice, individuals are willing to pay a sizable premium to reduce their emissions.

These findings have an important policy implication. If environmentally-minded consumers living in regions with high-carbon energy mixes are less likely to adopt a BEV due to the regional energy mix, this may lead to a dynamic inefficiency: reduced BEV sales lead to less demand for BEV infrastructure investments (e.g., for charging stations) that are needed to support future growth of the BEV fleet, which in turn may lead to high-emissions regions lagging behind in making the necessary investments to transitioning away from gasoline-powered vehicles.

The remainder of this paper is structured as follows: In Section 2, I discuss the literature surrounding electric vehicles and summarize key findings. Section 3 is devoted to survey design. The data and modeling approach are described in Section 4 and Section 5, respectively. Section 6 contains the results and discussion, and Section 7 offers concluding remarks.

2 Literature Review

The literature on consumer demand for BEVs covers a number of different topics, ranging from willingness-to-pay estimates for specific features to the impact of subsidies and predictions of adoption rates. In this section, I focus on the literature most relevant to this work.

A large body of literature has sought to determine the drivers of BEV adoption and to investigate what groups are most likely to adopt a BEV (Axsen and Kurani, 2013; Axsen et al., 2015; Bailey et al., 2015; Carley et al., 2013; DOE, 2019; Krupa et al., 2014; Lane and Potter, 2007; Lieven et al., 2011; Nayum and Klöckner, 2014; Peters and Dütschke, 2014; Rezvani et al., 2015). Several studies have confirmed that interest in adopting a BEV, hybrid vehicle, or plug-in hybrid vehicle is positively associated with environmental concerns (Axsen and Kurani, 2013; Carley et al., 2013). Furthermore, higher education levels, previous experience with hybrid vehicles, and concern about dependence on foreign oil have been found to predict interest in BEV adoption (Carley et al., 2013). Another driver of BEV adoption may be enthusiasm for new technologies (DOE, 2019). Of course, the limited range of a BEV may impose restrictions on a person's mobility behavior. Peters and Dütschke (2014) found that the perceived ability of a BEV to meet mobility needs affects adoption and leads to BEVs being more interesting to multiple-car households that already own a gasoline vehicle.

Overall, predictions of BEV adoption rates in the literature vary widely, as do the predictions of the aggregate environmental impacts of BEV adoption. Predictions of the environmental impacts are sensitive to underlying assumptions on the energy production mix used to power the BEVs and on the type of vehicle someone was driving before they switched to a BEV (Karplus et al., 2010; Helveston et al., 2015). Xing et al. (2019) and Carley et al. (2013)

found that BEVs tend to replace conventional vehicles and hybrid vehicles that are already more fuel-efficient than average, thus dampening the environmental benefits of BEV adoption at an aggregate level.

At present, BEVs generally have higher purchase prices than conventional vehicles, but some of the higher purchase price is offset by lower operational costs (Bubeck et al., 2016; Dumortier et al., 2015; Lévay et al., 2017; Palmer et al., 2018; Rusich and Danielis, 2015; Wu et al., 2015). A number of researchers has found that subsidies and financial incentives play a role in encouraging adoption (Breetz and Salon, 2018; Ko and Hahn, 2013; Helveston et al., 2015; Lévay et al., 2017). Providing potential vehicle purchasers with information on the total cost of ownership has been found to increase individuals' preference for hybrid vehicles, plug-in hybrid vehicles, and BEVs (Dumortier et al., 2015), but even controlling for total cost of ownership, a premium in willingness to pay for BEVs seems to persist (Bubeck et al., 2016). This supports the importance of other factors driving adoption besides the total cost of ownership.

Stated preference surveys have been widely used to determine individuals' willingness-to-pay for different attributes of BEVs (Bunch et al., 1993; Hidrue et al., 2011; Ito et al., 2013; Ko and Hahn, 2013; Tanaka et al., 2014; Hackbarth and Madlener, 2016; Ferguson et al., 2018; Choi et al., 2018). This body of research has primarily focused on features such as range, charging time, and speed (Ito et al., 2013; Ko and Hahn, 2013; Tanaka et al., 2014; Hackbarth and Madlener, 2016; Ferguson et al., 2018), but some have also included environmental impact variables. Based on a survey conducted in California, Bunch et al. (1993) found that respondents were willing to pay more for an alternative fuel vehicle with lower emissions than a conventional vehicle. The emissions reductions were presented in terms of a percentage of conventional vehicle emissions. Using nationwide survey data, Hidrue et al. (2011) reported a similar finding, where individuals were willing to pay for a reduction in emissions that was stated in terms of a percentage of the emissions of their preferred gasoline vehicle. These surveys did not focus on the energy production mix used to charge the BEV, but in another survey conducted in Korea (Choi et al., 2018), information on the energy production mix was included. Choi et al. (2018) gave participants information about the energy mix that would be used to charge a BEV, but information on the corresponding emissions impacts was not provided.

One of the key attributes where willingness-to-pay is critical is the reduction of emissions that driving a BEV entails. In prior literature, a number of papers have estimated individuals' willingness to pay for emissions reduction. For instance, Adaman et al. (2011); Alberini et al. (2018); Lim et al. (2018) examine how much individuals are willing to pay for cleaner power production, and Brouwer et al. (2008); Lu and Shon (2012); Shaari et al. (2020) explore individuals' willingness to pay to offset emissions from flying. Achtnicht (2012) found that German car buyers were willing to pay between €89.44 and €256.29 per ton of CO_2 reduced, and Hulshof and Mulder (2020) found that Dutch car buyers were willing to pay €199 for each ton of CO_2 reduced. While individuals' willingness to pay a premium to avoid emissions is a valuable input to policy development, it is equally important to estimate the social cost of carbon, i.e., the costs that are imposed on society by the emission of CO_2. However, the estimated social cost of carbon varies widely, as it depends on the assumptions made by researchers (Wang et al., 2019). In a meta analysis of 578 social costs of carbon, Wang et al. (2019) found that the average social cost per ton of CO_2 calculated in the literature was $54.70.

3 Survey Design

In order to evaluate the impact of the energy production mix on consumer preferences for BEVs, I conducted a discrete choice experiment. The experiment was designed to identify the causal impact of an exogenous change in the energy production mix. The discrete choice experiment was embedded in a larger survey about BEV adoption that also collected data on respondents' socio-demographics and household car ownership. The choice experiment involved eight labeled choice questions where survey participants were asked to choose between a conventional gasoline vehicle, a hybrid vehicle, and a BEV, with varying attribute levels for the purchase price, annual fuel costs, and emissions levels. Participants also had a "status quo" option, which read: "Even if these were my best options, I would not choose any of these vehicles."

The full text shown to participants of the hypothetical choice situation is in Appendix A. The majority of the information pertained to the carbon dioxide equivalent emissions of each type of vehicle. In the context of the BEV, this included an explanation of the concept of the energy production mix and how it is linked to the emissions produced by driving a BEV.

Table 1 shows all attributes and the levels they took for each type of vehicle. The attribute levels for purchase prices and fuel costs were generated from summary statistics for currently available vehicles of each type and were rounded to the nearest $5,000 and $10, respectively. Emissions levels were based on data from the Alternative Fuels Data Center (DOE, 2019) and were rounded to the nearest 1,000 pounds. The specific combinations of purchase prices and annual fuel costs of the three vehicle types varied randomly between all choice questions, following an orthogonal design that was derived from an original full factorial design. The emissions levels followed a scenario design, as explained later in this section.

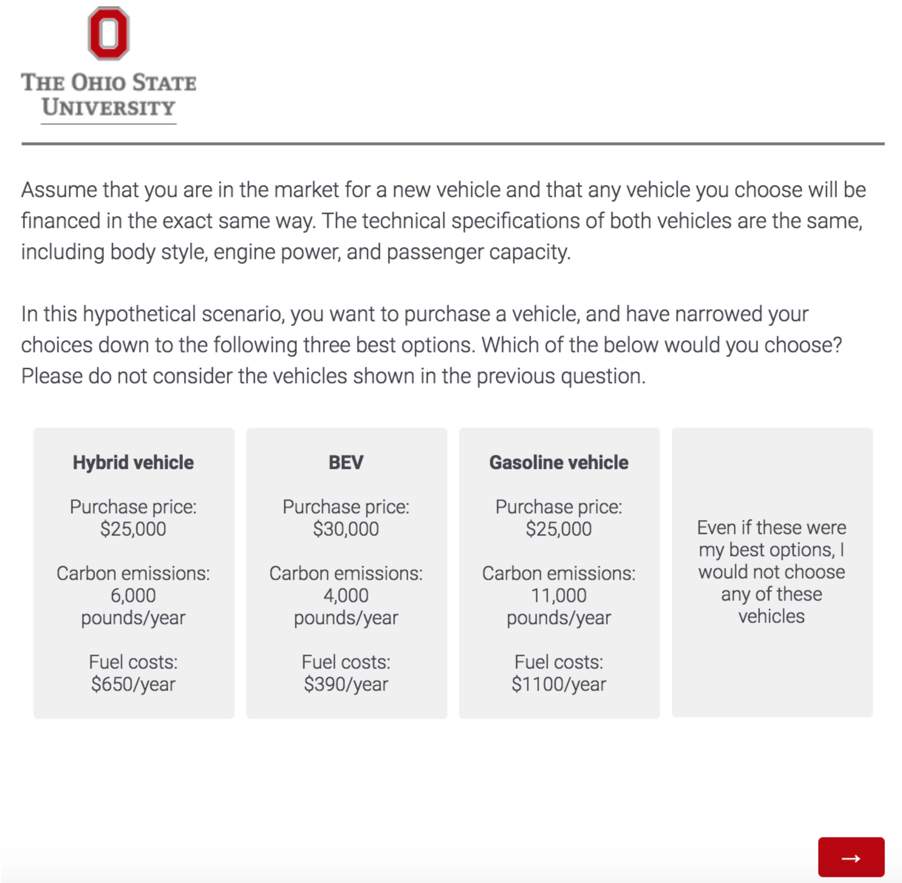
Table 1: Attribute Levels

Attribute	**Type of Vehicle**	**Levels**
Purchase Price	Gasoline	$15,000; $20,000; $25,000; $30,000
	Hybrid	$20,000; $25,000; $30,000; $35,000
	Battery Electric	$25,000; $30,000; $35,000; $40,000
Annual Fuel Cost	Gasoline	$1,100; $1,310; $1,520; $1,730
	Hybrid	$540; $650; $760; $870
	Battery Electric	$330; $390; $450; $510

Figure 1 shows an example of one of the choice questions presented to a subset of participants. In order to reduce the possibility of bias from order effects, the order of the three vehicle types was randomly generated for each choice situation, but the "status quo" option was always shown as the last (rightmost) option. If a participant consistently selected the "status quo" option for all eight choice situation, they were shown a free-form text question asking whether there was any reason for doing so other than the costs of the options they had seen.

In the first four choice questions that each participant answered, the emissions levels were set to the national average for each of the three vehicle types and did not vary. This is referred

Figure 1: Choice Situation Example



to as the “average emissions scenario” in the remainder of this paper. The annual carbon dioxide equivalent emissions from the gasoline vehicle, hybrid vehicle, and the BEV were 11,000, 6,000, and 4,000 pounds, respectively. Although the information on the emissions levels was provided in the question description, it was also included in the choice buttons in order to keep the values present in participants’ minds. After the first four choice situations, participants were randomly assigned to one of two treatment groups, the “low-emissions scenario” or the “high-emissions scenario”. Each scenario was framed as a change in the energy production mix, which would impact the carbon dioxide equivalent emissions of the BEV. The emissions levels of the gasoline and hybrid vehicles remained unchanged. In the “low-emissions scenario”, participants were informed that a new, low-cost, renewable energy production technology was adopted and that therefore, the emissions from driving a BEV decreased to 2,000 pounds per year. In the “high-emissions scenario” scenario, the share of fossil fuels in energy production increased, leading to an increase of the emissions associated with driving a BEV to 8,000 pounds per year. Appendix C shows the message presented to participants that were assigned to the high-emissions scenario. The low-emissions scenario was worded in the same way, except that the term "fossil fuels" was replaced with "renewable energy" and the emissions level was set to 2,000 pounds per year. Although they were presented in terms of technological changes, the two scenarios can be thought of as representing emissions levels of BEVs in different regions with different energy production mixes. For instance, the low-emissions scenario roughly reflects the energy production mix of California, and a corresponding example for the high-emissions scenario is Kentucky.

The emissions scenarios involved an additional four stated preference questions, bringing the total number of choice questions answered by each participant to eight. The purchase prices and annual fuel-equivalent costs in the emissions scenarios varied randomly, following an orthogonal design and using the attribute levels shown in Table 1. They were independent of the attribute level combinations shown in the first four choice scenarios. The survey was designed in such a way that respondents in either treatment scenario had the same probability of seeing certain combinations of attribute levels in order to ensure that no systematic differences between the choice situations in the two treatment conditions were introduced.

A known problem with choice experiments is that participants tend to overstate their willingness to pay due to the hypothetical nature of the experiment (Cummings and Taylor, 1999). In order to mitigate this problem, participants were shown a "cheap talk" script before the explanatory text introducing the choice experiment. The script was adapted from Varela et al. (2014) and modified slightly to fit a vehicle adoption choice situation. Additionally, based on the results of a pre-test with 15 students, the reference to the "status quo" option, which was included in Varela et al. (2014), was removed, as it appeared to be a source of confusion. The complete "cheap talk" script is shown in Appendix B.

4 Data

4.1 Data Collection

The survey was open to individuals who were planning to purchase a new (not used) car in the next 5 years. Recruitment and data collection occurred from May 2019 to January 2020 in the following metropolitan areas: Los Angeles, California; Atlanta, Georgia; and Cincinnati, Cleveland, and Columbus, Ohio (collectively referred to as “Ohio cities” below). The survey area was defined based on county boundaries, and a complete list of counties included in each metropolitan area can be found in Appendix D. In total, 1,658 individuals responded, of which 711 were from Los Angeles, 527 from Atlanta, and 420 from the three metropolitan areas in Ohio. Table 2 shows the number of individuals assigned to each of the two emissions scenarios. The median time to complete the survey was slightly below 20 minutes. Data validity was ensured through the inclusion of three attention check questions throughout the survey, and individuals who did not pass one or more of the attention checks were excluded from the final sample.

Table 2: Sample Size by Scenario and Region

	Low BEV Emissions	High BEV Emissions	Total
Los Angeles	365	346	711
Atlanta	275	252	527
Ohio Cities	210	210	420
Total	850	808	1,658

4.2 Descriptive Statistics

Table 3 contains demographic and attitudinal characteristics of the two groups of respondents that were randomly assigned to either of the emissions scenarios. Aside from gender, age, and income, respondents indicated how many vehicles were owned or leased by their household, whether at least one of their vehicles was a sedan, and whether at least one of their vehicles was a hybrid vehicle or BEV. Respondents were also asked how likely they were to adopt a BEV when they purchased or leased their next vehicle, with the responses from "extremely unlikely" to "extremely likely". Overall, it can be seen that individuals in the sample were relatively open to the idea of owning a BEV.

In addition to the mean value and standard deviation (where applicable) for each of the variables, the p-value of a two-sample t-test is reported. This t-test tested the null hypothesis that the two samples are drawn from the same underlying distribution, and the insignificance of the test result across all variables indicates that no systematic differences between the demographics and attitudes of the two treatment groups could be detected.

Table 3: Comparison of characteristics of the low-emissions and high-emissions scenario respondent groups

Variable	Low Em. Mean	Low Em. SD	High Em. Mean	High Em. SE	T-test p-value
Gender [% female]	0.70	0.02	0.70	0.02	0.89
Education	3.46	0.03	3.47	0.03	0.96
Age Bracket	5.88	0.10	5.79	0.10	0.53
Household Income	8.03	0.18	8.11	0.20	0.76
Number of Household Vehicles	1.84	0.03	1.91	0.03	0.16
Household owns Sedan (%)	0.59	0.02	0.63	0.02	0.17
Household owns BEV or Hybrid (%)	0.12	0.01	0.13	0.01	0.62

Table 4 shows the frequencies at which the different alternatives were chosen, and the corresponding percentages, by emissions scenario. Less than 8% of choices in each scenario were the "status quo" option, which suggests that in general, the options presented to participants were reasonable and within their budget sets. In all scenarios, the conventional (gasoline) vehicle was chosen the least out of all three vehicle types, and in the "average emissions" scenario, the BEV was selected slightly more frequently than the hybrid. However, an interesting difference can be seen: In the "low-emissions" scenario, the BEV was selected more frequently than the hybrid vehicle, whereas in the "high-emissions" scenario, the hybrid vehicle was selected more frequently.

Table 4: Choice Frequencies. Percentages in each column add up to 100%.

Vehicle Type Choice	Low BEV Emissions	Average BEV Emissions	High BEV Emissions
Conventional Gasoline	759	1,522	716
	(22.3%)	(22.9%)	(22.2%)
Hybrid	1,048	2,251	1,375
	(30.8%)	(33.9%)	(42.5%)
BEV	1,369	2,419	903
	(40.3%)	(36.5%)	(27.9%)
Status Quo	224	440	238
	(6.6%)	(6.6%)	(7.4%)
Total	3,400	6,632	3,232

5 Modeling Approach

5.1 The mixed multinomial logit model

The data from the choice experiment were analyzed using a random utility model (McFadden, 1981), which is founded on the idea that a rational individual will select the option out of a given set of available choices that maximizes their utility. In this work, the individual's utility U$_{ni}$ from selecting vehicle i is defined by:

$$U_{ni} = V_{ni} + \varepsilon_{ni} \tag{1}$$

$$V_{ni} = \beta' X_{ni} \tag{2}$$

V$_{ni}$ captures the deterministic part of the utility, while $\varepsilon\ _{ni}$ represents a stochastic error term. β'_n is the vector of coefficients for individual n, X_{nit} is the vector of observable variables for both the individual and vehicle, and ξ_{nit} is the stochastic error term.

The error term is not known to the researcher, so the researcher does not know the individual's true utility. The probability that individual n selects vehicle i is given by:

$$P_{ni} = Prob(U_{ni} > U_{nj}) \quad \forall j \neq i \tag{3}$$

$$= Prob(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj}) \quad \forall j \neq i \tag{4}$$

$$= Prob(\varepsilon_{ni} - \varepsilon_{nj} > V_{nj} - V_{ni}) \quad \forall j \neq i \tag{5}$$

Assuming ε_{ni} is independent and identically distributed (IID) and has a type 1 extreme value distribution, the probability of individual n picking vehicle i is:

$$P_{ni} = \frac{e^{X_i \beta}}{\sum_{j=1}^{J} e^{X_j \beta}} \quad i = 1, ..., J \tag{6}$$

Equation 6 represents the conditional multinomial logit model. It assumes homogeneity of preferences among individuals, but in the context of vehicle choice, this assumption may be tenuous. For instance, the diversity of vehicles on the market is testimony to a considerable heterogeneity of consumer preferences for vehicles and their attributes. In order to relax this assumption I specify a mixed multinomial logit model (McFadden and Train, 2000). This model structure allows the β values to be stochastic, which leads to the following utility of individual n choosing vehicle i:

$$U_{nit} = \beta_n' X_{nit} + \xi_{nit} \tag{7}$$

where β_n' is now individual-specific and can be expressed as the sum of the average β and an individual-specific deviation. The analyst can only estimate the distribution of β. Given the heterogeneity in tastes, the probability of individual n selecting vehicle i in choice situation t is:

$$P_{nit} = \int \left(\frac{e^{\beta' X_{nit}}}{\sum_{j=1}^{J} e^{\beta' X_{njt}}}\right) f(\beta) d\beta \tag{8}$$

where f(β) represents the probability density function of β. Equation 8 is the general version of the mixed multinomial logit model. If T different choices are observed per individual, then the probability of the individual's choice sequence $I = \{i_1, ..., i_T\}$ is expressed as:

$$L_{iT}(\beta) = \prod_{t=1}^{T} (\frac{e^{\beta_n' X_{nit}}}{\sum_{j=1}^{J} e^{\beta_n' X_{njt}}}) \tag{9}$$

After integrating over β the unconstrained choice probability is:

$$P_{iT} = \int L_{iT}(\beta) f(\beta) d\beta \tag{10}$$

Thus, the mixed multinomial logit model allows us to model multiple choice observations per individual and to account for heterogeneity in preferences for vehicle types.

5.2 Model specification

The model was specified as a choice between the three alternative vehicle types, so the "status quo" option was excluded. Accordingly, the model was estimated using only the observations in which one of the three vehicle types was chosen. The model specification included eight variables: the purchase price, the annual fuel cost, the alternative specific constants for the hybrid vehicle and the BEV, and binary indicator variables denoting the low- and high-emissions treatments. The binary indicators for the emissions scenarios were specific to the hybrid and BEV fuel types. The coefficient of the purchase prices was held constant across individuals, whereas the remaining coefficients were allowed to vary by individual. The utility equations for each of the three vehicle types were therefore as follows:

$$U_{n,Gasoline} = \beta_p \cdot PurchasePrice_{ng} + \beta_f \cdot AnnualFuelCost_{ng} + \varepsilon_{ng} \tag{11}$$

$$U_{n,Hybrid} = \beta_{nh} \cdot Hyb\_ASC + \beta_{nhl} \cdot Hyb\_Low + \beta_{nhh} \cdot Hyb\_High + \beta_p \cdot PurchasePrice_{nh} + \beta_f \cdot AnnualFuelCost_{nh} + \varepsilon_{nh} \quad (12)$$

$$U_{n,BEV} = \beta_{nb} \cdot BEV\_ASC + \beta_{nbl} \cdot BEV\_Low + \beta_{nbh} \cdot BEV\_High + \beta_p \cdot PurchasePrice + \beta_f \cdot AnnualFuelCost + \varepsilon_{nb} \quad (13)$$

The subscripts g, h, and b refer to the gasoline vehicle, the hybrid vehicle, and the BEV, respectively, and ASC stands for the alternative specific constant. Hyb_Low is a binary variable associated with the hybrid alternative in the low emissions scenario and Hyb_High is associated with the high emissions scenario. Thus, these two variables represent changes in the constant of the hybrid vehicle in the two emissions scenarios. BEV_Low and BEV_High are the corresponding binary variables for the BEV. I first estimated a model using the full data set, i.e., all metropolitan areas combined. Following that, I estimated separate regional models for the Los Angeles metropolitan area, the Atlanta metropolitan area, and the three Ohio cities.

6 Results and Discussion

Next, I present the results from the mixed multinomial logit model. First, a combined model for the full data set (including all cities) was estimated, followed by individual regional models. The models are estimated in willingness-to-pay space and the model results are discussed from the perspective of willingness to pay for the three different vehicle types.

6.1 Mixed Logit Results

Table 5 shows the results of the mixed multinomial logit model for all cities combined.

Table 5: Combined willingness-to-pay model for all cities

	(1)	(2)
Variables	Mean	SD
Annual Fuel Cost	-9.121***	18.19***
	(0.613)	(0.502)
Hybrid ASC	5,705***	5,779***
	(456.2)	(314.9)
BEV ASC	6,751***	9,103***
	(620.0)	(339.2)
HASC Low	323.0	369.8
	(423.1)	(454.3)
BEVASC Low	2,312***	2,820***
	(480.1)	(698.3)
HASC High	1,699***	2,403***
	(427.3)	(638.2)
BEVASC High	-3,830***	4,750***
	(549.2)	(554.7)
Observations	37,086	

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The most meaningful interpretation of the mixed multinomial logit model results is in terms of willingness to pay. Therefore, we estimated the mixed multinomial logit model in willingness to pay space and are presenting all of our results in willingness to pay estimates. As can be seen in Table 5, the coefficients of the purchase price and annual fuel costs are negative, which conforms to expectations. All else being equal, as the purchase price or annual fuel costs of a vehicle increase, individuals are less likely to select that vehicle. The means and standard deviations of the alternative specific constants for the hybrid vehicle and the BEV are statistically significant, and the interaction terms between the emissions scenarios and the alternative specific constants are statistically significant in every case except for the hybrid vehicle in the low-emissions scenario.

According to the results in Table 5, an individual is willing to pay $9.12 more in purchase costs for every $1.00 reduction in annual fuel costs. In addition, under the average emissions scenario, individuals are on average willing to pay $5,705 more for a hybrid vehicle than for a gasoline vehicle, although the standard deviation of this willingness to pay is very high. The range of plus/minus one standard deviation from the mean is -$74 to $11,484, indicating that some individuals are willing to put a premium of up to $11,484 on purchasing a hybrid vehicle, while others would have to be compensated $74 in order to switch from a gasoline vehicle to a hybrid vehicle. Similarly, individuals are on average willing to pay an additional $6,751 for a BEV compared to a gasoline vehicle in the average emissions scenario. The range of plus/minus one standard deviation yields a willingness to pay range of -$2,352 to $15,854, indicating the presence of a large amount of heterogeneity in willingness to pay for a BEV.

Each of the alternative specific constants under the high and low-emissions scenarios function as a shift in the alternative specific constant under the average emissions scenario. For the low-emissions scenario, the willingness to pay for a hybrid vehicle does not change, which indicates that when the emissions level of the BEV changes, individuals' valuation of the hybrid vehicle relative to the gasoline vehicle is not affected. It is noteworthy that in both the average emissions scenario and the low-emissions scenario, the ordering of the three alternatives in terms of levels of emissions is the same, yet, individuals are willing to pay a higher premium on BEVs in the low-emissions scenario – on average, $9,063, an increase of $2,312 over the average emissions scenario. As the costs are controlled for, and the vehicle types remain unchanged, this shows that individuals are on average willing to pay an increased premium for a BEV that reduces emissions more. The standard deviation for the interaction term of the BEV alternative specific constant under the low-emissions scenario shows that individuals react heterogeneously to the emissions reduction.

In the high-emissions scenario, the hybrid vehicle is the most environmentally friendly option, resulting in individuals being willing to pay a premium of \$7,404 for hybrid vehicles. This represents an increase of \$1,699 over the baseline scenario. Nonetheless, the high standard deviation of the respective coefficient indicates the presence of a lot of heterogeneity. Conversely, the premium on the BEV decreases in the high-emissions scenario by \$3,830, to an average of \$2,921. While this still represents a positive premium with respect to the gasoline vehicle, it is lower than the premium on the hybrid vehicle. In other words, under the high-emissions scenario, participants on average still prefer the BEV over the gasoline vehicle, but they do not prefer the BEV over the hybrid vehicle. This reversal indicates that individuals are willing to pay the highest premium for the vehicle that reduces emissions the most, which is the hybrid in the high emissions scenario.

Table 6 presents the results of the three regional models. The first two columns show the mean and standard deviation for the Los Angeles sample. Columns 3 and 4 present the mean and standard deviation for Atlanta. The final two columns show the mean and standard deviation for the three major cities in Ohio.

Table 6: Regional willingness-to-pay models

	Los Angeles		Atlanta		Ohio	
Variable	Mean	SD	Mean	SD	Mean	SD
Fuel Cost	-10.80***	18.08***	-5.523***	15.09***	-9.256***	17.76***
	(1.087)	(1.130)	(1.323)	(1.072)	(1.080)	(1.063)
Hybrid ASC	6,581***	2,812***	5,652***	6,781***	5,031***	1,925***
	(739.1)	(638.6)	(783.1)	(452.9)	(666.6)	(329.3)
BEV ASC	7,882***	13,329***	6,979***	8,981***	5,269***	13,351***
	(1,157)	(802.5)	(1,052)	(666.8)	(979.3)	(889.7)
HASC Low	-284.7	810.2	-260.5	916.3	466.1	1,774
	(638.4)	(725.1)	(733.0)	(998.9)	(840.0)	(1,286)
BEVASC Low	1,638**	1,282	2,938***	5,686***	11,033	1,811
	(756.5)	(871.6)	(905.6)	(1,221)	(891.1)	(1,265)
HASC High	2,527***	4,351***	2,237***	5,584***	475.6	4,020***
	(808.0)	(973.9)	(791.8)	(862.8)	(694.5)	(435.0)
BEVASC High	-4,326***	5,038***	-1,662*	1,277	-5,129***	1,883**
	(1,057)	(1,114)	(933.0)	(1,804)	(1,135)	(733.1)
Observations	16,113		11,586		9,387	

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The results show slight variations in preferences for vehicle types between Los Angeles, Atlanta, and the three major cities of Ohio. Individuals in Los Angeles are willing to pay an additional $6,581 premium for a hybrid vehicle, while individuals in Atlanta and Ohio are willing to pay premiums of $5,562 and $5,031 respectively. These estimates are not statistically significantly different, which shows that the average willingness to pay for hybrids does not vary much across our three regions. Interestingly, the three locations only differ in their standard deviations for hybrid vehicles, with Atlanta having a much higher standard deviation. The divergence between locations in the premiums that individuals are willing to pay for a BEV is a bit higher than for hybrid vehicles. Willingness to pay for a BEV is highest in Los Angeles, followed by Atlanta then the cities in Ohio. Unlike the combined model, mean willingness to pay a premium for a hybrid vehicle in the low-emissions scenario is insignificant for all three sub-samples but remains significant for BEVs in Los Angeles and Atlanta, ranging from $1,638 to $2,938.

The premiums for hybrid vehicles in the high-emissions scenario are significant in Los Angles and Atlanta, but are insignificant in the Ohio cities. Individuals in Los Angeles and Atlanta are on average willing to pay an additional $2,527 and $2,237 for a hybrid vehicle. In the high-emissions scenario, the additional willingness to pay for a BEV is negative across all regions, with the drop ranging from $1,662 in the case of Atlanta to $4,326 in the case of Los Angeles and $5,129 in the Ohio cities.

While the exact willingness to pay and order of preference under the three emissions scenarios differs across individuals and cities, the overall results confirm the inversion of preferences observed in the combined model results: When a hybrid vehicle is the lowest-emissions option (i.e., in the high-emissions scenario), individuals are willing to pay a higher premium for the hybrid vehicle than for the BEV.

6.2 Marginal Willingness to Pay for Emissions Reduction

As the previous section shows, individuals are willing to pay a sizable premium for a hybrid vehicles or a BEV over a conventional gasoline vehicle in order to reduce the emissions caused by driving. From this premium, it is possible to calculate individuals' marginal willingness to pay to reduce their carbon emissions. This is achieved by dividing the premium that respondents are willing to pay for a hybrid or BEV in one of the emissions scenarios by the annual emissions savings due to driving a hybrid or BEV instead of a conventional gasoline vehicle. For example, since driving a hybrid vehicle creates 6,000 pounds of CO_2 per year, while a conventional vehicle creates 11,000 pounds of CO_2 per year, the hybrid vehicle's change in emissions from the conventional vehicle is 5,000 pounds of CO_2 per year. The average willingness to pay for a hybrid vehicle over a gasoline vehicle in our results is $5,705, so the marginal willingness to pay is the willingness to pay divided by the 5,000 pounds of CO_2 per year of avoided emissions.

Table 7 presents the marginal willingness to pay for emissions reduction, including the results from the combined model (all metropolitan areas) as well as the regional models.

Table 7: Marginal Willingness to Pay (MWTP) for Emissions Reduction

	Hybrid ASC	BEV ASC Avg	BEV ASC Low	BEV ASC High
Change in Carbon Emissions from Conventional Vehicle (Pounds of CO_2 per year)	5000	7000	9000	3000
WTP Combined ($)	5,705	6,751	9,063	2,921
MWTP Combined ($)	1.14	0.96	1.01	0.97
WTP California ($)	6,581	7,882	9,520	3,556
MWTP California ($)	1.32	1.13	1.06	1.19
WTP Georgia ($)	5,652	6,979	9,917	5,317
MWTP Georgia ($)	1.13	1.00	1.10	1.77
WTP Ohio ($)	5,031	5,269	5,735	140
MWTP Ohio ($)	1.01	0.75	0.63	0.05

Table 8 contains the average marginal willingness to pay for one pound of CO_2 reduction per year of the four emissions scenarios. That estimate is then converted into the marginal willingness to pay for each metric ton of emissions reduction from the pounds of emissions presented to participants. This number represents the marginal willingness to pay over the lifetime of a vehicle, so the number is then divided by 10 assuming the vehicle will be on the road for 10 years on average.

Table 8: Yearly WTP for Ton of CO_2 Reduction

	Average MWTP ($)	Converted to Metric Tons ($)	Yearly Over 10 Years ($)
Combined	1.02	2,249	225
Los Angeles	1.18	2,602	260
Atlanta	1.25	2,756	276
Ohio	0.61	1,345	135

7 Conclusions

Despite a broad range of literature on BEV adoption, the question of how the indirect emissions due to differences in regional energy production associated with driving a BEV affects the purchase decisions of individuals has so far been overlooked. This gap in the literature is addressed by the present paper. The results show not only that there is a clear impact of the indirect emissions due to power production, but also, they imply that one of the benefits of BEVs that individuals are willing to pay for is the fact that, all else being equal, they are a technology for reducing carbon dioxide emissions.

Using a discrete choice experiment, I unpack how the energy production mix, and thus, the emissions generated by charging a BEV, impacts willingness to adopt a BEV and the premium that consumers are willing to pay for it. Survey participants first answered four discrete choice questions where the carbon dioxide emissions levels of the different vehicle types were set at the national average; this formed the baseline scenario. Individuals were then randomly given one of two different treatments regarding emissions levels, which I refer to here as the low-emissions scenario and the high-emissions scenario. In the former, the emissions of the BEV are further lowered. In the latter scenario, the emissions generated by driving a BEV are increased. A mixed multinomial logit model allows me to capture heterogeneity in preferences for different vehicle types across individuals.

I find that under the baseline scenario, individuals are willing to pay an average premium of \$5,705 for a hybrid vehicle and \$6,751 for a BEV. Changes in the emissions level of the BEVs are observed to directly affect willingness to pay for a BEV: If the emissions level of the BEV drops, the premium for the BEV increases while it remains unchanged for hybrid vehicles. On the other hand, if the emissions level of the BEV increases, individuals become willing to pay a higher premium for a hybrid vehicle than a BEV. This indicates that consumers are sensitive to the emissions levels of BEVs, and that they have a direct impact on purchasing decisions.

Additionally, I find that individuals are willing to pay 225 dollars per ton of CO_2 emissions prevented by adopting a hybrid or BEV, which is considerably higher than the current social cost of carbon being used by the US Federal Government and in previous literature. In Wang et al. (2019) the average social cost of carbon used in literature is around 55 dollars per ton; however, Hulshof and Mulder (2020) found that Dutch car buyers were willing to pay a similar premium to our estimate. Further analysis is required to figure out why consumers are willing to pay more than four times the social cost of carbon to avoid their own emissions from driving.

One major caveat to my analysis is that I presented the emissions levels of each vehicle, front and center. At this point further research is required to know how much information individuals have on the emissions of different vehicle options, when purchasing a new vehicle. Additionally, in some locations individuals are able to purchase renewable energy even if the over all grid is more fossil fuel dependent, so individuals may not always be tied to their region's energy production mix.

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A Vehicle Information Text

Figure 2: Vehicle Information Text

THE OHIO STATE UNIVERSITY

Imagine that you are in the market for a new sedan. You have the choice between three different types of vehicles: a conventional gasoline vehicle, a hybrid vehicle, or a BEV. The range of the BEV is 150 miles and the BEV cannot run without being charged.

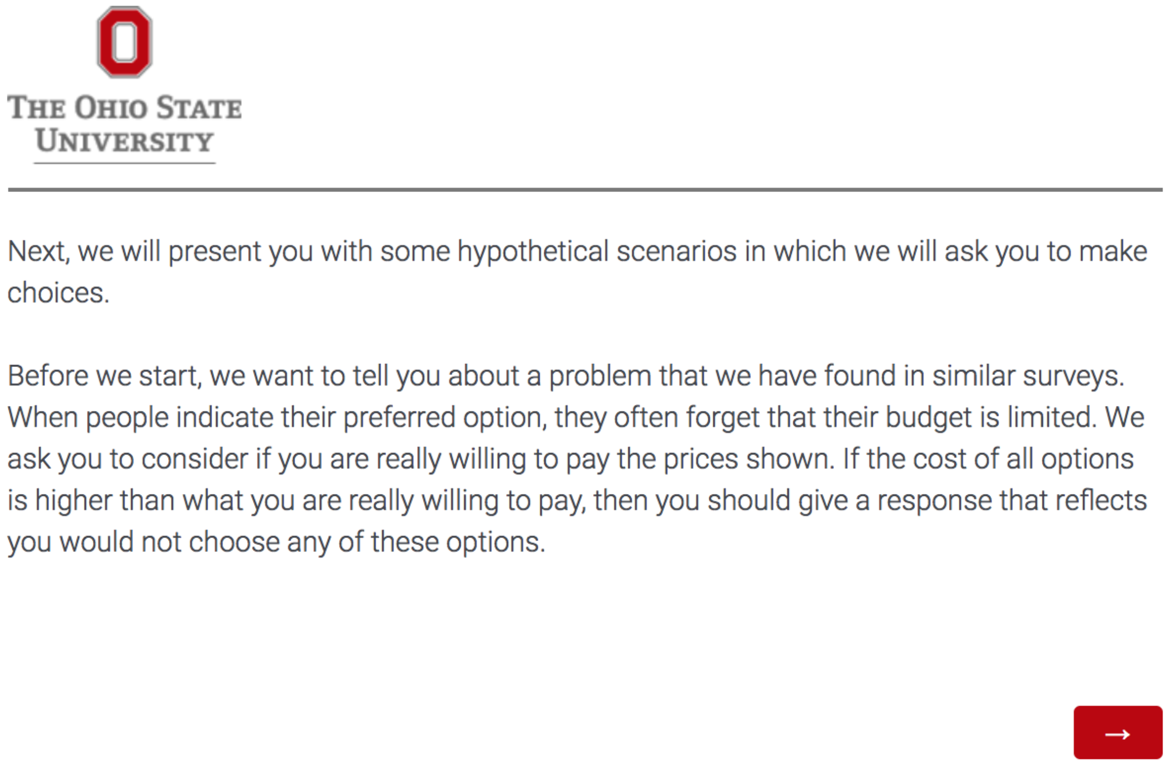
Assume that the distance you will drive is about 12,000 miles a year. With this amount of driving, the annual carbon dioxide emissions for a gasoline vehicle are about **11,000** pounds/year and the annual carbon dioxide emissions for a hybrid vehicle are about **6,000** pounds/year.

The annual carbon dioxide emissions for a BEV depend on how electricity is produced in your region. Electricity is most commonly produced through fossil fuels (coal, natural gas, and oil) and renewable energy (wind, hydroelectric, geothermal, and solar). Suppose your region's electricity production is the same as the national average. Given this, the carbon dioxide emissions for a BEV are about **4,000** pounds/year. You cannot change the way electricity is generated in your region. Carbon dioxide emissions are referred to as carbon emissions throughout the following questions.

→

B Cheap Talk Script

Figure 3: Cheap Talk Script



THE OHIO STATE UNIVERSITY

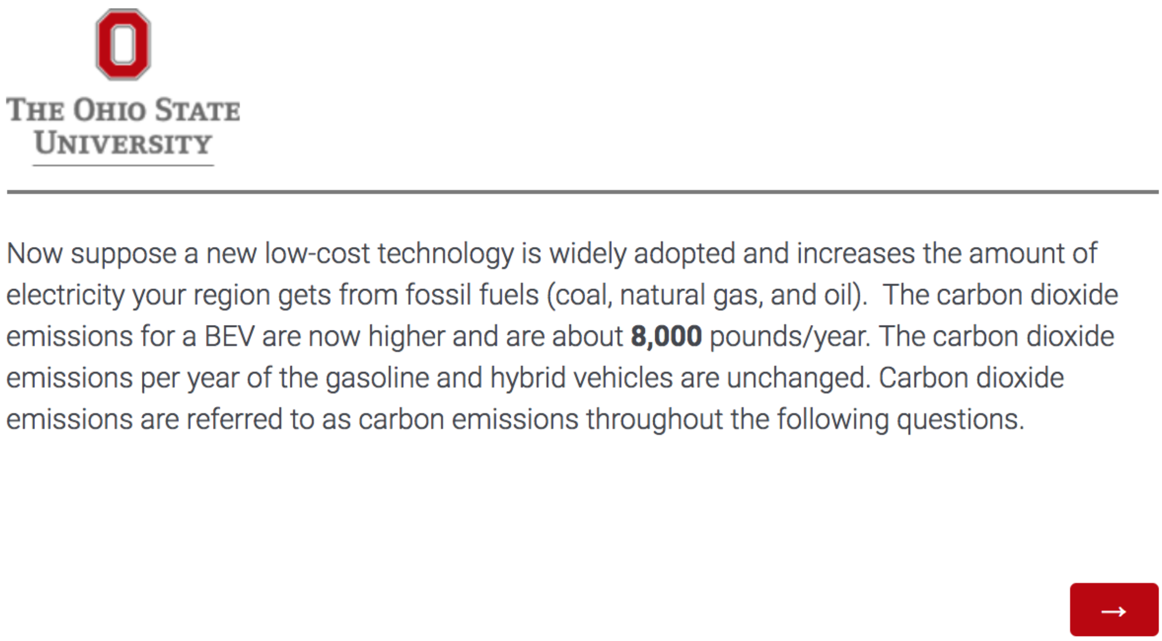
Next, we will present you with some hypothetical scenarios in which we will ask you to make choices.

Before we start, we want to tell you about a problem that we have found in similar surveys. When people indicate their preferred option, they often forget that their budget is limited. We ask you to consider if you are really willing to pay the prices shown. If the cost of all options is higher than what you are really willing to pay, then you should give a response that reflects you would not choose any of these options.

→

C Treatment Information Text

Figure 4: Treatment Information Text



D Counties Surveyed

The surveyed area of the Los Angeles metropolitan area includes Los Angeles and Orange Counties. The surveyed area of the Atlanta metropolitan area includes Barrow, Bartow, Carroll, Cherokee, Clayton, Cobb, Coweta, De Kalb, Douglas, Fayette, Forsyth, Fulton, Gwinnett, Hall, Henry, Newton, Paulding, Rockdale, Spalding, and Walton Counties. The Cincinnati metropolitan area includes Brown, Butler, Clermont, Hamilton, and Warren Counties. The Cleveland metropolitan area includes Cuyahoga, Geauga, Lake, Lorain, and Medina Counties. The Columbus metropolitan area includes Delaware, Fairfield, Franklin, Hocking, Licking, Madison, Morrow, Perry, Pickaway, and Union Counties.