

PROBABILITY OF SUPPORTING A GAS TAX FOR THE DEVELOPMENT OF  
RENEWABLE ENERGY

THREE SCENARIOS: EVIDENCE FROM A CONTINGENT VALUATION SURVEY IN U.S

by

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(Under the Direction of Jeff Mullen)

ABSTRACT

This study made use of a contingent valuation survey where respondents were presented with three framing scenarios: a control group with no framing, a natural disaster group with questions framed around the cost of natural disasters, and a Ukraine War group in which the question was framed around the volatility of gasoline prices due to foreign conflicts. The result showed a significant increase in the probability of supporting a gas tax at \$2.50/gallon, compared to the current, higher, price of gasoline. The probit regression estimates also showed that the framing of the questions did not significantly affect the probability of supporting the tax. The proportion of income spent on gas and other socioeconomic variables had a significant effect on their probability of supporting a gas tax. The average amount of tax expected to be paid monthly by the respondents was \$4.40 and \$7.34 at the current gas price and \$2.50/gallon.

INDEX WORDS: Contingent Valuation, Natural disaster, Ukraine War, Renewable Energy.

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of the Requirements for the Degree

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## DEDICATION

This research is dedicated to my late father, whose wisdom and guidance continue to light my path even after he is gone. His belief in the power of perseverance and education has been the cornerstone of my journey. Though he is not here to witness this milestone, his spirit and love have been my constant companions, motivating me to strive for excellence. This accomplishment is not just my own, but a testament to his enduring influence and the lessons he instilled in me. With all the love and gratitude I hold in my heart, I dedicate this work to my father.

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## CHAPTER 1

### INTRODUCTION

#### **1.1 Background Study**

Climate change is one of the greatest challenges facing the world today; it affects everyone and every country around the world (Abbaaa *et al.*, 2022). It is important to note that the issue of climate change is a raft with a lot of interconnected issues that are impacting the economic, social, and political well-being of society (Irwin, 2022). Today, the world is faced with the issue of global warming, flooding, and changes in weather patterns amongst many other issues that have either direct or indirect impacts on our well-being and that of the generations yet unborn (Williams *et al.*, 2023). Climate is the change in the atmospheric condition over a long period (Moazami *et al.*, 2019). This definition points to the fact that our actions in the present have a lot to do with what happens in the future regarding climate. That is why the best description of climate change mirrors a long-term shift in atmospheric conditions such as temperature, rainfall, and wind because of different forms of human activities such as farming, manufacturing, and transportation among other areas (Howe *et al.*, 2019). These activities have led to the uncontrolled release of greenhouse gases such as carbon dioxide (CO<sub>2</sub>), methane (CH<sub>4</sub>), and nitrous oxide (N<sub>2</sub>O) into the atmosphere among other substances (Nayal *et al.*, 2020). These greenhouse gases (GHG) act like a blanket, trapping the sun's heat and leading to a gradual increase in global temperatures, through a phenomenon commonly known as global warming (Nayak *et al.*, 2020).

It is a known fact that climate change is real, with evidence supporting the fact that it is human-induced and has the potential for catastrophic consequences. As the concerns for GHG emissions increase across the world, global emissions from human activities continue to rise, primarily due to the burning of fossil fuels and land use changes because of the growing population

and the need to provide food and shelter (Holechek *et al.*, 2022). The increase in human activities across the world has led to an increase in the earth's average temperature which has led to a range of climate impacts, that have affected ecosystems, economies, and societies in the forms of heatwaves, wildfires, hurricanes, sea-level rise, and loss of biodiversity (Krishnan *et al.*, 2020). Globally, the response to the impact of climate change has been the commitment of nations to address the issues around it as laid out in the Paris Agreement which stipulates countries to take actions to reduce emissions and enhance resilience. The Paris Agreement of 2015 which came into force in November 2016, stipulates that all countries, including the United States, limit global warming to below 2 degrees Celsius above pre-industrial levels, with efforts to further reduce it to 1.5 degrees Celsius (UNFCC, 2023). The main purpose of the agreement was to strengthen and coordinate the global response to the issue of climate change through different ratifications of the agreement (UNFCC, 2023). The Paris Agreement set out to have long-term goals on temperature, focused on mitigation, and looked at climate neutrality, sinks, and reservoirs, adaptation strategies, and areas of support among other key areas that have a direct bearing on climate change.

In the United States, climate change has become a sensitive issue, with a divide along partisan lines and this has influenced policy decisions and action at the federal level. The withdrawal of the country from the Paris Agreement and less action on the environment during President Trump's era has had a tremendous effect on the ability of the country to meet its climate goals. According to NOAA (2023) data, the US experienced 18 weather events in 2022 (figure 1) as compared to 20 weather events in 2021. These events range from wildfires, hurricanes, hailstorms, flooding, and Tornadoes, among many others. In terms of occurrences of the events in the US in 2022, information obtained from Statista (2023), showed that severe thunderstorms occurred the most in the US (62 times) while wildfire, heat waves, and drought were reported to

occur 26 times within the year under review. Flood and flash flood events were reported to have occurred about 15 times within the year under review while winter storms/cold waves and tropical cyclones occurred 13 and 3 times respectively (Statista, 2023).

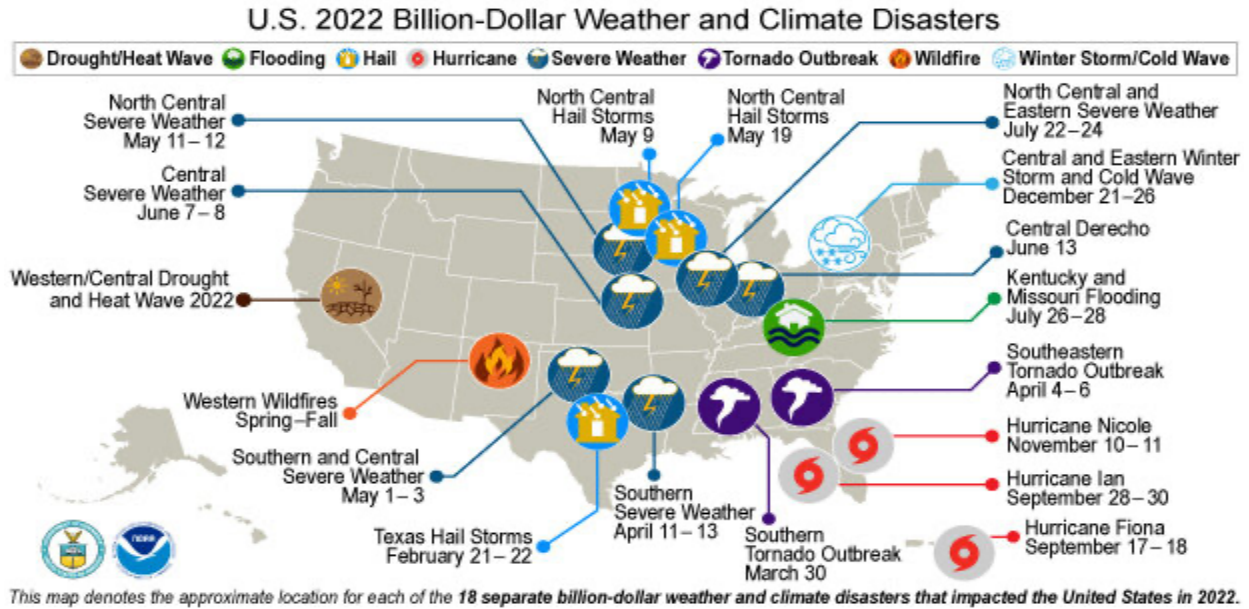


Figure 1: Weather and Climate Disasters in the US in 2022 (Source: NOAA, 2023)

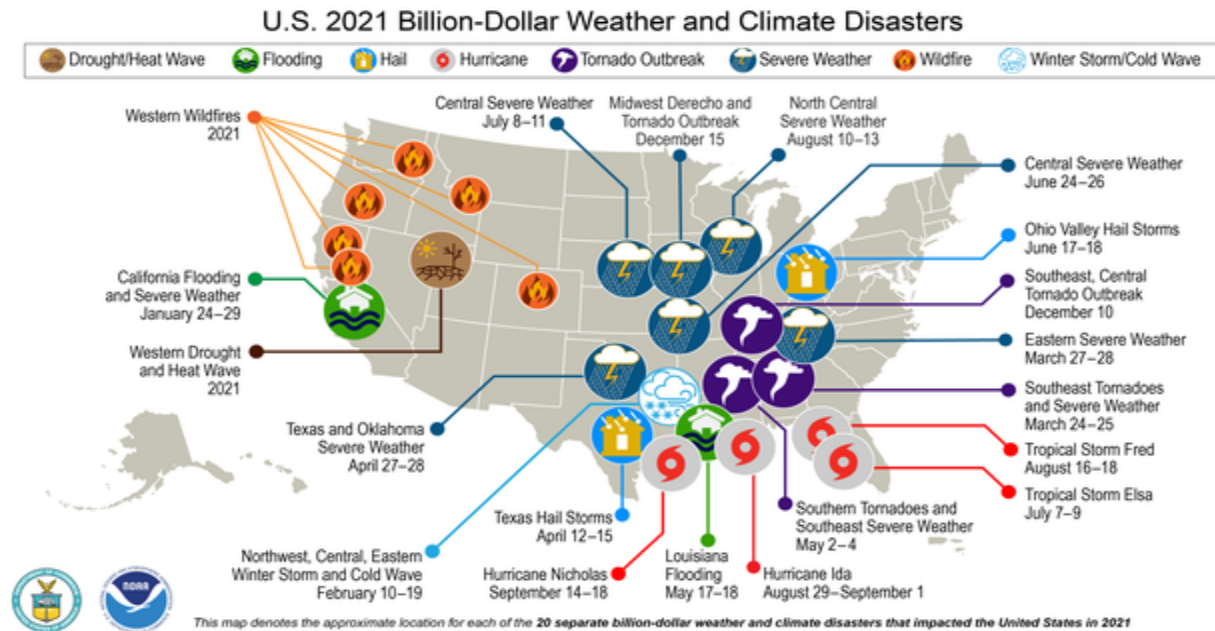
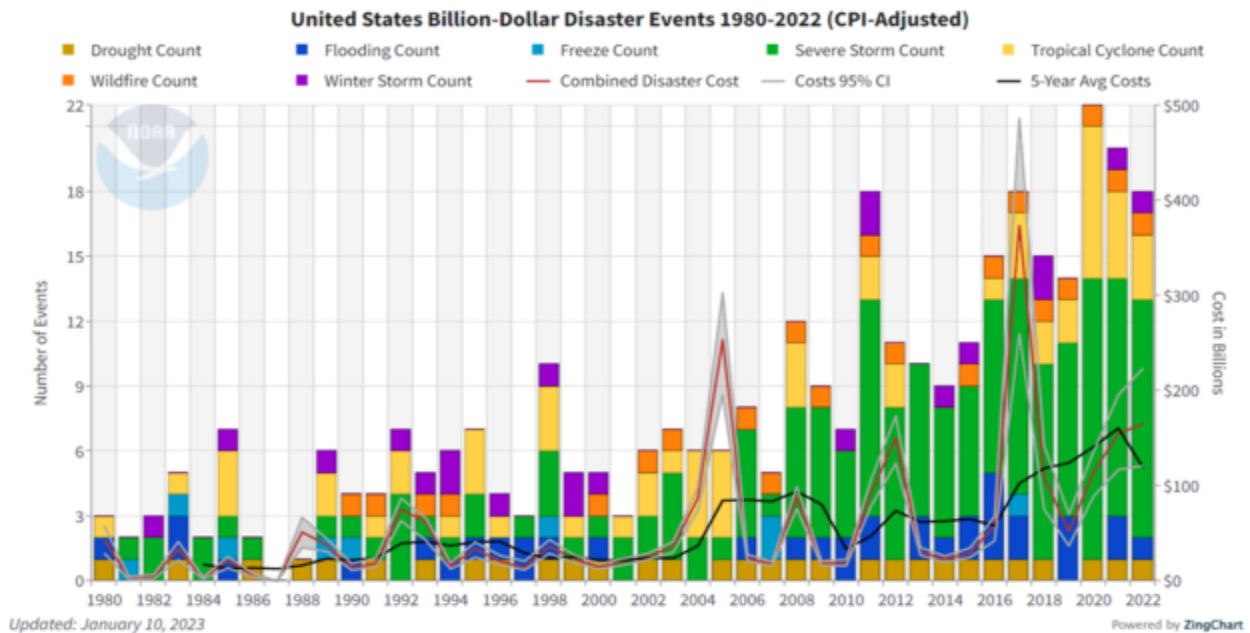


Figure 2: Weather and Climate Disasters in the US in 2021 (Source: NOAA, 2022)

The trend of disaster in the USA shows a close link between climate change and natural disasters and this is acknowledged by Benevolenza and Derigne (2019) who reported that the United States is experiencing an increase in natural disasters because of climate change as shown in figure 3. According to NOAA (2023). The occurrence of natural disasters has gradually increased from 1980 to 2022 with issues such as severe storms, tropical cyclones, and wildfires gaining prominence over the years. This is affirmed because of the nature of natural disasters experienced in the county which is closely linked to climate change events. For instance, the increase in global temperatures has led to frequent and intense heatwaves in some parts of the country. Also, Warmer Ocean temperatures provide the energy required for hurricanes and tropical storms to occur while the rising global temperatures have led to the melting of glaciers and polar ice caps, contributing to sea-level rise, and increasing the level of flooding. Other major disasters in the US that can be linked to climate change include drought and wildfires which are a consequence of changes in rainfall patterns and increase in temperature.

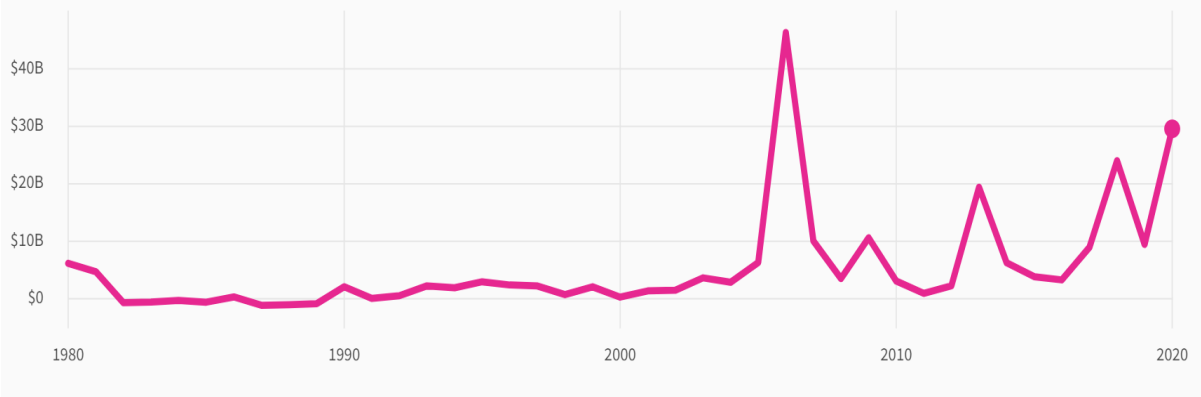


**Figure 3: Occurrence of Natural Disaster in the US from 1980 to 2022 (Source: NOAA, 2023).**

As a result of climate change, there is a cost that is paid by the government at the federal, state, and local government levels to manage the impact of climate change. This cost by the government is usually ramped up because of natural disasters caused by climate change events. As shown in Figure 4 the government spending on disaster has increased from the year 2000 when the issue of climate change started coming to the fore and peaked at the highest in 2006 during Hurricane Katrina which caused a whole lot of damage. In 2013, there was another peak in natural disasters, and these include tornadoes, which caused \$3.6 billion in damages, and then flash and river flooding with damages of about \$2.2 billion, and hail, \$1.2 billion (NWS, 2013). In 2018, there was another peak in government spending on natural disasters, according to NOAA (2018), this was due to tropical cyclones, severe storms, droughts, and wildfires. USA Facts (2023) further noted that there was a spike in government fiscal spending on disaster relief at about \$29.6 billion with per capita spending of about \$90 per person. This according to NOAA (2021) was because of the occurrence of around 22 weather and climate disasters which include wildfire, drought and heat waves, tornados, cyclones, and other severe weather events. This event has led to the loss of life and properties which when quantified are beyond the one billion dollars in losses experienced. This implies that there is a cost involved in not taking proper action to stem the tide of climate change in our society and this cost keeps increasing because of the high prevalence of natural disasters in the society.

### Government spending on disaster relief, inflation-adjusted

In fiscal year 2020, federal, state, and local governments spent \$29.7 billion on disaster relief.

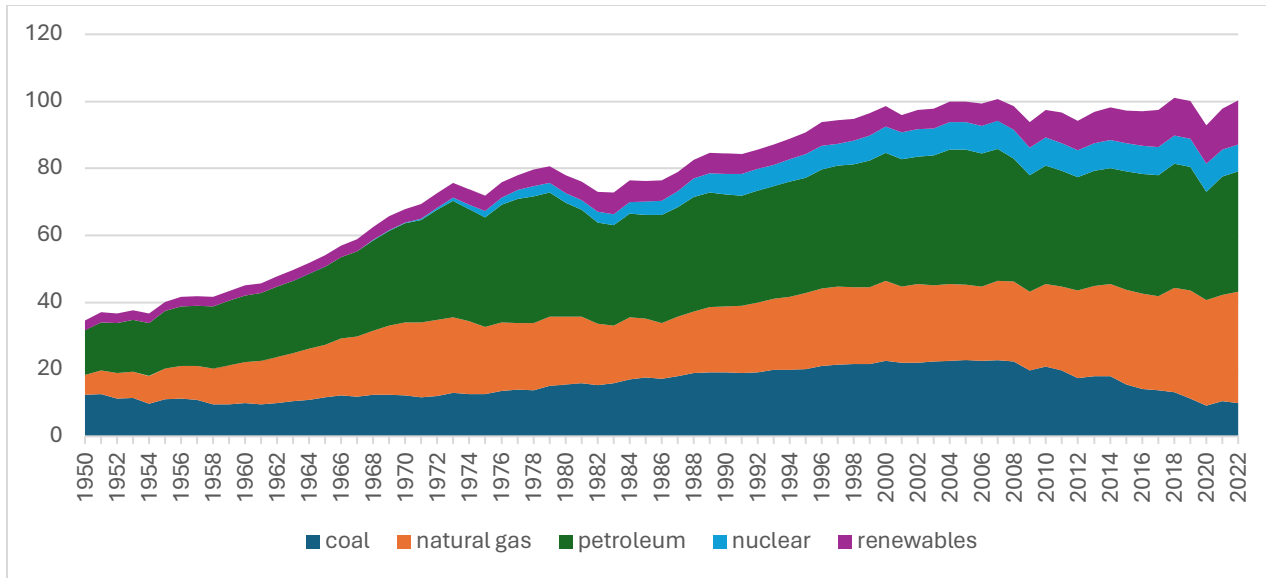


**Figure 4: US Government Spending on Disaster Relief from 1980 – 2020 (Source: USA Facts, 2023).**

However, many U.S. states and local governments have taken steps to address climate change in the absence of federal leadership by setting renewable energy goals and implementing carbon pricing mechanisms. However, the challenges of climate change still exist, and thus a need for a more concerted effort to resolve the issue of climate change and strengthen the global goal of ensuring sustainability. However, to be able to effectively address the issue of climate change we must understand the causes of climate change.

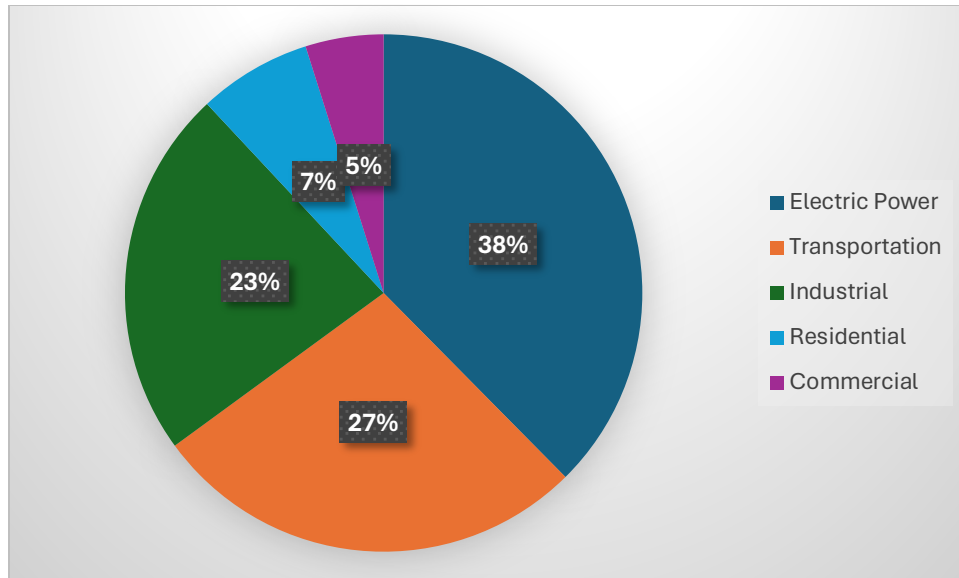
One of the major causes of climate change in the USA is the clearing of forests for agriculture, and urban development, and this process the earth's capacity to absorb CO<sub>2</sub>, a process known as carbon sequestration. In addition, land use change which involves converting natural landscapes into urban areas or agricultural land has disrupted ecosystems and these contribute to climate change. Lastly, the burning of fossil fuels for energy, industrial processes, and transportation is a major contributor to greenhouse gas emissions. This includes coal, oil, and natural gas. According to Hao *et al.* (2019), the use of fossil fuels is one of the greatest contributors

to fossil fuel emissions in the US. Perea *et al.* (2022), noted that tons of CO<sub>2</sub> and methane have been released into the atmosphere through the production and burning of fossil fuels for energy and transportation. Peresa *et al.* (2022), noted that the emission of fossil fuel has exponentially increased by more than 500% from 1950 to 2020 and this increase correlated with the increase in fossil fuel consumption in the US. This is confirmed by the energy consumption data obtained from the US Energy Information Administration (2023), the information showed that the US has a diverse mix of energy consumption sources. Energy consumption from different sources has shown slightly different trends over time as shown in figure 5. For instance, the consumption of coal has drastically reduced among the energy sources that are being used in the US because it is being replaced in electricity production with other sources. However, the consumption of petroleum and natural gas has continued to increase with a decrease in consumption occurring between 2020 and 2021 because of the Covid 19 pandemic. On energy consumption in the US, it was discovered that fossil energy sources like natural gas, petroleum, and coal make up about 79% of the energy consumption in the US while other sources such as nuclear energy (8%) and renewable sources (13%) make up the rest. This is pointing to the fact that primary energy production is mainly dependent on fossil energy sources with renewable energy sources making a very small percentage of the energy sources.



**Figure 5: Yearly proportion of the Consumption of different Energy sources in the US (Source: United State Energy Information Administration (EIA), 2023)**

Further information obtained from the United States Energy Information Administration (2023) shows that the major sectors consuming energy are electricity generation (38%), transportation (27%), and industrial (23%) among others as shown in Figure 6. Additionally, energy-related carbon dioxide emission per capita was estimated at 14.9 metric tons per person which is quite high, and the major culprit among the energy sources being coal, petroleum, and natural gas. This was affirmed by Salari *et al* (2021) who opined that non-renewable energy sources like petrol, coal, and gas had a positive effect on the emission of carbon dioxide while renewable energy sources had a negative effect.

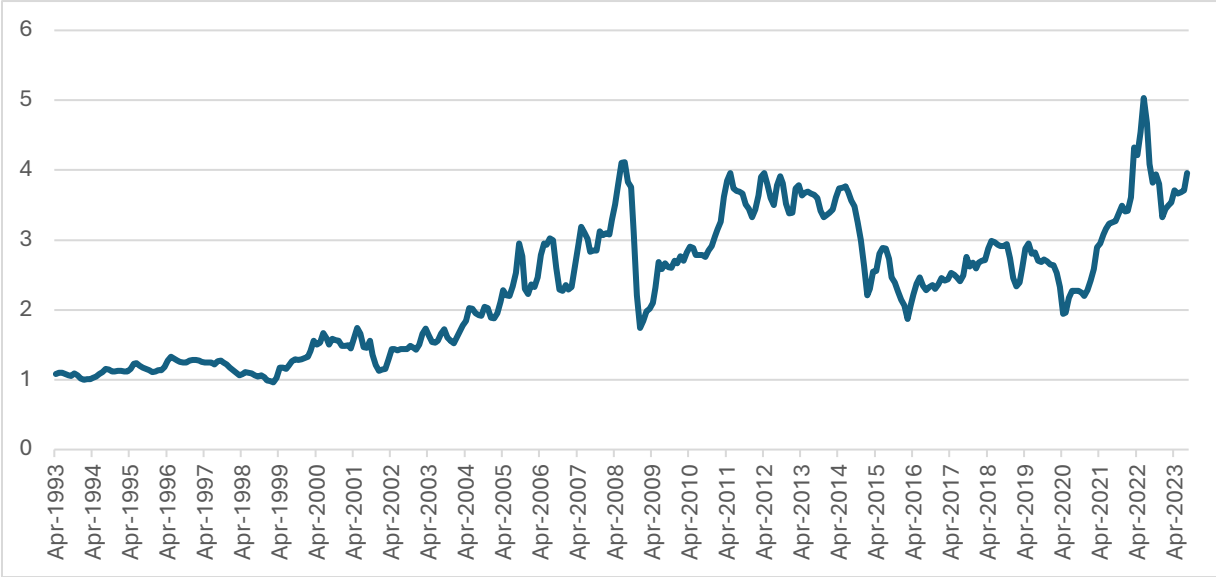


**Figure 6: Energy Consumption by Sector (Source: United States Energy Information Administration (EIA), 2023a)**

This goes to show that there is a need to reduce the level of fossil fuel consumption in the US by shifting to other sources for various reasons. First is the issue of climate change which has been highlighted earlier due to the high level of greenhouse gases being released from the consumption and use of fossil fuel sources which has been indicted as being one of the main players in releasing such gases and the increasing level of consumption of the fossil fuels (figure 5) portends a lot of danger for the environment.

Additionally, the price of gasoline which is one of the fossil fuels has not been stable and has been highly volatile over time (Figure 7) (kamyabi and Chidmi, 2022). According to the Energy Information Administration data, the retail price of gasoline has gradually increased from \$1.078 per gallon in 1994, to \$4.059 per gallon in 2022 with peaks in prices occurring in 2008, 2011, 2012, 2014, and of recent 2022. Further inquiry shows that these price increases were a result of fluctuations in the prices of international crude oil which tremendously affected the local

retail price of gasoline in the US. For instance, in 2008, there was an increase in the demand for crude oil in China and the Middle East because of industrialization, but the increasing demand was soon affected by the global financial crisis which caused the price to drop drastically in the following year. In 2011 and 2012, there was also a predominant increase in the price of gasoline, this was tagged to disruption in the oil production of Libya and then unrest in the Middle East which is one of the major producers of oil. This fallout of unrest was also carried on into the year 2012, with Iran a major crude oil-producing country being the subject of the sharp increase. Recently, the Russian-Ukraine war has significantly affected the oil industry leading to a high increase which can only be compared to that of 2008. This implies that the price of gasoline in the US is highly volatile and subject to fluctuations due to external forces beyond the control of the US. It is important to note that these fluctuations in gas prices are more noticeable to consumers because about 90% of the aggregate U.S. gasoline consumption is used by light-duty vehicles (Kamyabi and Chidmi, 2022).



**Figure 7: Monthly trend of gas prices in the US from 1993 to 2022. (Source: USEIA, 2023b)**

Additionally, we must consider the unsustainable production process which has left the production of fossil fuels with so many issues. One of the issues is pollution which is damaging the environment at an alarming rate. Pollution from the production of fossil fuel fuels includes air pollution, land pollution, and water pollution. According to Buonocore *et al.* (2023), the resultant effect of air pollution in the US oil and gas sector has led to cases of asthma in about 410,000 persons, new cases of childhood asthma in 2,200 persons, excess deaths, and a reported health impact of about \$77 billion with Nitrogen dioxide being the main pollutant. Additionally, oil spills have been noted to cause devastating effects on the soil and even on water destroying species on water and natural vegetation. The Wilderness Society (2021) reported that people live within proximity of oil production sites and are exposed to various dangers such as air pollution which is often referred to as the “invisible killer” and can be said to be the cause of 13% of death in people that are 1 year or older. The report also added that the exploration of fossil fuels even poses a danger to soil and water by causing cancer, birth defects, and liver damage.

Other major impacts of fossil fuel production include the fact that it contributes to natural disasters such as wildfires, heatwaves, and flooding among others. This is because the release of greenhouse gases has been seen as the main cause of the ozone layer depletion which exposes the earth to extreme heat from the sun with the eventual outcome being natural disaster events. USGS (2021) tried to explain if there is a link between earthquakes and the exploration of gasoline and outlined some processes of extraction of shale oil which includes fracking and induced earthquakes with a magnitude less than 1 (Wang *et al.*, 2014). However, a magnitude 4 category earthquake was reported as the largest earthquake through fracking (Frohlich *et al.*, 2022). This could mean that natural disasters could be directly or indirectly linked to oil production. Also, it was observed from Figure that different types of natural disasters were reported within states that are major oil

producers in the United States such as Texas, New Mexico, and North Dakota, Alaska, Colorado. This therefore calls for urgent action to reduce the demand for fossil fuel and transition to renewable energy sources that would help in reducing the negative impact of fossil energy sources. That is why this study is exploring how gas tax can be used as a tool to develop renewable energy sources by reducing the demand for fossil energy sources.

## **1.2 Objectives**

The main objective of this research is to examine consumers' probability of supporting a gasoline tax for the development of renewable energy in the United States using a stated preference survey with a referendum-style question. The secondary objective is to determine if the probability of supporting a gasoline tax is affected by the framing of the referendum question. To accomplish that, three versions of the survey were distributed: a control with no framing information; one treatment that provides information about the increasing trend of U.S. disaster expenditures and frames the referendum question around reversing this trend; and a final treatment that provides information about the correlation between gasoline prices and foreign conflicts and frames the referendum question around the stability of energy prices. The third objective is to examine if the prevailing price of gasoline at the time of the survey affects the likelihood of supporting the gasoline tax, while the final objective is to determine if the likelihood of support is affected by respondents' proportion of income spent on gasoline.

## **1.3 Hypothesis**

The following hypothesis will be tested in the study.

1. The probability of supporting a gasoline tax for the development of renewable energy is contingent on the framing of the problem.

2. There is no significant relationship between the socioeconomic factors of the respondents and their probability of supporting a gasoline tax.
3. The prevailing price of gasoline at the time of the survey does not significantly affect the probability of supporting a gasoline tax.
4. There is no significant relationship between the support for a gasoline tax and the proportion of income spent on gas.

## CHAPTER 2

### ECONOMIC FOUNDATION AND REVIEW OF RELEVANT LITERATURE

#### **2.1. Environmental Valuation Techniques**

The use of environmental valuation techniques comes into play when evaluating goods and services, which cannot be valued using monetary terms as in the case of market goods (Cuccia, 2020). The application of this method is significant in understanding the value of environmental goods and services (Gujarro and Tsinaslanidis, 2020). It is also important for guiding policy decisions in the effective management of environmental resources and for guiding efforts towards sustainability and conservation of environmental resources (Cuccia, 2020). It should be noted that unlike economic goods and services, which have economic value and can be valued based on the cost of production, environmental goods have an intrinsic value, which is based on their inherent ability to provide value to humans (Raihan, 2023). The valuation of environmental goods comes from the perception of people about the benefit that they tend to enjoy from such environmental goods or services (Massenberg *et al.*, 2023).

Some of the major benefits derivable from the use of an environmental valuation technique in this study include the fact it can help in guiding decision-making as to the acceptability of a gas tax for the development of renewable energy among consumers (Mariel *et al.*, 2021). It can also be used to understand the cost and benefits associated with the development of renewable energy sources (Mishan and Quah, 2020). This is because of the need to invest in developing renewable energy sources and the expectation that people will accept it by supporting it through a tax, which would further enhance the development. Additionally, the use of environmental valuation techniques helps in the effective management of environmental resources by encouraging the

development of more sustainable sources and alternatives, which helps in balancing the need of man with the need to protect the environment. Another area where environmental valuation techniques come into play is in the creation of awareness about environmental goods and services and the need for them to be valued in a way that will promote environmental stewardship.

It is important to build a classification to understand that there are market-based valuation techniques and there are those, which are more applicable to non-market environmental goods and services. Market-based valuation techniques are used for environmental goods and services that already have established market prices like timber while non-market-based environmental goods do not have a well-defined market value and whose values are not properly defined. In the context of our study, the introduction of a gas tax for the development of renewable energy sources is classified as a non-market environmental good (Perni *et al.*, 2021). This is because of the broader environmental and social impact been considered for the introduction of the gas tax, which has not been captured by any market dynamics. For instance, the benefits or the contexts associated with the introduction of a gas tax such as the reduction in the dependence on fossil fuel and reduction in natural disasters are non-market values, which are for the greater good of the society. Other non-market values that it imposes, include the reduction in GHG emissions and environmental degradation. Although the gas tax may require a market dynamic, the impact mitigated through the process is non-market. On the other hand, we could argue that renewable energy being developed through the gas tax is a market good that has value but what is important to note is that the overall value being marketed through the process is what makes it a non-market good.

The valuation of environmental goods and services can be done using different techniques such as the market price method, which was used by Thapa *et al* (2020) in the evaluation of ecosystem services in wetlands in Nepal. This process makes use of the market prices that are

related to the market goods and services being evaluated (Thapa *et al.*, 2020). For instance, the price of timber can be used in evaluating the value of a forest among other approaches. Another major evaluation technique is the hedonic pricing method, which is used to infer the value of environmental attributes of properties or real estate (Liang and Yuan, 2021). Studies that have applied the hedonic pricing method include Sohn *et al.* (2020), who used it in estimating the value of green infrastructure in single-family housing while Lazareva, and Dong (2021), used it in measuring the value of urban green space.

Additionally, the choice experiment method is used in the valuation of market goods and services, and this is done by presenting the respondents with hypothetical scenarios involving different attributes and costs, with respondents allowed to pick their choices from the different attributes presented (Tran *et al.*, 2021). Studies that have made use of choice experiments include Tran *et al.* (2022) who used it to establish the willingness to pay for food labeling in Vietnam while Ureta *et al.* (2021), used it in evaluating the preferences for stormwater ponds. Additionally, Xu *et al.* (2022) used it in estimating the recreational value of coastal wetland parks. The travel cost method also falls among the categories of methods used for evaluating environmental goods. This approach estimates the cost that people incur in visiting a recreational site and the frequency of visits to determine the value of such site or environmental facility (Merciu *et al.*, 2021). Some of the studies where it has been applied include Idris (2022), Merciu *et al.* (2021), and Batubara *et al.* (2020).

The benefit transfer method is another method, that can be used in the valuation of environmental goods and services, and this method uses an approach of transferring the value of a similar product to another area with a similar context (Badamifrooz *et al.*, 2021). Although this method is not popular in usage, studies that have used it include Sica and Nestico (2021) in the

evaluation of urban forests. This method is cheaper because previous data from similar contexts can be applied to a new context.

Furthermore, the contingent valuation method also falls among the major methods for evaluating environmental goods and services and finds its applicability when the environmental goods and services being evaluated are non-market goods. The method involves asking the respondents directly about their willingness to pay for environmental goods or services and has broad applicability in accessing the value of non-market goods (Hwan *et al.*, 2020). For instance, in the study of Belay *et al.* (2020), it was used as an approach to evaluate the willingness to pay for soil conservation while Hwang *et al.* (2020) used it in the evaluation of fireflies as a tourist attraction. This shows the applicability of the approach in different contexts as seen in the studies reviewed. Generally, the use of CVM in this study is more justified because of the non-market nature of the goods and services being evaluated, thus giving the flexibility of estimating the economic value of the non-market attribute being proposed as part of the benefit from the gas tax (Shan *et al.*, 2023). Additionally, the CVM approach allows for eliciting individual preferences based on the different scenarios and prices that are presented to the consumers, thus giving the consumers the freedom to experience their preferences under the different scenarios that are presented to them (Eregae *et al.*, 2021). Furthermore, the flexibility of the approach in not just presenting scenarios but allowing the consumers to weigh their preferences and choices (Eregae *et al.*, 2021). This makes the approach a flexible one and gives a good estimate of the consumer's willingness to pay in the study (Zhang *et al.*, 2022). Additionally, it gives the ability to estimate the costs and the benefits associated with each of the options presented to the consumer by enabling policymakers to understand the context in which consumers make their decisions (Ku *et al.*, 2022).

## **2.2. Stated Preference Surveys and Contingent Valuation Methods**

Stated preference (SP) surveys are a type of economic valuation technique that relies on surveys to elicit individuals' preferences for goods, particularly non-market goods, where traditional market data is unavailable (Hanemann, 1984). Contingent Valuation Method (CVM) is a specific form of SP survey that directly asks respondents their willingness to pay (WTP) or willingness to accept (WTA) compensation for a hypothetical change in the provision of a good (Mitchell & Carson, 1989). These methods are crucial for assessing consumers' WTP for environmental goods, such as the benefits associated with renewable energy sources, which often lack established markets.

The theoretical underpinnings of CVM draw upon welfare economics, particularly the concept of compensating surplus (Hanemann, 1984). Revealing an individual's WTP for a change in environmental quality, CVM helps estimate the economic value of that change. This information is valuable for cost-benefit analysis of renewable energy projects, as it allows governments and policymakers to weigh the environmental benefits against the implementation costs (Bateman et al., 2002).

CVM has seen extensive application in renewable energy research. For instance, Yu et al. (2012) employed CVM to assess public WTP and support renewable energy adoption in emerging economies. Similarly, Mirasgedis et al. (2014) utilized CVM to understand public preferences for wind energy development, considering factors like visual impact and noise. These studies highlight the versatility of CVM in capturing the economic value of various aspects associated with renewable energy implementation.

However, it is important to acknowledge that CVM is not without its limitations. Respondents may struggle to accurately value hypothetical scenarios, and strategic bias can arise if individuals believe their responses will influence policy decisions (Murphy et al., 2005). Additionally, we can also have the payment vehicle bias where consumers tend to prefer certain methods of payment to others due to various factors such as convenience, habit, perception of security, and cultural norms (Haab *et al.*, 2020). Zhang *et al* (2022), found a significant linkage between WTP for pollution control and the payment vehicle used. This is because of the perception of the payment vehicle being used (Morrison *et al.*, 2000).

However, payment vehicle bias can occur with the use of gas tax because of the bias towards taxes as being regressive because of the burden it may place on low-income earners who are likely to spend more on energy. Additionally, the lack of linkage between the payment of taxes and the benefits expected can also create a bias. However, highlighting the benefits of the gas tax to the respondents in terms of the development of renewable energy alternatives, reduction in natural disasters, or other public benefits can help in overcoming the bias associated with it (Hassan *et al.*, 2018). Careful survey design and data analysis techniques are essential to mitigate these concerns (Arrow et al., 1993)

### **2.3 Framing in Stated Preference Surveys**

The growing use of stated preference surveys (SPS) for valuing environmental goods necessitates a closer look at how question framing can influence respondents' WTP (willingness to pay) estimates. Studies by Hanemann (1994) and Kragt & Bennett (2008) demonstrate that framing effects can significantly impact WTP responses in SPS. For example, presenting environmental policy changes in terms of gains (avoiding pollution) can lead to higher WTP compared to framing focused on losses (cost of reducing pollution). Additionally, research by Cutter et al. (2007)

highlights how attribute framing, where specific details of the policy are emphasized, can influence WTP. Highlighting positive attributes, like improved air quality, has the potential of higher WTP compared to focusing on negative aspects, such as potential infrastructure disruptions.

It is essential to note that limited research has explored the long-term effects of framing on WTP stability. Furthermore, the field lacks comprehensive studies on how framing interacts with other factors influencing WTP, such as individual risk preferences or the complexity of the policy. Addressing these gaps is vital for designing effective SPS that accurately capture public preferences for environmental policies.

#### **2.4 Methodological Approaches in Stated Preference Surveys**

A variety of methodological approaches exist within SP surveys, each with its strengths and weaknesses (Hanemann, 1994; Carson & Hanemann, 2006). One common approach is the referendum-style format, which presents respondents with a hypothetical scenario describing an environmental policy change. Respondents are then asked to vote for or against the policy, often accompanied by a specific cost associated with it (Mitchell & Carson, 1989). This method offers simplicity and ease of understanding, but limitations include the potential for strategic voting and difficulty in capturing the range of WTP across individuals (Murphy et al., 2005).

Another approach utilizes open-ended willingness to pay (WTP) questions, where respondents directly state the maximum amount, they are willing to pay for the environmental good. This method tends to provide richer data, but concerns exist regarding hypothetical bias and framing effects influencing responses (Arrow et al., 1993).

To address these limitations, payment card, and choice experiment designs have emerged in recent times. Payment card methods involve presenting respondents with a series of cards, each offering

different levels of environmental good at different price points. Respondents then choose their most preferred option (Hanemann, 1984; Ready et al., 2001). Choice experiments offer respondents a series of hypothetical scenarios where they choose between different combinations of environmental quality and other attributes, like cost (Bateman et al., 2002). Both methods provide more information about the distribution of WTP across the population and help mitigate hypothetical bias.

## **2.5 Consumer Behavior and WTP for Renewable Energy**

Understanding consumer attitudes and behaviors towards renewable energy is essential for promoting widespread adoption. Research suggests a generally positive sentiment, with environmental concerns about climate change and pollution acting as key drivers (Gardan et al., 2023). However, translating positive attitudes into concrete actions can be challenging.

Economic factors play a significant role in consumer decisions. While many express a willingness to pay a premium for renewable energy, this willingness is often limited (Ayodele et al., 2021; Gardan et al., 2023). Consumers are more likely to adopt renewable options if the upfront costs are comparable to traditional energy sources, or if there are clear financial benefits in the long run (Asif et al., 2023).

Policy support emerges as another critical factor influencing consumer behavior. Studies by Asif et al. (2023) and Sebri (2015) highlight the positive impact of government incentives, like subsidies or feed-in tariffs, on consumer decisions to invest in renewable technologies like solar panels. These incentives have the potential to bridge the cost gap between renewables and traditional options, making them more attractive to consumers.

Beyond environmental concerns, economic factors, and policy support, additional determinants of WTP for renewable energy have been identified. Research by Azlina et al. (2022) suggests that trust in energy providers and the perceived effectiveness of renewable technologies also influence consumer decisions. Additionally, Klæboe & Sundfør (2016) found that factors like aesthetics and noise associated with certain renewable projects (e.g., wind farms) can influence public preferences and WTP.

## **2.6 Gasoline Prices and Environmental Policies**

The relationship between gasoline prices and public support for environmental policies, particularly those promoting renewable energy, is a topic of increasing interest. A potential negative correlation between high gas prices and consumer backing for environmental initiatives was noted in some works. Studies by Carballo & Sisco, (2022) and the Fondazione Centro Studi sui Conflitti Tributivi e Sociali (CMCC) (2019) indicate that periods of increased gasoline prices can lead to decreased public support for policies like phasing out gas-powered vehicles or carbon pricing. This decline in support is often attributed to heightened economic concerns during periods of high energy costs (CMCC, 2019).

However, the impact of gasoline prices on environmental policy preferences tends to be more robust. Analyses by Allcott & Wozny (2021) and, Carballo & Sisco (2020) suggest that while support for some environmental policies, like phasing out combustion engines, might decrease with rising gas prices, general environmental concern does not necessarily diminish. This implies that economic factors may influence specific policy choices, but underlying environmental values might persist.

Furthermore, research by Drews & van den Bergh (2016) highlights the potential role of policy design in mitigating the negative influence of commodity prices. Their study suggests that framing environmental policies in terms of long-term economic benefits, such as energy independence or job creation in renewable energy sectors, can help maintain public support even during periods of high gas prices.

## **2.7 Empirical Studies on WTP for Renewable Energy and Gasoline Taxes**

Several studies have explored US consumers' WTP for increased renewable energy adoption. The recent studies by Ayodele et al. (2021), Dumortier & Elobeid (2021), Gonzalez-Ramirez et al. (2021) and Zhou et al. (2023) confirm continued public support for renewables, with WTP estimates ranging from \$5.7 to \$18 per month for an increase in renewable energy use. These studies primarily employed referendum-style or payment card formats, where respondents were presented with hypothetical scenarios describing a switch to renewables at different costs.

Several studies explored how factors like income, environmental concern, and policy design influence WTP. Boyle et al. (1993) and Dumortier & Elobeid (2021) pointed to a positive correlation between income and WTP for both renewables and gasoline taxes. Additionally, studies by Meyer & Liebe (2020) and Kim & Kim (2020) found that individuals with higher environmental concerns expressed a greater WTP for both policies. Furthermore, research by Streimikiene et al. (2019) suggests that framing gasoline tax increases in terms of environmental benefits can lead to higher WTP compared to a focus on revenue generation.

There is some consensus regarding positive public sentiment towards renewable energy, with consumers expressing a willingness to pay a premium for its increased adoption. However, the specific WTP estimates vary across studies, likely due to differences in methodologies, sample

characteristics, and the specific design of the renewable energy policy scenario presented (Ayodele et al., 2021).

For gasoline taxes, the picture is less clear. While some studies report a modest WTP for gasoline tax increases dedicated to environmental goals, the estimates are generally lower compared to those for renewable energy. Additionally, the influence of question design on WTP responses for gasoline taxes warrants further investigation (Murphy et al., 2005; Kaplowitz & McCright, 2015).

Furthermore, a key area of disagreement lies in the generalizability of SP survey results to real-world policy implementation. Concerns exist about hypothetical bias, where respondents tend to overstate their WTP in a survey setting (Arrow et al., 1993). Furthermore, SP surveys may not fully capture the complexities of real-world policy design and potential distributional impacts (Willis, 2014). Hence, it is recommended that studies should consider employing additional techniques, like follow-up surveys or cheap talk scripts, to mitigate these concerns and enhance the reliability of their findings (Murphy et al., 2005).

In addition to the studies mentioned above, several other works contribute to the understanding of US consumers' WTP for renewable energy and gasoline taxes. Hanemann (1994) explored WTP for improved air quality, a potential benefit of increased renewable energy adoption. This finding aligns with the positive sentiment towards renewable energy and its potential environmental benefits.

Moving beyond average WTP estimates, some studies delve deeper into the distribution of WTP across the population. For instance, Yoo & Ready (2013) employed a choice experiment design to examine WTP for renewable energy electricity. Their analysis revealed significant

heterogeneity in WTP, with some individuals expressing a strong willingness to pay a premium for renewables, while others were less enthusiastic. Understanding this distribution is crucial for policymakers when designing renewable energy policies that cater to a diverse population.

While most studies focus on national-level surveys, some explore regional variations in WTP. For example, Oluoch et al. (2020) and De Laurentis & Perason (2021) suggest potential geographic disparities in public preferences for renewable energy, which policymakers might need to consider when developing regional or state-level clean energy initiatives.

## **2.8 Summary and Gaps in the Literature**

This chapter provides a comprehensive overview of key areas relevant to understanding consumers' willingness to pay (WTP) for renewable energy and gasoline taxes in the United States. Stated preference surveys and contingent valuation methods (CVM) are essential tools for assessing WTP for environmental goods, such as renewable energy sources, despite their inherent limitations. Framing effects in stated preference surveys have been shown to significantly influence WTP estimates, highlighting the importance of carefully designing survey questions. Various methodological approaches exist within stated preference surveys, each with its strengths and weaknesses, highlighting the need for individual researchers to consider the most appropriate methodology for their study objectives.

Consumer behavior studies reveal a generally positive sentiment towards renewable energy, driven by environmental concerns, economic factors, and policy support, although the specifics of WTP estimates vary. The relationship between gasoline prices and environmental policies is complex, with mixed findings on how changes in gas prices influence public support for initiatives like gasoline taxes.

Finally, empirical studies on WTP for renewable energy and gasoline taxes provide valuable insights into public preferences, but concerns remain about the generalizability of stated preference survey results to real-world policy implementation.

## CHAPTER 3

### THEORETICAL FRAMEWORK AND METHODOLOGY

#### 3.1. Theoretical Framework of Choice Experiment

The contingent valuation method (CVM) is used as a means of evaluating the economic value of environmental and public goods and this has become a valuable tool in guiding decision-making as regards public policies (Bance and Chassy, 2019). The contingent valuation method is also known as a stated preference method (Atinkut *et al.*, 2020). CVM is grounded in welfare economics, which assumes that individual preference can be used as a standard in estimating the value that individuals place on goods and services (Belzer and Theroux, 2019). The contingent valuation methods started gaining popularity after the studies of Ciriacy-Wantrup (1947) who in his study recommended that an important way of valuing non-market goods was to directly ask how much consumers were willing to pay for that good. Davis (1963) applied it to recreation planning to see how much people are willing to pay for recreation to see if it is wise to invest in it. Since the invention of this technique, a large literature of studies has used this approach to evaluate the benefit of non-market goods and to support policy decisions towards the proper management of environmental resources.

CVM uses hypothetical scenarios where respondents are allowed to express their willingness to pay for a public good (Bance and Chassy, 2019). In the case of this study, a gas tax will be used as the payment vehicle for the development of renewable energy sources. This study made use of a hypothetical scenario without any context, then, another hypothetical scenario regarding the Russian-Ukraine war while the third scenario referred to natural disasters as a reason to pay for the gas tax. However, the probability of paying a gas tax under the three scenarios could

vary significantly because of the context in which they are presented. These can therefore be represented as:

$$P(Y=1) = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \varepsilon$$

Where:

Y = Probability of supporting a gas tax

$\beta_0$  represents the intercept which expresses the mean willingness to pay when all the scenarios are at their base level.

$\beta_1$ ,  $\beta_2$ , and  $\beta_3$  represent the coefficients associated with the different scenarios presented to the respondents. Each coefficient shows the extent to which each of the scenarios presented to the respondents affects the Probability of supporting a gasoline tax.

Therefore, CVM is derived from the utility maximization concept (Cook *et al.*, 2020) where it is believed that the respondents will allocate their resources towards paying for the gas tax if they perceive that the gas tax will maximize their overall well-being. However, this might be contingent on the scenario in which it is presented to them.

The CVM has open-ended and close-bounded formats. In the open-ended format, the respondents are allowed to state their maximum willingness to pay. The close-bounded format restricts the respondent's response to a set of values provided in the survey (Bishop and Hberlein, 2019). In this study, the close bounded format was used - respondents were presented with a single level of gas tax and asked to answer yes or no, regarding their support for the tax.

In addition, there is also the single bounded format where respondents are presented with only one scenario of the question in the CVM. For the double-bounded format, the respondents

are presented with two scenarios; one at a higher level and the other at a lower level, and for each scenario, their willingness to pay is accessed (Wegedia *et al.*, 2020; Hasan *et al.*, 2020). This study made use of the single-bounded format to evaluate the probability of paying the gasoline tax by the respondent. Using the approach, respondents are given a single scenario, and their WTP is estimated based on that scenario. Their response is typically binary, with options like "yes" or "no". As such, the approach is straightforward to administer. In addition, the study is interested in the WTP of the respondent based on the defined scenario, making the single bounded format a better fit.

Respondents were asked whether they would be willing to pay a gas tax to support renewable energy development in the US. The level of the tax was randomly drawn from \$0.05 - \$0.45, in increments of \$0.10. As a single-bound referendum survey, the respondents' minimum willingness to pay for the non-marketable good will be captured.

From the perspective of utility maximization, individuals will allocate their resources (money) in a way that maximizes their overall well-being (Cook *et al.*, 2020). By assessing people's willingness to pay for non-market goods through CVM, we can estimate the utility that individuals derive from these goods, and therefore, how much they value them (Orlowki and Wicker, 2019). As such, the WTP can take on only two values which represent a choice between alternatives and these choices are dependent on various conditions as shown in the following equation where the indirect utility of the respondent ( $V$ ) is derived from the income ( $Y$ ) and other conditioning factors ( $S$ ) such as the socio-economic characteristics, price among others (Nguyen *et al.*, 2021).

$V(Y; S)$  Therefore, from the CVM, each of the respondents is faced with the situation of supporting a gas tax with a specified amount (A) within the constraint of their income and with the belief that it would help develop renewable energy sources. It is believed that the respondents will accept the gas tax under the condition that the gas tax will increase their utility level as shown in the following equation. Where the respondents will accept a gas tax (A) if it maximizes their utility and reject it if otherwise (Hanemann, 1984; Lee and Han, 2002):

$$V(1, Y - A; S) + \epsilon_1 \geq V(0, Y; S) + \epsilon_0$$

$\epsilon_1$  and  $\epsilon_0$  are the random variables in the question with zero means. As such, the utility difference between the present state of the respondent and the desired state which is the development of renewable energy through a gas tax is expressed as:

$$\Delta V = V(1, Y - A; S) - V(0, Y; S) + (\epsilon_1 - \epsilon_0)$$

An approximation of utility difference was used for the empirical analysis as shown by Hanemann (1984), who assumed the linearity of the individual's utility function and thus the linearity of the WTP function which is represented as:

$$WTP(X, U_j) = \alpha + X\beta + U_j$$

Where  $U_j = \epsilon_1 - \epsilon_0$  and j can be 0 or 1

X in the equation represents income and other socio-economic characteristics of the respondents.

The DC format of CVM is a binary choice dependent variable, which can be analyzed using a qualitative choice econometric model which will be used to estimate the mean willingness to pay. The probit and logit models are the two common models that are used; however, the probit model will be used in this study for estimation.

In conclusion, the results of CVM studies can support decisions on public policy by quantifying the value of non-market goods or services and can be used to allocate resources, design environmental regulations, establish pricing for public goods, or assess the benefits of social programs.

### **3.2. Description of the Survey**

The survey data used for this study was done in March 2022 by a survey company, and the questionnaire was administered online. The survey sampled respondents of diverse demography with the minimum age for participation being 18 years. In the design, respondents were given different categories of gender such as male, female, binary, others, and those who prefer not to say. Five possible age groups were created which include 18-24, 25-34, 35-44, 45-54, and 55 while race was categorized into four groups made up of white, black, Asian, and natives. The income category had six groups of \$0-\$25k, \$25k-\$50k, \$50k-\$75k, \$75k-\$100k, \$100k-\$150k, and \$150k+ and the educational level was divided into five groups made up of less than high school, high school, some college, bachelor's degree, and master's or higher. Other important information obtained from the respondents includes the price of gas, their monthly expenditure on gasoline, perception of risk, and global warming among other important information. Specifically, the study made use of three hypothetical scenarios with each one presenting a scenario of paying a gasoline tax at the current gas price and a lower price of \$2.50. The gas tax presented to the respondent ranged between \$0.05 - \$0.45.

### **3.3 Description of Data**

For this study, information was obtained from 608 respondents, hereafter referred to as the original dataset. However, to further improve the data, data cleaning was done to remove illogical

responses from the data. The illogical responses were made up of respondents who supported the gas tax at the current gas price but did not support it at \$2.50, which was a lower price. This response was illogical because it was assumed that a respondent willing to support a gas tax at a high price should also be willing to support it at a lower gasoline price since they will have more disposable income when the price of gasoline drops. After the data cleaning, 567 logical responses were remaining. These 567 responses were referred to as the cleaned dataset in the study. One of the major reasons for this is to compare both datasets to see the effect of illogical responses on the models used.

Additionally, the description of the variables used in the analysis is shown in Table 3.1 to give context to some of the analyses done in the study.

**Table 3.1. Description of Variables****Description of Variables Used in the Analysis**

<b>Variable</b>	<b>Description</b>
Bid	A randomly assigned gas tax bid ranged from \$0.05-\$0.45
Age	calculated 2022-yearborn
Male	1=male, else zero
Education	Year of Schooling
Location	1= Urban 0 = non-urban. Nonurban residents represent respondents from both rural and suburban regions
Income	\$0-25k, 2=25k-50k, 3=50k-75k, 4=75k-100k, 5=100k-150k, 6=150+k
Gas Price	\$ per gallon
Global Warming Harm	0=Don't know, 1=Not at all, 2=Only a little, 3=A moderate amount, 4=A great deal
Fossiltax.	0=Strongly against, 1=Somewhat against, 2=Neither in favor or against, 3=Somewhat in favor, 4=Strongly in favor
Natgas	Home heating fuel: Natgas = 1 other =0
Household Size	Number of People Living in a Household
Democrat	1 = Democrat else=0
General Risk attitude	Continuous. 1 denotes completely unwilling and 10 denotes completely willing
Risk attitude on Health	Continuous. 1 denotes completely unwilling and 10 denotes completely willing
Bidgas	Bid/gasoline price
Proportion of income on gasoline	$(12 * \text{Monthly Gas Expenditure}) / \text{Income Mid}$

### 3.4 Econometric model

#### 3.4.1 Z-Test

The Z-test statistics follow the standard normal distribution which is assumed to have a mean of zero and a standard deviation of 1. To know if the gas price has an impact on people's probability of supporting a gas tax, the Z test was used to test the null hypothesis that the proportion of yes votes is equal for current gas price and future gas price using the two data sets (Original dataset and the Cleaned dataset). The null hypothesis ( $H_0$ ) states that the proportion of people voting yes at the present price and at \$2.50 is the same i.e.  $H_0: P_1 = P_2$  while ( $H_a$ ) which is the alternative states that they are different i.e.  $H_a: P_1 \neq P_2$

First, we would need to compute the difference between our sample proportions as:

$$dif = P_1 - P_2$$

Where  $P_1$  and  $P_2$  are the proportion of success for the sample at the current gasoline price and \$2.50 respectively. This can be estimated as:

$$P_1 = \frac{X_1}{n_1}; P_2 = \frac{X_2}{n_2}$$

Where  $X_1$  = the number of consumers willing to pay the gas tax at the current gas price

$n_1$  = the sample size of the consumers at the current gas price

$X_2$  = the number of consumers willing to pay the gas tax at \$2.50

$n_2$  = the sample size of the consumers at \$2.50

Then, the null hypothesis claims that both subpopulations have the same proportion of success.

We would estimate this as:

$$P = \frac{P_1 * n_1 + P_2 * n_2}{n_1 + n_2}$$

Where P is the pooled sample proportion

Next, the standard error (SE) for the difference under H<sub>0</sub> is:

$$SE = \sqrt{p * (1 - p) * \left(\frac{1}{n_1} + \frac{1}{n_2}\right)}$$

We can now compute our test statistics Z as:

$$Z = \frac{dif}{SE}$$

Where Z is a random variable that follows a standard normal distribution with a mean of 0 and a standard deviation of 1 {Z~N (0, 1)}.

### 3.4.2 Probit Model

The primary research interest is to see whether respondents will support a gasoline tax at the current price and future price. The probit model is then employed to estimate the coefficient of the selected explanatory variables on the dependent variable (current price and price at \$2.50)

The standard probit model assumes an underlying WTP function:

$$WTP_i = X_i\beta + \mu_i$$

Where X<sub>i</sub> is a set of explanatory variables, β is the estimated coefficients, and μ is the error term.

However, the WTP function cannot be observed directly, respondents' votes on the WTP referendum are used to develop an indicator Y<sub>i</sub>, where Y<sub>i</sub>=1 means that respondents are willing to pay, and Y<sub>i</sub>=0 denotes that they are not willing to pay. In other terms:

$$Y_i = 1 \text{ if } WTP_i \geq PRICE_i, Y_i = 0 \text{ otherwise}$$

The probit model is then adopted to estimate the probability of voting for the proposed gas tax in hypothetical scenarios.

$$(Y = 1|X_n) = \phi(\beta_0 + \beta_1Ukr + \beta_2Natdis + \beta_3propofincongas + \beta_4Bidgas + \beta_5Hhsize + \beta_6democrat + \beta_7Riskhealth + \beta_8GWharm + \beta_9Urban + \beta_{10}Natgas + \mu_i)$$

Where  $\phi$  is the cumulative normal distribution. Proportion of income on gas, Bid, Household size, democrat, risk attitude with personal health, GWharm, Urban, and are the explanatory variables included. Additionally, treatment Ukr and Natdis are dummy variables included in the probit model. These variables were used to assess how the perceived information about Russia's invasion of Ukraine and the damage caused by natural disasters in the U.S. influenced their willingness to pay. Additionally,  $\beta$  in the equation is the vector of coefficients to be estimated.

### 3.4.3 AIC/BIC Test

To find the most suitable regression model for both datasets we are using, the Akaike Information Criterion and Bayesian Information Criterion are tested. The AIC and BIC statistic is calculated for logistic regression as follows:

$$AIC = -\frac{2}{N} * LL + 2 * k/N$$

$$BIC = -2 * LL + \log(N) * k$$

Where  $\log ()$  has the base-e called the natural logarithm, LL is the log-likelihood of the model, N is the number of examples in the training dataset, and k is the number of parameters in the model. The model with the lowest AIC/BIC score is selected as the most suitable one.

### 3.4.4 Pearson Correlation Coefficient

To measure the extent to which certain independent variables are correlated, the Pearson test for correlation coefficient was calculated using the formula below:

$$r = \frac{\sum(X - \bar{X})(Y - \bar{Y})}{\sqrt{\sum(X - \bar{X})^2 \sum(Y - \bar{Y})^2}}$$

Where  $r$  is the Pearson correlation coefficient,  $X$  and  $Y$  are the sample point index,  $\bar{X}$  and  $\bar{Y}$  are the means of the sample point  $X$  and  $Y$  respectively. This formula results in a value between -1 and 1 where 1 means a perfect positive correlation, -1 means a perfect negative correlation and 0 means no linear correlation.

## CHAPTER 4

### RESULTS AND ANALYSIS

#### 4.1 Survey and Sampling

The survey aims to assess the probability of supporting a gas tax to develop renewable energy sources in the United States. The data from this study was obtained from a nationwide survey of 608 American adults between the ages of 18 and above on their willingness to pay gas tax using a contingent valuation method. The survey catered to the different demographics of the population such as age, sex, race, income, and education among other demographic variables. This was to ensure that the findings from the study account for all the various characteristics of the population and can be generalized to the population. As such, the study ensured that a sizeable proportion of the different demographic groups of the population was involved in the study.

In the design of the study, various categorizations were made to ensure ease of analysis and to ensure that those groups had representation. For instance, sex was categorized into male and female while age was divided into five groups of 18-24, 25-34, 35-44, 45-54, and 55+ with each group having a proportion of 17.4%, 19.4%, 18.9%, 9.0% and 35.2% respectively. The race categorization was done into five groups which include American Indian or Alaskan Native, Asian, Black, or African American, Native Hawaiian or Other Pacific Islander, and Whites with proportions of 3.0%, 6.7%, 14.5%, 0.9%, and 74.9% respectively. The income of the respondents was categorized into \$0-\$25k, \$25k-\$50k, \$50k-\$75k, \$75k-\$100k, \$100k-\$150k, and \$150k+ with the distribution of the population into the different income groups being 18.3%, 20.7%, 19.6%, 13.5%, 17.6%, and 10.4%, respectively, in the dataset. Education level was divided into five divisions: less than high school, high school, some college, bachelor's degree, and master's or higher, with proportions of 9%, 28%, 25%, 24%, and 14%, while political category was divided

into democrat (38.5%), Republican (31.4%), Independent (24.8%), Libertarian (1.6%) and Others (3.6%).

Additionally, responses were elicited from the respondents about their perception of different issues such as global warming harm, attitudes toward a fossil fuel tax, and a variety of risk attitudes. The survey was implemented through a survey company with expertise in recruiting participants for studies. However, this does not eliminate the risk of bias in the sampling and the possibility of giving illogical responses by the respondents.

## **4.2 Estimation Results**

### **4.2.1 Estimation of the Original Dataset**

#### **4.2.1.1 Summary Statistics of the Original Dataset**

The summary statistics of the variables used in the study are shown in Table 4.1 and this shows that the average tax bid given to the respondent varies from \$0.05 to 0.45\$ with the average of the bid being 0.25\$. The mean age of the respondents was 43.87 while the average year of schooling by the respondents is 14.56 years. The average income of the respondents was \$74,218.75 while the average expenses on gas and gas prices at the time of the survey were \$189.71 and \$5.07. The average amount of gasoline tax to be paid monthly by the respondents was \$5.00 at the current gas price and \$6.87 when the gasoline price was reduced to \$2.50/gallon.

**Table 4.1: Summary Statistics of Variables in the Original Dataset**

Variable	N	Mean	SD	Max	Min
Bid	608	0.25	0.14	0.45	0.05
Age	608	43.87	17.31	84	18
Male	608	0.47	0.50	1	0
Education	608	14.56	2.39	20	10
Income	608	74,218.75	50,358.13	175,000	12,500
White	608	0.70	0.46	1	0
Democrat	608	0.39	0.49	1	0
Gas Price	608	5.07	1.27	10	0
Global Warming Harm	608	2.63	1.09	4	0
Fossil tax.	608	2.30	1.28	4	0
General Risk attitude	608	5.65	2.23	10	1
Risk attitude on Health	608	5.24	2.60	10	1
Bidgas	608	0.06	0.18	4.50	0.01
GasExp	608	189.71	119.15	500	0
GasTax	608	9.84	9.17	61.59	0
Urban	608	0.34	0.47	1	0
Rural	608	0.21	0.41	1	0
Suburban	608	0.45	0.50	1	0

The study is made up of two treatment groups: The Ukraine war group, the Natural disaster group, and the control group. Out of the 608 responses (Table 4.2), 204 respondents were in the Ukraine war group, 201 respondents were in the natural disaster group, and 203 respondents were in the control group. The distribution of the respondents based on how they voted for the gas tax

(Table 4.3) showed that more of the respondents voted yes for the gasoline tax at \$2.50 which is a lower price. This is quite reasonable as it is expected that more people will be willing to pay the gas tax if the price is reduced and vice versa showing an inverse relationship between the gasoline price and the gasoline tax. However, the number of respondents who are not willing to pay for the gasoline tax may be attributed to the fact that their willingness to pay is still below the bid offered to them or the fact they are not interested in paying for the gasoline tax, bearing in mind the need to develop renewable energy sources.

**Table 4.2: Distribution of Treatment Group in the Original Dataset**

Treatment Group	Freq.	Percentage
Control	203	33.39
Disaster	201	33.06
Ukraine	204	33.55
	608	100.0

**Table 4.3: Distribution of the Respondent’s Willingness to pay using the Original Dataset**

Treatment Group	Current Price		Price \$2.5	
	Yes	No	Yes	No
Control	93	110	140	63
Disaster	96	105	145	56
Ukraine	104	100	142	62
Total	293	315	427	181

**4.2.1.2 Z-test Analysis using the original dataset.**

A two-sample Z-test was used to test the null hypothesis that the proportion of people voting yes is equal between the current gasoline price situation and the future gas price at \$2.50. This was done with the original dataset which had all the responses and analyzed using Stata software. The dataset that was analyzed had 608 observations and after analysis, the result was presented in Table 4.4. From the result, the mean of the variable for the current price was 0.4819, and its standard

error was estimated to be 0.0406. Similarly, the mean for the willingness to pay of the respondent using the future gas price referendum was 0.7023, and its standard error of 0.0406. However, the difference in mean between the current price and the future price was -0.2204 while the test statistic (z) is estimated to be -3.8427 with a p-value of 0.0001. This suggests that there is a significant difference between the mean of the current gas price and that of the future gas price. Therefore, the null hypothesis is rejected that the proportion of people voting yes under both scenarios is the same.

**Table 4.4: Z test Analysis Result Using the Original Dataset.**

Variable	Observation	Mean	Std. error	Std. Dev	Z	P value
Price_~t	608	0.4819	0.0406	1		
Pric~250	608	0.7023	0.0406	1	-3.8427	0.0001
Diff		-0.2204	0.0574			

#### **4.2.1.3. Probit Estimation of the probability of supporting a gas tax as a function of Proportion of income spent on Gas and Problem framing (Original Dataset)**

Table 4.5 presents results from six distinct models: CGP (1), CGP (2), and CGP (3) analyze the referendum responses under the current gasoline price, while Gp\_25 (1), Gp\_25 (2), and Gp\_25 (3) analyze the referendum responses if the gasoline price were \$2.50. The independent variables in both CGP (1) and Gp\_25 (1) did not include the information treatment variables (Ukraine and Disaster) and the tax level (Bidgas), the CGP (2) and Gp\_25 (2) model had the inclusion of the information treatment variables but without the tax level, while the CGP (3) and Gp\_25 (3) models had the inclusion of both the tax level and the information treatment.

The selection of models CGP (1) and Gp\_25(1) from the probit estimations presented in Table 4.5 was guided by their AIC and BIC values. The model with lower AIC or BIC is preferred, as a smaller value suggests a favorable balance between goodness of fit and model simplicity.

The coefficient of natural disaster and the Ukraine war was not significant in any of the models, which suggests the two contexts did not significantly affect the decision of the respondents to support a gas tax. However, the proportion of income spent on gas was negative and significant in the current gas price model ( $\alpha = 0.05$ ) and the \$2.50 models ( $\alpha = 0.10$ ). This implies that as the proportion of the income spent on the purchase of gas increases, the likelihood of supporting a gas tax fall. In other words, people are less likely to support a gas tax when gasoline expenditures are a more prominent share of their budget.

The household size variable was positive and significant at the current gas price ( $\alpha = 0.05$ ) and the \$2.50 price models ( $\alpha = 0.01$ ). This shows that the probability of supporting a gas tax increases as the household size increases. This could imply that larger households might be more concerned about the environmental impact of fossil fuels and climate change. They may see a gas tax that funds renewable energy development as an investment in a cleaner and safer future for their children.

The political orientation variable was also significant in determining the probability of supporting a gas tax at the current price ( $\alpha = 0.05$ ), implying that Democrats have a higher probability of supporting the gas tax at the current gas price when compared to other political orientations. This is consistent with the fact that Democrats have been more likely to advocate for regulatory and tax-based approaches to address environmental issues. However, the variable was not significant at the \$2.50 price model, implying no significant difference in the support for a gas

tax among the different political affiliations. With the decrease in gas price, respondents of all political persuasions increased their support for a gas tax, but the non-Democrats willingness to support the gas tax increased more than the Democrats. This effectively diminished the disparity in the support for gas tax between Democrats and non-democrats compared to the current price level.

The perception of global warming harm also positively and significantly affected the probability of supporting a gas tax at the current price ( $\alpha = 0.01$ ) and \$2.50 ( $\alpha = 0.01$ ). This indicates that people who believe global warming will cause significant harm are prepared to bear the additional costs of a gas tax aimed at combating global warming.

Like the support by self-identifying democrats, those more willing to take health-related risks are also more likely to support the gas tax at the current price ( $\alpha = 0.01$ ). This is counterintuitive, as we would expect less risk-averse people to be less likely to support a tax to reduce future risks. Among the various risk factors considered are car risk, financial risk, family risk, sports risk, and job-related risk. The health-related risk was chosen for its pertinence to the study. Subsequent correlation analysis revealed a high degree of correlation among all risk variables (Table 4.6). Nonetheless, when incorporated individually into the model, the inclusion of any risk factor did not alter the statistical significance of other variables.

The location of the respondents significantly affected their probability of supporting gas tax. At the current gas price, the urban residents were more willing to support a gas tax ( $\alpha = 0.05$ ). This could be a result of urban populations having a more progressive attitude toward environmental conservation and being willing to invest in sustainable practices. Furthermore, descriptive statistics (Table 4.7) were carried out to explore the rationale behind the higher

inclination of urban residents to support a gas tax. It was observed that despite facing higher gas prices at an average of \$5.26 per gallon in comparison to their nonurban counterparts at \$4.98 per gallon. The people in nonurban areas allocate a greater proportion of their income to gasoline, averaging 5.2%, as opposed to urban residents at 4.82%. This further explains that as the proportion of income spent on gas increases, the likelihood of supporting a gas tax reduces. Hence, those in nonurban areas are less willing to support a gas tax. In contrast, at the \$2.50 gasoline price model their location has no significant effect on their probability of supporting a gas tax. This implies that there is no difference between the probability of supporting a gas tax by the rural and urban residents. Just as we saw in the Democrats, the proportion of people living in rural areas that are willing to support the gas tax increased more than those in the urban area, thereby nullifying the significance of urban from the current gas price.

Natural gas was significant ( $\alpha = 0.05$ ) and negative at the current gas price, which could imply that people who have the option of natural gas based on infrastructure and location are less likely to support the gas tax. The natural gas variable seems to be standing in as a proxy for something else such as location which we do not have information on.

The selection of models CGP (1) and Gp\_25(1) from the probit estimations presented in Table 4.5 was guided by their AIC and BIC values. The model with lower AIC or BIC is preferred, as a smaller value suggests a favorable balance between goodness of fit and model simplicity.

Finally, the bidgas variable, although not included in our selected models (CGP 1 and Gp\_25 1) was not significant in the CGP (3) and Gp\_25 (3) models. This came as a surprise as we expect that this should have a significant impact on their decision-making to either support a gasoline tax or not. Leaving this variable out will be an omitted variable. However, this doesn't

matter as it is not very correlated with other variables in the regression as shown in the correlation table (Appendix B)

**Table 4.5: Probit Estimation of the Original Dataset**

Variable	CGP (1)	CGP (2)	CGP (3)	Gp_25 (1)	Gp_25 (2)	Gp_25 (3)
<b>Ukr_c</b>		0.1949 (0.1329)	0.1886 (0.1332)		0.0192 (0.1347)	0.0139 (0.1348)
<b>Natdis</b>		0.0205 (0.1332)	0.0225 (0.1333)		0.0568 (0.1372)	0.0566 (0.1372)
<b>Propofincongas</b>	-2.3727** (0.9528)	-2.3554** (0.9536)	-2.4573** (0.9663)	-2.8718* (1.4992)	-2.8428* (1.5004)	-3.0059** (1.5125)
<b>Bidgas</b>			2.3011 (1.6657)			0.4277 (0.7897)
<b>Hhsize</b>	0.0829** (0.0371)	0.0845** (0.0372)	0.0834** (0.0373)	0.1259*** (0.0399)	0.1253*** (0.0399)	0.1246*** (0.0399)
<b>Democrat</b>	0.2455** (0.1137)	0.2420** (0.1140)	0.2486** (0.1142)	0.1865 (0.1201)	0.1898 (0.1204)	0.1915 (0.1204)
<b>Riskhealth</b>	0.0719*** (0.0221)	0.0726*** (0.0221)	0.0729*** (0.0221)	-0.0037 (0.0229)	-0.0035 (0.0229)	-0.0037 (0.0229)
<b>GWharm</b>	0.3413*** (0.0555)	0.3438*** (0.0557)	0.3404*** (0.0558)	0.2915*** (0.0534)	0.2901*** (0.0535)	0.2886*** (0.0536)
<b>Urban</b>	0.2772** (0.1182)	0.2871** (0.1185)	0.3089** (0.1128)	-0.2056* (0.1228)	-0.2046* (0.1229)	-0.1987 (0.1232)
<b>Natgas</b>	-0.2652** (0.1122)	-0.2751** (0.1125)	-0.2756** (0.1128)	-0.0361 (0.1148)	-0.0355 (0.1149)	-0.0340 (0.1149)
<b>AIC</b>	741.76	743.17	742.26	698.12	701.95	703.19
<b>BIC</b>	777.01	787.24	790.73	733.38	746.01	751.67

\*Statistically significant at 90% level.

\*\*Statistically significant at 95% level.

\*\*\*Statistically significant at 99% level.

#### 4.2.1.4 Correlation Coefficient of the Risk Variables from the Original Dataset

The correlation analysis of various risk variables from Table 4.6 revealed a consistent pattern of positive correlation, suggesting that individuals who are willing to take risks in one area are also willing to take risks in other areas. Most notably, there is a strong correlation between risk family and risk financial as well as between risk family and risk car (above 0.7) which suggests that there is an intertwined relationship where issues that contribute to taking family risks are closely related to those in financial and automotive contexts.

Also, the correlation between risk health with risk jobs and risk sports (below 0.7) although moderately strong, points to a tendency for personal health considerations to be reflected in their risky nature towards their jobs and recreational activities.

**Table 4.6: Risk Variables Correlation Coefficient of the Original Dataset**

	<b>Risk Health</b>	<b>Risk Family</b>	<b>Risk Finance</b>	<b>Risk Car</b>	<b>Risk Job</b>	<b>Risk Sports</b>
<b>Risk Health</b>	1.0000					
<b>Risk Family</b>	0.7716	1.0000				
<b>Risk Finance</b>	0.7360	0.7343	1.0000			
<b>Risk Car</b>	0.6708	0.7262	0.6898	1.0000		
<b>Risk Job</b>	0.6431	0.6553	0.7141	0.6847	1.0000	
<b>Risk Sports</b>	0.5741	0.5128	0.6078	0.5836	0.6163	1.0000

**Table 4.7: Descriptive Statistics of The Regions based On the Proportion of Income Spent on Gas and Gas Prices (Original Dataset)**

Variable	Region	Observations	Mean	S. D	Min	Max
Prop of inc	Nonurban	403	0.0522399	0.0628911	0	0.46
	Urban	203	0.0481858	0.0590773	0	0.38
Gas Price	Nonurban	403	4.981538	1.118838	0.1	10
	Urban	203	5.258537	1.503143	0	10

#### **4.2.1.5 Multicollinearity Diagnostics for the Different Models using VIF and Condition Number (Original Dataset)**

The correlation analysis was conducted to assess multicollinearity among variables (Appendix A) revealed correlation coefficients below 0.70 for all variables, indicating minimal collinearity. Further examination using the variance Inflation Factor (VIF) and tolerance levels (Table 4.8) found all variables with VIF values under 5 and tolerance levels nearing 1, aligning with acceptable thresholds that suggest no significant multicollinearity concerns. Despite these findings, the condition number criteria placed CGP (2), CGP (3), Gp\_25 (2), and Gp\_25 (3) models in the moderate multicollinearity range (condition number between 10 and 30) (Belsey 1991) while the preferred models (CGP 1 and Gp\_25 1) had condition numbers less than 10, suggesting a low level of multicollinearity.

**Table 4.8: Multicollinearity Diagnostics for the models (Original Dataset)**

	CGP (1)		CGP (2)		CGP (3)		GP_25 (1)		GP_25 (2)		GP_25 (3)	
	VIF	TL	VIF	TL	VIF	TL	VIF	TL	VIF	TL	VIF	TL
<b>Ukr</b>			1.34	0.75	1.34	0.75			1.33	0.75	1.34	0.75
<b>Natdis</b>			1.34	0.75	1.34	0.75			1.34	0.75	1.34	0.75
<b>Propofincon gas</b>	1.01	0.99	1.02	0.99	1.02	0.98	1.02	0.98	1.04	0.96	1.04	0.96
<b>Bidgas</b>					1.01	0.99					1.03	0.98
<b>Hhsize</b>	1.04	0.96	1.04	0.96	1.04	0.96	1.04	0.96	1.04	0.96	1.04	0.96
<b>Democrat</b>	1.08	0.93	1.08	0.93	1.08	0.93	1.08	0.93	1.08	0.93	1.08	0.93
<b>Riskhealth</b>	1.14	0.88	1.14	0.88	1.14	0.88	1.14	0.88	1.14	0.88	1.14	0.88
<b>GWharm</b>	1.13	0.88	1.13	0.88	1.13	0.88	1.13	0.89	1.13	0.88	1.13	0.88
<b>Urban</b>	1.08	0.92	1.09	0.92	1.09	0.92	1.08	0.92	1.09	0.92	1.09	0.92
<b>Natgas</b>	1.01	0.99	1.01	0.99	1.01	0.99	1.01	0.99	1.01	0.99	1.01	0.99
<b>Mean VIF</b>	1.07		1.13		1.12		1.07		1.13		1.12	
<b>Condition Number</b>	9.44		10.5		10.6		9.42		10.5		10.59	

#### 4.2.1.7. Marginal Effect of the Selected Model CGP 1 without the Information Treatment and the Bid variables (Original Dataset)

An analysis of the average marginal effect (Table 4.9) examined how a one-unit change in the independent variables affects the likelihood of supporting a gas tax at the current price, with the outcome variable set to 1.

For a 1% increase in the proportion of income spent on gas, the probability of supporting a gas tax at the current price decreases by 0.8065 percentage points. A unit increase in the risk health score and household size increased the probability of supporting a gas tax by 0.0245 and 0.0282 percentage points respectively. Similarly, being a Democrat and living in an urban area also increases the likelihood of supporting a gas tax by 0.0835 and 0.0942 percentage points

respectively. A unit increase in the perceived harm of global warming also increases the probability of supporting a gas tax by 0.1160 percentage points. Lastly, A unit increase in the accessibility to natural gas decreases the probability of supporting a gas tax by 0.09 percentage points.

This illustrates that the proportion of income allocated to gas expenses plays a significant role in influencing individuals' decisions regarding the support for gas tax. The more substantial portion of their income that people spend on gas, the less likely they are to endorse a gas tax at the current price. Conversely, while the perceived health risks affect individuals' support for the gas tax, this impact is relatively modest.

Appendix K shows the marginal effect of all the variables including the information treatment variables (Ukraine and Natural disaster) and bidgas.

**Table 4.9: Marginal Effect of CGP 1 variables (Original Dataset)**

	<b>dy/dx</b>	<b>z</b>	<b>p value</b>
ProportionofincomeongasCP	-0.8065 (0.3190)	-2.53	0.011
hhsz	0.0282 (0.0125)	2.26	0.024
democrat	0.0835 (0.0382)	2.18	0.029
RiskHealth	0.0245 (0.0073)	3.35	0.001
GWharm	0.1160 (0.0171)	6.79	0.000
urban	0.0942 (0.0396)	2.38	0.017
natgas	-0.0901 (0.0376)	-2.40	0.017

## 4.2.2 Estimation of the Cleaned Dataset

### 4.2.2.1 Summary Statistics of the Cleaned Dataset

The result in Table 4.1.1 shows the mean, standard deviation, minimum, and maximum values of the variables that were used in the analysis after the data was cleaned and illogical responses removed. The average tax bid given to the respondent varies from \$0.05 to 0.45\$ with the average

of the bid being 0.25\$. The mean age of the respondents was 44.74 while the average year of schooling by the respondents is 14.56 years. The average income of the respondents was \$74,691.36 while the average expenses on gas and gas prices at the time of the survey were \$186.92 and \$5.09 respectively. The average amount of gasoline tax to be paid monthly by the respondents was \$4.40 at the current gas price and \$7.34 when the gasoline price was reduced to \$2.50.

The summary statistics were conducted on 41 illogical responses to determine if respondent's demographics influenced their contradictory view on gasoline tax. These individuals supported a gasoline tax at the current gas price but not at a reduced price of \$2.50 per gallon. As shown in Appendix M, their average gasoline expenditure was \$227.71, higher than \$186.92 observed in the cleaned dataset. Despite similar average incomes between both age groups, the expectation was that respondents would support the tax at a lower gas price, contrary to their actual decision. Therefore, these responses were deemed illogical.

**Table 4.1.1: Summary Statistics of Variables for the Cleaned Dataset**

Variable	N	Mean	SD	Max	Min
Bid	567	0.25	0.13	0.45	0.05
Age	567	44.74	17.34	84	18
Male	567	0.47	0.50	1	0
Education	567	14.56	2.38	20	10
Income	567	74,691.36	50,624.56	12,500	175,000
Gas Price	567	5.09	1.27	10	0
Global Warming Harm	567	2.63	1.107	4	0
Fossil tax.	567	2.29	1.31	4	0
General Risk attitude	567	5.63	2.29	10	1
Risk attitude on Health	567	5.18	2.65	10	1
Bidgas	567	0.06	0.19	4.50	0
GasExp	567	186.92	118.92	500	0
GasTax	567	9.61	9.10	61.59	0
Urban	567	0.33	0.47	1	0
Rural	567	0.21	0.40	1	0
Suburban	567	0.47	0.50	1	0

**4.2.2.2. Distribution of the Treatment Group Using the Cleaned Data**

After the data was cleaned, the distribution of the treatment groups is shown in Table 4.1.2. The control group made up 33.16% of the sample while the Natural disaster group made up 33.16% of the sample and the Ukraine was about 33.69% of the sample which shows an almost equal sample size for each of the treatment groups.

**Table 4.1.2: Distribution of Treatment Group from the Cleaned dataset**

<b>Treatment Group</b>	<b>Freq.</b>	<b>Percentage</b>
<b>Control</b>	188	33.16
<b>Disaster</b>	188	33.16
<b>Ukraine</b>	191	33.69
	567	100.0

**4.2.2.3. Distribution of the Respondents based on their Willingness to Pay using the Cleaned Dataset.**

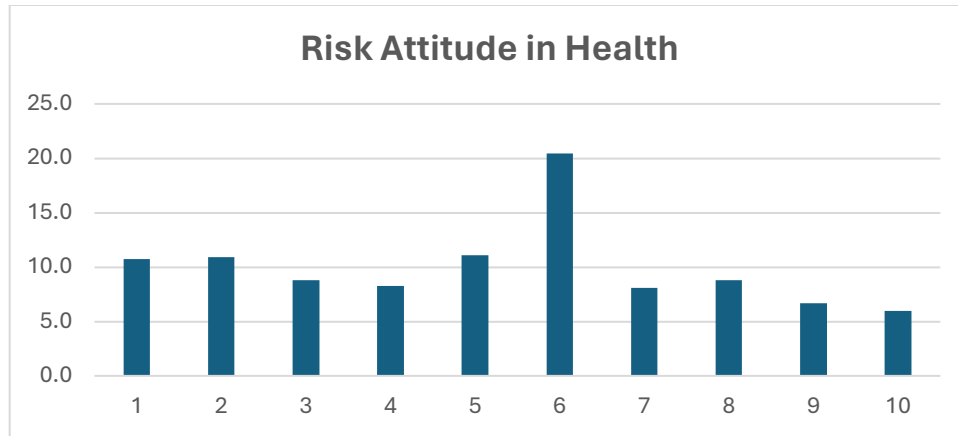
The contingent valuation method was used in estimating the WTP of the respondents for a gas tax for the development of renewable energy sources. The five bids presented to the respondents are \$0.05, \$0.15, \$0.25, \$0.35, and \$0.45 using a dichotomous choice question. In the study, the control group was given a random gas tax bid to support renewable energy without any context. In contrast, the Ukraine group was provided the context of the war in making decisions and the same for the natural disaster group who were given the task within the context of a natural disaster. Under the willingness to pay a general trend was observed across the different groups (Table 4.1.3). It was discovered that the number of respondents who said yes increased when the price was moved from the current price to \$2.50. From the control group, out of 188 respondents 78 gave a yes response at the current price and this increased to 140 when the price changed to \$2.50. Also, for the natural disaster group, 83 respondents out of 188 responded yes at the present price while it increased to 145 when the price changed to \$2.50. Likewise, for the Ukraine group, 91 out of 191 respondents gave a yes response for the current price bid while this increased to 142 at \$2.50. This shows a common trend that respondents will be willing to vote yes at a reduced price.

**Table 4.1.3: Distribution of the Respondents based on their Willingness to Pay (Cleaned dataset)**

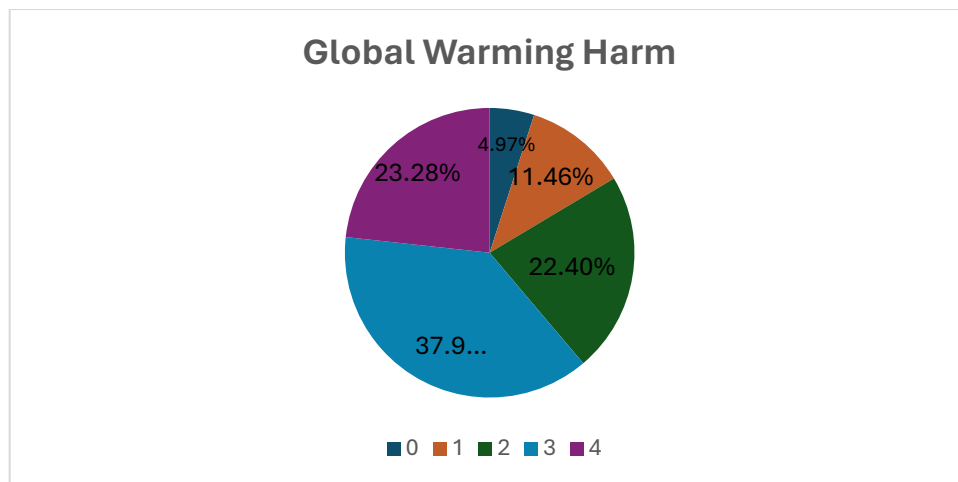
Treatment Group	Current Price		Price \$2.5	
	Yes	No	Yes	No
<b>Control</b>	75	113	136	52
<b>Disaster</b>	76	112	137	51
<b>Ukraine</b>	88	103	137	54
<b>Total</b>	239	328	410	157

#### **4.2.2.4. Distribution of the Respondents (Cleaned Dataset)**

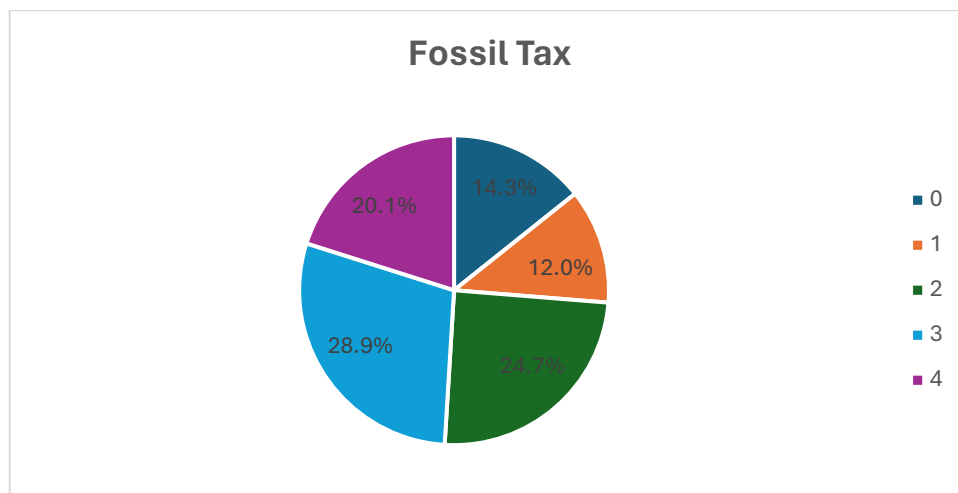
There is a moderate level of risk towards health with over 30% of respondents at levels 5 and 6 as shown in Figure 8. A mean of 5.18 shows that respondents are neither risk-averse nor risk-seeking. Figure 9 shows the distribution of respondents based on their concern for global warming harm. Most of the respondents (over 60%) believe global warming harm is at least a moderate concern, 23.28% view it as a great concern while a small percentage (4.97%) does not see it as a concern at all. Figure 10 indicates a polarized distribution with a considerable proportion of the respondents expressing strong feelings, either in favor (strongly or somewhat) or against (strongly or somewhat) a fossil tax. The largest single group is those who are strongly in favor, suggesting a substantial base of support for the policy among the respondents. However, when combining the categories of opposition (strongly or somewhat against), they make up about 34.4%, which indicates a sizeable opposition as well. The neutral respondents are the smallest group. While there is more support than opposition, the support of fossil tax is likely divisive with strong opinions on both sides.



**Figure 8. Distribution of the Respondents based on their Risk Attitude to Health**



**Figure 9. Distribution of the Respondents based on their Concern for Global Warming Harm**



**Figure 10. Distribution of the Respondents based on their Support for Fossil Tax**

#### 4.2.2.5. Z-test estimation of the Cleaned Data set

A Z test was carried out to test the hypothesis that the proportion of people willing to vote yes was equal for the current gas price and the future gas price using the Z test. From the result in Table 4.1.4, the willingness to pay for a gas tax under the current price has a mean of 0.4444 and a standard error value of 0.0420 while the WTP for a gas tax at \$2.50 has a mean value of 0.7531 and a standard error of 0.0420. The difference in mean between the WTP under the current price and at \$2.50 was -0.3086. This means that more people were willing to more at the lower price of \$2.50. The Z test statistic was -5.1967 which indicates that there is a significant difference between the proportion of people willing to vote for a tax under the current gas price and at \$2.50. This means that the null hypothesis that the proportion of people voting yes is equal between the current gas price situation and the future gas price situation will be rejected. The result points to the fact that the yes responses are higher in the future price (\$2.50) than the current price.

**Table 4.1.4: Z test Analysis result using the Cleaned Dataset**

Variable	Observation	Mean	Std error	Std Dev	Z	P Value
Price_~t	567	0.4444	0.0419	1		
Pric~250	567	0.7531	0.0419	1	-5.1967	0.0000
Diff		-0.3086	0.0593			

#### 4.2.2.6. Probit Estimation of Willingness to pay as a function of Proportion of income spent on Gas and Problem framing (Cleaned Dataset)

Table 4.1.5 presents results from six distinct models: CGP (1), CGP (2), and CGP (3) analyze the referendum responses under the current gasoline price, while Gp\_25 (1), Gp\_25 (2), and Gp\_25 (3) analyze the referendum responses if the gasoline price were \$2.50. The independent variables in both CGP (1) and Gp\_25 (1) did not include the information treatment variables (Ukraine and

Disaster) and the tax level (Bidgas), the CGP (2) and Gp\_25 (2) model had the inclusion of the information treatment variables but without the tax level, while the CGP (3) and Gp\_25 (3) models had the inclusion of both the tax level and the information treatment.

The coefficient of natural disaster and the Ukraine war was not significant in any of the models, which suggests the two contexts did not significantly affect the decision of the respondents to support a gas tax. However, the proportion of income spent on gas was negative and significant in the current gas price model ( $\alpha = 0.01$ ) and the \$2.50 models ( $\alpha = 0.10$ ). This implies that as the proportion of the income spent on the purchase of gas increases, the likelihood of supporting a gas tax fall. In other words, people are less likely to support a gas tax when gasoline expenditures are a more prominent share of their budget.

The household size variable was positive and significant at the current gas price ( $\alpha = 0.05$ ) and the \$2.50 price models ( $\alpha = 0.01$ ). This shows that the probability of supporting a gas tax increases as the household size increases. This could imply that larger households might be more concerned about the environmental impact of fossil fuels and climate change. They may see a gas tax that funds renewable energy development as an investment in a cleaner and safer future for their children.

The political orientation variable was also positive and significant in determining the probability of supporting a gas tax at the current price ( $\alpha = 0.05$ ) and the \$2.50 models ( $\alpha = 0.05$ ), implying that Democrats have a higher probability of supporting the gasoline tax. This is consistent with the fact that Democrats have been more likely to advocate for regulatory and tax-based approaches to address environmental issues.

The perception of global warming harm also positively and significantly affected the probability of supporting a gas tax at the current price ( $\alpha = 0.01$ ) and \$2.50 ( $\alpha = 0.01$ ). This indicates that people who believe global warming will cause significant harm are prepared to bear the additional costs of a gas tax aimed at combating global warming.

Those more willing to take health-related risks are also more likely to support the gas tax at the current price ( $\alpha = 0.01$ ). This is counterintuitive, as we would expect less risk-averse people to be less likely to support a tax to reduce future risks. Among the various risk factors considered are car risk, financial risk, family risk, sports risk, and job-related risk. The health-related risk was chosen for its pertinence to the study. Subsequent correlation analysis revealed a high degree of correlation among all risk variables (Table 4.1.6). Nonetheless, when incorporated individually into the model, the inclusion of any risk factor did not alter the statistical significance of other variables.

The location of the respondents significantly affected their probability of supporting gasoline tax. At the current gas price, the urban residents were more willing to support a gas tax ( $\alpha = 0.10$ ). This could be a result of urban populations having a more progressive attitude toward environmental conservation and being willing to invest in sustainable practices. Furthermore, descriptive statistics (Table 4.1.7) were carried out to explore the rationale behind the higher inclination of urban residents to support a gas tax. It was observed that despite facing higher gas prices at an average of \$5.26 per gallon in comparison to their nonurban counterparts at \$5.0 per gallon. The people in nonurban areas allocate a greater proportion of their income to gasoline, averaging 5.15%, as opposed to urban residents at 4.7%. This further explains that as the proportion of income spent on gas increases, the likelihood of supporting a gas tax reduces. Hence, those in nonurban areas are less willing to support a gas tax. In contrast, at the \$2.50 gasoline price

model their location has no significant effect on their probability of supporting a gas tax. This implies that there is no difference between the probability of supporting a gas tax by the urban and nonurban residents. The proportion of people living in nonurban areas that are willing to support the gas tax increased more than those in the urban area, thereby nullifying the significance of urban from the current gas price.

Natural gas was significant ( $\alpha = 0.05$ ) and negative at the current gas price, which could imply that people who have the option of natural gas based on infrastructure and location are less likely to support the gas tax. The natural gas variable seems to be standing in as a proxy for something else such as location which we do not have information on.

The selection of models CGP (1) and Gp\_25(1) from the probit estimations presented in Table 4.1.5 was guided by their AIC and BIC values. The model with lower AIC or BIC is preferred, as a smaller value suggests a favorable balance between goodness of fit and model simplicity.

Finally, the bidgas variable, although not included in our selected models (CGP 1 and Gp\_25 1) was not significant in the CGP (3) and Gp\_25 (3) models. This came as a surprise as we expect that this should have a significant impact on their decision-making to either support a gasoline tax or not. Leaving this variable out will be an omitted variable. However, this doesn't matter as it is not very correlated with other variables in the regression as shown in the correlation table (Appendix B)

**Table 4.1.5: Probit Model Estimation using the Cleaned Dataset**

<b>Variable</b>	<b>CGP (1)</b>	<b>CGP (2)</b>	<b>CGP (3)</b>	<b>Gp_25 (1)</b>	<b>Gp_25 (2)</b>	<b>Gp_25 (3)</b>
<b>Ukr</b>		0.2242 (0.1387)	0.2162 (0.1390)		0.0071 (0.1469)	0.0001 (0.1472)
<b>Natdis</b>		-0.0021 (0.1396)	-0.0016 (0.1396)		0.0049 (0.1500)	0.0018 (0.1501)
<b>Propofincongas</b>	-2.9479*** (1.0404)	-2.9694*** (1.0439)	-3.0432*** (1.0561)	-2.4904 (1.5718)	-2.4877 (1.5778)	-2.7953* (1.6023)
<b>Bidgas</b>			1.8246 (1.7229)			1.4269 (1.8459)
<b>Hhsize</b>	0.0758** (0.0379)	0.0789** (0.0379)	0.0783** (0.0380)	0.1462*** (0.0432)	0.1462*** (0.0433)	0.1449*** (0.0433)
<b>Democrat</b>	0.2658** (0.1179)	0.2629** (0.1183)	0.2663** (0.1184)	0.2968** (0.1338)	0.2969** (0.1341)	0.2959** (0.1341)
<b>Riskhealth</b>	0.0626*** (0.0227)	0.0624*** (0.0227)	0.0627*** (0.0228)	0.1218 (0.0245)	0.0122 (0.0245)	0.0121 (0.0245)
<b>GWharm</b>	0.3675*** (0.0582)	0.3721*** (0.0587)	0.3691*** (0.0588)	0.3119*** (0.0568)	0.3119*** (0.0571)	0.3095*** (0.0572)
<b>Urban</b>	0.2229* (0.1235)	0.2375 (0.1239)	0.2568** (0.1251)	-0.1505 (0.1360)	-0.1501 (0.1363)	-0.1336 (0.1377)
<b>Natgas</b>	-0.2403** (0.1163)	-0.2534** (0.1168)	-0.2538** (0.1171)	-0.0862 (0.1240)	-0.0862 (0.1241)	-0.0864 (0.1243)
<b>AIC</b>	684.81	685.29	685.10	584.64	588.63	589.43
<b>BIC</b>	719.52	728.68	732.83	619.34	632.02	637.15

\*Statistically significant at 90% level.

\*\*Statistically significant at 95% level.

\*\*\*Statistically significant at 99% level.

**Table 4.1.6: Risk Variables Correlation Coefficient of the Cleaned Dataset**

	Risk Health	Risk Family	Risk Financial	Risk Car	Risk Job	Risk Sports
<b>Risk Health</b>	1.0000					
<b>Risk Family</b>	0.7789	1.0000				
<b>Risk Financial</b>	0.7408	0.7457	1.0000			
<b>Risk Car</b>	0.6810	0.7467	0.6947	1.0000		
<b>Risk Job</b>	0.6464	0.6608	0.7249	0.6897	1.0000	
<b>Risk Sports</b>	0.5800	0.5209	0.6098	0.5869	0.6236	1.0000

**Table 4.1.7: Descriptive Statistics of The Regions based On the Proportion of Income Spent on Gas and Gas Prices (Cleaned Dataset)**

Variable	Region	Observations	Mean	S. D	Min	Max
Prop of inc	Nonurban	382	0.0515698	0.0634264	0	0.46
	Urban	184	0.047011	0.0575866	0	0.38
Gas Price	Nonurban	382	5.000681	1.127314	0.1	10
	Urban	184	5.262054	1.515521	0	10

#### 4.2.2.7 Multicollinearity Diagnostics for the Different Models using VIF and Condition Number (Cleaned Dataset)

The correlation analysis was conducted to assess multicollinearity among variables (Appendix A) revealed correlation coefficients below 0.70 for all variables, indicating minimal collinearity. Further examination using the variance Inflation Factor (VIF) and tolerance levels (Table 4.1.8) found all variables with VIF values under 5 and tolerance levels nearing 1, aligning with acceptable thresholds that suggest no significant multicollinearity concerns. Despite these findings, the condition number criteria placed CGP (2), CGP (3), Gp\_25 (2), and Gp\_25 (3) models in the

moderate multicollinearity range (condition number between 10 and 30) (Belsey 1991) while the preferred models (CGP 1 and Gp\_25 1) had condition numbers less than 10, suggesting a low level of multicollinearity.

**Table 4.1.8: Multicollinearity Diagnostics for the models (Cleaned Dataset)**

	CGP (1)		CGP (2)		CGP (3)		GP_25 (1)		GP_25 (2)		GP_25 (3)	
	VIF	TL	VIF	TL	VIF	TL	VIF	TL	VIF	TL	VIF	TL
<b>Ukr</b>			1.34	0.74	1.35	0.74			1.34	0.74	1.35	0.74
<b>Natdis</b>			1.35	0.74	1.35	0.74			1.35	0.74	1.35	0.74
<b>Propofincon gas</b>	1.01	0.99	1.02	0.99	1.02	0.98	1.02	0.98	1.02	0.98	1.04	0.96
<b>Bidgas</b>					1.01	0.99					1.03	0.97
<b>Hhsize</b>	1.04	0.96	1.04	0.96	1.04	0.96	1.04	0.96	1.04	0.96	1.04	0.96
<b>Democrat</b>	1.08	0.93	1.08	0.93	1.08	0.93	1.08	0.93	1.08	0.92	1.08	0.92
<b>Riskhealth</b>	1.15	0.87	1.15	0.87	1.15	0.87	1.15	0.87	1.15	0.87	1.15	0.87
<b>GWharm</b>	1.14	0.88	1.15	0.87	1.15	0.87	1.14	0.88	1.15	0.87	1.15	0.87
<b>Urban</b>	1.09	0.92	1.09	0.92	1.09	0.92	1.09	0.92	1.09	0.92	1.09	0.92
<b>Natgas</b>	1.01	0.99	1.01	0.99	1.01	0.99	1.01	0.99	1.01	0.99	1.01	0.99
<b>Mean VIF</b>	1.07		1.14		1.13		1.07		1.14		1.13	
<b>Condition Number</b>	9.24		10.3		10.4		9.21		10.3		10.38	

#### 4.2.2.9 Marginal Effect of the variables in the CGP (1) model using the Cleaned Dataset

An analysis of the average marginal effect (Table 4.1.9) examined how a one-unit change in the independent variables affects the likelihood of supporting a gas tax at the current price, with the outcome variable set to 1.

For a 1% increase in the proportion of income spent on gas, the probability of supporting a gas tax at the current price decreases by 0.9882 percentage points. A unit increase in the risk health score and household size increased the probability of supporting a gas tax by 0.0210 and

0.0254 percentage points respectively. Similarly, being a Democrat and living in an urban area also increases the likelihood of supporting a gas tax by 0.0890 and 0.0747 percentage points respectively. A unit increase in the perceived harm of global warming also increases the probability of supporting a gas tax by 0.1232 percentage points. Lastly, A unit increase in the accessibility to natural gas decreases the probability of supporting a gas tax by 0.0805 percentage points.

This illustrates that the proportion of income allocated to gas expenses plays a significant role in influencing individuals' decisions regarding the support for gas tax. The more substantial portion of their income that people spend on gas, the less likely they are to endorse a gas tax at the current price. Conversely, while the perceived health risks do affect individuals' support for the gas tax, this impact is relatively modest.

Appendix L shows the marginal effect of all the variables including the information treatment variables (Ukraine and Natural disaster)

**Table 4.1.9: Marginal Effect of CGP 1 Variables (Cleaned Dataset)**

	<b>dy/dx</b>	<b>z</b>	<b>p value</b>
Proportionofincomeongas	-0.9882 (0.3416)	-2.89	0.004
hhsiz	0.0254 (0.0126)	2.02	0.043
democrat	0.0891 (0.0390)	2.29	0.022
RiskHealth	0.0210 (0.0075)	2.82	0.005
GWharm	0.1232 (0.0175)	7.05	0.000
urban	0.0747 (0.0410)	1.82	0.069
natgas	-0.0805 (0.0386)	-2.09	0.037

### 4.3 Comparison of the Result from the Original Dataset and Cleaned Dataset

In comparison with the previous result, it was discovered that the z-test statistics using the cleaned data had a larger negative test statistic (-5.1967) when compared to the value obtained from that

of the original dataset. Additionally, the mean difference for the cleaned data was larger than that of the original dataset. This means that the difference in means between the willingness to support gas tax under the current price and at \$2.50 is even more statistically significant using the cleaned dataset. This could be a result of the illogical responses that were removed from the dataset which enhanced the quality of the estimation.

Additionally, the observation shows that removing the illogical responses made AIC and BIC values estimated for the new dataset smaller than that of the original dataset, implying that removing the illogical responses helped make the model more fit for the data. Also, it was observed that the significant variables did not change much. However, the magnitude of significance of some coefficients changed such as the democrat variable which could imply some form of consistency because of removing illogical responses from the dataset.

## CHAPTER 5

### CONCLUSION AND DISCUSSION

Considering the numerous issues associated with fossil fuel usage, the motivation behind this study was to analyze consumers' probability of supporting a gasoline tax that would fund renewable energy development. This study focused on exploring how the framing of the question, gasoline price at the time of the survey, and individual monthly gasoline expenditure affected their probability of supporting a gasoline tax. The study utilized data from 608 respondents, known as the original dataset. After a thorough review and cleansing of any illogical responses, a refined set of 567 responses was obtained, which was referred to as the cleaned dataset. The purpose of utilizing both the original and cleaned datasets in the study was to compare the outcomes and ascertain the impact of illogical responses on the study's results.

The study employed a key method that involved segmenting respondents into 3 distinct groups: the control group, the Ukraine group, and the natural disaster group. Respondents in the control group were asked to consider a gasoline tax without any specific context. In contrast, the Ukraine group was presented with information about the conflict's impact on gasoline prices, and the natural disaster group was informed about the consequences of global warming caused by fossil fuels. This aspect of the study aimed to determine whether the framing of the question would significantly affect their probability of supporting a gasoline tax. In addition, the study presented a scenario with the current gasoline price and a reduced price of \$2.50 to examine whether gasoline prices would affect the likelihood of supporting a gasoline tax.

A Z-test analysis was conducted to determine whether there was a statistical difference in the proportion of respondents willing to vote in favor of a gasoline tax at the current price and \$2.50.

The result indicated a statistical difference with both the original and cleaned datasets showing that respondents were more inclined to vote in support of a gas tax when the price of gasoline was projected to be \$2.50.

The probit regression was used to analyze the factors influencing the likelihood of supporting a gasoline tax. The framing of the question based on the Ukraine war and natural disasters did not statistically affect their likelihood of supporting a gasoline tax. However, the analysis showed that the proportion of income spent on the purchase of gas was a significant factor in their likelihood of supporting a gasoline tax at both the current and future prices in the original dataset, but only at the current price in the cleaned dataset. The negative coefficient of this variable indicated that an increase in the proportion of income spent on gas decreases the likelihood of supporting a gasoline tax. Other significant factors that influenced their support for a gasoline tax at the current gas price using both the original and cleaned datasets included household size, being Democrat, urban residency, concern about health risks, harm from global warming, and natural gas. At the \$2.50 model, the significant variables were household size, and global warming harm in the original dataset but with the inclusion of Democrat in the cleaned dataset. These findings point to key variables that could be targeted in other to encourage consumers to pay for a gasoline tax to develop renewable energy.

Additionally, a probit analysis (Appendix N and O) was conducted by dividing respondents into regions. Although the result showed no significant difference overall compared to the initial probit analysis using the preferred model, it was noted that respondents in the Midwest were less inclined to support a gasoline tax at both the current gasoline price and \$2.50 per gallon.

The average amount of gasoline tax to be paid monthly by the respondent using the original dataset was about \$5.00 at the current price and \$6.87 when the price per gallon is reduced to \$2.50. This is similar to the estimated average amount of gas tax value using the cleaned dataset with a value of \$4.40 at the current gasoline price and \$7.34 when the price per gallon is reduced to \$2.50 per gallon. This shows that there was more approval for the payment of a gasoline tax when the price was lower at \$2.50.

Some of the lessons picked from the study were that the cleaned dataset improved the result with improvement in the value of the z statistics and even the average value of the probability of paying a gas tax. Additionally, the value of the AIC and BIC improved showing that the removal of the illogical responses in the study helped in making the data better and the findings more robust.

In all, the study has shown the public's perceptions and preferences as regards renewable energy adoption and has been able to establish the fact that the probability of paying a gas tax varies across different demographic segments. The study also established the fact that consumers will be more willing to support a gas tax if the price of gasoline is reduced.

### **5.1. Limitation**

This study, while providing valuable insights into the probability of supporting a gasoline tax by the respondents, is not without its limitations. One significant limitation arises from the methodology employed in eliciting responses. Respondents were presented with a predefined set of bids in the closed bounded format, with the minimum and maximum bids set at \$0.05 and \$0.45, respectively. This approach inherently constrains the range of responses and may not fully encapsulate the diversity of the respondents' valuation. There exists a possibility that some respondents might have been willing to pay more than the highest bid level of \$0.45. Conversely,

the minimum bid level of \$0.05 might exceed the willingness to pay of other respondents. This limitation in the bid range could lead to an underestimation or overestimation of their probability of supporting a gasoline tax and may affect the conclusion regarding the average bid level of the respondents.

By acknowledging this limitation, the study underscores the need for a cautious interpretation of the findings.

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## APPENDIX A

### CORRELATION OF VARIABLES USING THE ORIGINAL DATASET

#### CGP 1 Correlation for Original Dataset

	Proportion~P	Ukraine	Disaster	BidGAs	hhsiz	democrat	RiskHe~h	GWharm	Urban	natgas
Proportion~P	1.0000									
Ukraine	-0.0023	1.0000								
Disaster	-0.0118	-0.4981	1.0000							
BidGAs	-0.0195	0.0594	-0.0288	1.0000						
hhsiz	-0.0191	-0.0158	0.0155	0.0064	1.0000					
democrat	-0.0888	0.0088	-0.0349	-0.0369	0.0475	1.0000				
RiskHealth	0.0151	-0.0306	0.0045	0.0090	0.1694	0.0978	1.0000			
GWharm	0.0062	-0.0330	0.0547	0.0195	0.0921	0.1702	0.2956	1.0000		
urban	-0.0311	-0.0395	-0.0049	-0.0494	0.1243	0.1983	0.1737	0.1459	1.0000	
natgas	-0.0781	0.0351	-0.0229	-0.0285	-0.0191	0.0574	-0.0339	0.0122	0.0020	1.0000

#### GP\_2.5 Correlation for Original Dataset

	Prop~250	Ukraine	Disaster	BidGAs	hhsiz	democrat	RiskHe~h	GWharm	urban	natgas
Prop~250	1.0000									
Ukraine	0.0122	1.0000								
Disaster	-0.0271	-0.4981	1.0000							
BidGAs	0.1347	0.0594	-0.0288	1.0000						
hhsiz	-0.0210	-0.0158	0.0155	0.0064	1.0000					
democrat	-0.1064	0.0088	-0.0349	-0.0369	0.0475	1.0000				
RiskHealth	-0.0154	-0.0306	0.0045	0.0090	0.1694	0.0978	1.0000			
GWharm	-0.0120	-0.0330	0.0547	0.0195	0.0921	0.1702	0.2956	1.0000		

urban	-0.0440	-0.0395	-0.0049	-0.0494	0.1243	0.1983	0.1737	0.1459	1.0000
natgas	-0.0877	0.0351	-0.0229	-0.0285	-0.0191	0.0574	-0.0339	0.0122	0.0020 1.0000

## APPENDIX B

### CORRELATION OF VARIABLES USING THE CLEANED DATASET

#### CGP Correlation for Cleaned Dataset

```
| Propor~P Ukraine Disaster hhsiz democrat RiskHe~h GWharm urban natgas
-----+-----
Proporti~P | 1.0000
Ukraine | 0.0173 1.0000
Disaster | -0.0440 -0.5013 1.0000
hhsiz | -0.0339 -0.0325 0.0211 1.0000
democrat | -0.0804 0.0008 -0.0260 0.0282 1.0000
RiskHealth | 0.0042 -0.0208 -0.0072 0.1666 0.1097 1.0000
GWharm | 0.0098 -0.0389 0.0752 0.1038 0.1704 0.3124 1.0000
urban | -0.0347 -0.0566 -0.0063 0.1188 0.2079 0.1675 0.1505 1.0000
natgas | -0.0636 0.0389 -0.0257 -0.0204 0.0468 -0.0181 0.0092 -0.0168 1.0000
```

#### GP\_2.5 Correlation for Cleaned Dataset

```
| Prop~250 Ukraine Disaster BidGAs hhsiz democrat RiskHe~h GWharm Urban natgas
-----+-----
Proporti~250 | 1.0000
Ukraine | 0.0319 1.0000
Disaster | -0.0553 -0.5013 1.0000
BidGAs | 0.1366 0.0625 -0.0289 1.0000
hhsiz | -0.0292 -0.0325 0.0211 0.0055 1.0000
democrat | -0.0985 0.0008 -0.0260 -0.0348 0.0282 1.0000
RiskHealth | -0.0236 -0.0208 -0.0072 0.0098 0.1666 0.1097 1.0000
GWharm | -0.0077 -0.0389 0.0752 0.0198 0.1038 0.1704 0.3124 1.0000
urban | -0.0433 -0.0566 -0.0063 -0.0504 0.1188 0.2079 0.1675 0.1505 1.0000
natgas | -0.0771 0.0389 -0.0257 -0.0272 -0.0204 0.0468 -0.0181 0.0092 -0.0168 1.0000
```

APPENDIX C

PROBIT ANALYSIS FOR CURRENT GAS PRICE USING THE ORIGINAL DATASET

Stepwise entry

Probit Regression and AIC/BIC value for the Current Gas Price Model Using the Original Dataset (Step 1)

```

-----
Price_Current | Coefficient Std. err.   z   P>|z|   [95% conf. interval]
-----+-----
    Ukraine |   .1297281   .1243815   1.04  0.297   -.1140551   .3735112
    Disaster |   .0490028   .1248717   0.39  0.695   -.1957413   .2937468
      _cons |  -1.1051508   .0881423  -1.19  0.233   -2.2779066   .067605
-----
  
```

```

-----
Model |      N ll(null) ll(model)   df   AIC   BIC
-----+-----
. |    608 -421.0354 -420.4801    3  846.9601  860.1906
-----
  
```

Probit Regression and AIC/BIC value for the Current Gas Price Model Using the Original Dataset (Step 2)

```

-----
Price_Current | Coefficient Std. err.   z   P>|z|   [95% conf. interval]
-----+-----
    Ukraine |   .1290276   .1248338   1.03  0.301   -.1156421   .3736974
    Disaster |   .0466561   .1254698   0.37  0.710   -.1992603   .2925725
Proportionofincomeong~P | -1.960335   .8737386  -2.24  0.025   -3.672831   -.2478384
      _cons |  -0.0059648   .0984677  -0.06  0.952   -1.198958   .1870285
-----
  
```

```

-----
Model |      N ll(null) ll(model)   df   AIC   BIC
-----+-----
. |    606 -419.6478 -416.4774    4  840.9549  858.5824
-----
  
```

-----  
**Probit Regression and AIC/BIC value for the Current Gas Price Model Using the Original Dataset (Step 3)**  
 -----

Price_Current	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
Ukraine	.1368126	.1257122	1.09	0.276	-.1095787	.383204
Disaster	.0445885	.1262655	0.35	0.724	-.2028873	.2920643
Proportionofincomeong~P	-1.946585	.8836698	-2.20	0.028	-3.678546	-.2146239
hhsiz	.1279943	.0353774	3.62	0.000	.0586559	.1973327
_cons	-.3709944	.1412429	-2.63	0.009	-.6478253	-.0941635

Model	N	ll(null)	ll(model)	df	AIC	BIC
.	606	-419.6478	-409.8443	5	829.6886	851.723

-----  
**Probit Regression and AIC/BIC value for the Current Gas Price Model Using the Original Dataset (Step 4)**  
 -----

Price_Current	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
Ukraine	.1434231	.126465	1.13	0.257	-.1044437	.3912899
Disaster	.064085	.1273356	0.50	0.615	-.1854883	.3136582
Proportionofincomeong~P	-1.702268	.8918734	-1.91	0.056	-3.450307	.0457719
hhsiz	.1243955	.0356413	3.49	0.000	.0545398	.1942512
democrat	.4018138	.1068314	3.76	0.000	.1924281	.6111995
_cons	-.5362789	.1488913	-3.60	0.000	-.8281006	-.2444573

Model	N	ll(null)	ll(model)	df	AIC	BIC
.	606	-419.6478	-409.8443	5	829.6886	851.723

```
.|    606 -419.6478 -402.7322    6 817.4645 843.9058
```

-----  
**Probit Regression and AIC/BIC value for the Current Gas Price Model Using the Original Dataset (Step 5)**  
 -----

```
Price_Current | Coefficient Std. err.    z  P>|z|  [95% conf. interval]
-----+-----
Ukraine | .1657984 .1284368    1.29 0.197  -.0859331 .4175299
Disaster | .0725209 .1291689    0.56 0.574  -.1806455 .3256873
Proportionofincomeong~P | -2.008256 .9269291  -2.17 0.030  -3.825004 -.1915081
hhsizsize | .096406 .0363512    2.65 0.008  .025159 .1676529
democrat | .3650107 .1084852    3.36 0.001  .1523836 .5776378
RiskHealth | .1111729 .0208858    5.32 0.000  .0702375 .1521082
   _cons | -1.02386 .1774441   -5.77 0.000  -1.371644 -.6760755
```

```
-----+-----
Model |      N ll(null) ll(model)  df    AIC    BIC
```

```
.|    606 -419.6478 -388.2494    7 790.4987 821.3469
```

-----  
**Probit Regression and AIC/BIC value for the Current Gas Price Model Using the Original Dataset (Step 6)**  
 -----

```
Price_Current | Coefficient Std. err.    z  P>|z|  [95% conf. interval]
-----+-----
Ukraine | .1642687 .1315577    1.25 0.212  -.0935796 .422117
Disaster | .0167042 .132103    0.13 0.899  -.2422129 .2756213
Proportionofincomeong~P | -2.157628 .9338425  -2.31 0.021  -3.987926 -.3273305
hhsizsize | .0896381 .0369077    2.43 0.015  .0173003 .1619758
democrat | .274249 .1113056    2.46 0.014  .0560941 .4924039
RiskHealth | .0794329 .0218189    3.64 0.000  .0366686 .1221972
   GWharm | .3452344 .0551006    6.27 0.000  .2372391 .4532297
```

\_cons | -1.701257 .2140714 -7.95 0.000 -2.12083 -1.281685

```
-----
-----
Model |      N ll(null) ll(model)  df    AIC    BIC
-----+-----
. |    606 -419.6478 -367.5476   8  751.0952  786.3502
-----
```

Probit Regression and AIC/BIC value for the Current Gas Price Model Using the Original Dataset (Step 7)

```
-----
Price_Current | Coefficient Std. err.   z  P>|z|  [95% conf. interval]
-----+-----
Ukraine | .1797234 .1320475  1.36 0.173  -.079085 .4385319
Disaster | .0214249 .1326885  0.16 0.872  -.2386398 .2814897
Proportionofincomeong~P | -2.108187 .9339617 -2.26 0.024  -3.938718 -.2776556
hhsiz | .0831316 .0370755  2.24 0.025  .010465 .1557982
democrat | .2255354 .1133732  1.99 0.047  .003328 .4477429
RiskHealth | .0735666 .0219885  3.35 0.001  .0304701 .1166632
GWharm | .337879 .0553659  6.10 0.000  .2293638 .4463943
urban | .2870076 .1180553  2.43 0.015  .0556235 .5183916
_cons | -1.717953 .21479 -8.00 0.000  -2.138934 -1.296972
-----
```

```
-----
-----
Model |      N ll(null) ll(model)  df    AIC    BIC
-----+-----
. |    606 -419.6478 -364.5892   9  747.1783  786.8402
-----
```

Probit Regression and AIC/BIC value for the Current Gas Price Model Using the Original Dataset (Step 8)

```
-----
Price_Current | Coefficient Std. err.   z  P>|z|  [95% conf. interval]
-----+-----
```

```

Ukraine | .1949311 .1328585 1.47 0.142 -.0654668 .4553291
Disaster | .0204511 .1331973 0.15 0.878 -.2406108 .281513
Proportionofincomeong~P | -2.35541 .95356 -2.47 0.014 -4.224353 -.486467
hhsizel | .0845197 .0372187 2.27 0.023 .0115724 .157467
democrat | .2420019 .1140404 2.12 0.034 .0184868 .465517
RiskHealth | .0725821 .02207 3.29 0.001 .0293256 .1158385
GWharm | .3437568 .0556935 6.17 0.000 .2345994 .4529141
urban | .2871214 .1185065 2.42 0.015 .0548529 .51939
natgas | -.2750568 .1125437 -2.44 0.015 -.4956384 -.0544753
_cons | -1.624273 .2189255 -7.42 0.000 -2.053359 -1.195187

```

```

-----
-----
Model |      N ll(null) ll(model)  df    AIC    BIC
-----+-----
. |    606 -419.6478 -361.5847   10  743.1694  787.2382
-----

```

APPENDIX D

PROBIT USING DIFFERENT RISK VARIABLES WITH THE CGP (1) MODEL (ORIGINAL DATASET)

Probit Regression and AIC/BIC value for the Current Gas Price Model Using the Risk family variable (Original Dataset)

```

-----
Price_Current | Coefficient Std. err. z P>|z| [95% conf. interval]
-----+-----
Ukraine | .1950052 .1333249 1.46 0.144 -.0663068 .4563171
Disaster | .0056129 .1336523 0.04 0.967 -.2563407 .2675666
Proportionofincomeong~P | -2.587397 .9569472 -2.70 0.007 -4.462979 -.7118149
hhsiz | .0899585 .0372128 2.42 0.016 .0170227 .1628942
democrat | .2205441 .1145681 1.93 0.054 -.0040053 .4450935
RiskFamily | .077032 .0198484 3.88 0.000 .0381298 .1159342
GW | .3492413 .0549744 6.35 0.000 .2414934 .4569891
urban | .2886313 .1187167 2.43 0.015 .0559509 .5213117
natgas | -.2698368 .1127508 -2.39 0.017 -.4908244 -.0488493
_cons | -1.642307 .2172501 -7.56 0.000 -2.06811 -1.216505
-----

```

```

-----
Model | N ll(null) ll(model) df AIC BIC
-----+-----
. | 606 -419.6478 -359.44 10 738.8801 782.9489
-----

```

Probit Regression and AIC/BIC value for the Current Gas Price Model Using the Risk financial variable (Original Dataset)

```

-----
Price_Current | Coefficient Std. err. z P>|z| [95% conf. interval]
-----+-----
Ukraine | .1765531 .1324569 1.33 0.183 -.0830577 .4361639
Disaster | .0119057 .1328141 0.09 0.929 -.2484051 .2722165
-----

```

```

Proportionofincomeong~P | -2.275955 .9448066 -2.41 0.016 -4.127742 -.4241679
    hhsiz | .0888461 .0371436 2.39 0.017 .0160459 .1616463
    democrat | .2277697 .1138813 2.00 0.045 .0045665 .4509729
    RiskFinancial | .0523135 .022281 2.35 0.019 .0086436 .0959834
    GWharm | .3599724 .0549584 6.55 0.000 .2522559 .467689
    urban | .3085895 .1177991 2.62 0.009 .0777074 .5394715
    natgas | -.2833074 .1120835 -2.53 0.011 -.502987 -.0636278
    _cons | -1.573346 .219751 -7.16 0.000 -2.00405 -1.142642

```

```

-----
-----
Model |      N ll(null) ll(model)  df   AIC   BIC
-----+-----
. |    606 -419.6478 -364.2732   10  748.5464  792.6152
-----

```

Probit Regression and AIC/BIC value for the Current Gas Price Model Using the Risk Care variable (Original Dataset)

```

-----
Price_Current | Coefficient Std. err.  z  P>|z|  [95% conf. interval]
-----+-----
    Ukraine | .1827182 .1324335  1.38 0.168  -.0768467 .442283
    Disaster | .0224659 .1329266  0.17 0.866  -.2380654 .2829971
Proportionofincomeong~P | -2.424927 .9494289 -2.55 0.011 -4.285773 -.5640803
    hhsiz | .0871469 .0372431  2.34 0.019  .0141518 .160142
    democrat | .2202428 .1141279  1.93 0.054  -.0034437 .4439294
    RiskCar | .0575641 .0219179  2.63 0.009  .0146058 .1005223
    GWharm | .3591025 .0547981  6.55 0.000  .2517001 .4665048
    urban | .3101494 .117821  2.63 0.008  .0792245 .5410743
    natgas | -.2801225 .1122021 -2.50 0.013  -.5000346 -.0602104
    _cons | -1.565599 .2162964 -7.24 0.000 -1.989532 -1.141666

```

```

-----
-----
Model |      N ll(null) ll(model)  df   AIC   BIC
-----+-----

```

```
-----+-----
. |    606 -419.6478 -363.5787   10  747.1575  791.2263
-----
```

Probit Regression and AIC/BIC value for the Current Gas Price Model Using the Risk Sports variable (Original Dataset)

```
-----+-----
Price_Current | Coefficient Std. err.   z   P>|z|   [95% conf. interval]
-----+-----
Ukraine | .1957651 .1322621   1.48  0.139   -.0634639 .4549941
Disaster | .0223496 .1327348   0.17  0.866   -.2378058 .282505
Proportionofincomeong~P | -2.152549 .9355835  -2.30  0.021   -3.986259 -.3188387
hhsiz | .0922811 .0369873   2.49  0.013   .0197872 .1647749
democrat | .2203115 .1141983   1.93  0.054   -.003513 .444136
RiskSports | .0432736 .0227819   1.90  0.058   -.001378 .0879253
GWharm | .3654874 .0548342   6.67  0.000   .2580143 .4729606
urban | .3117139 .117608   2.65  0.008   .0812064 .5422214
natgas | -.2844364 .1120375  -2.54  0.011   -.5040259 -.0648468
_cons | -1.560134 .223289  -6.99  0.000   -1.997772 -1.122495
-----
```

```
-----+-----
Model |      N ll(null) ll(model)  df    AIC    BIC
-----+-----
```

```
. |    606 -419.6478 -365.2296   10  750.4592  794.528
-----
```

Probit Regression and AIC/BIC value for the Current Gas Price Model Using the Risk family variable (Original Dataset)

```
-----+-----
Price_Current | Coefficient Std. err.   z   P>|z|   [95% conf. interval]
-----+-----
Ukraine | .1781673 .1331476   1.34  0.181   -.0827973 .4391319
Disaster | .0290626 .1337184   0.22  0.828   -.2330205 .2911458
Proportionofincomeong~P | -2.328116 .9416156  -2.47  0.013   -4.173649 -.4825836
-----
```

hhsize	.0833453	.0374288	2.23	0.026	.0099862	.1567043
democrat	.2403885	.1144563	2.10	0.036	.0160581	.4647188
RiskJob	.0903742	.0230225	3.93	0.000	.0452509	.1354976
GWharm	.3404958	.0555576	6.13	0.000	.2316049	.4493867
urban	.279323	.1189241	2.35	0.019	.046236	.5124101
natgas	-.2901372	.1128863	-2.57	0.010	-.5113902	-.0688841
_cons	-1.726541	.2258218	-7.65	0.000	-2.169143	-1.283938

-----

Model	N	ll(null)	ll(model)	df	AIC	BIC
.	606	-419.6478	-359.2486	10	738.4973	782.5661

APPENDIX E

PROBIT ANALYSIS FOR GAS PRICE AT \$2.5 USING THE ORIGINAL DATASET

Probit Regression and AIC/BIC value for Gas Price at \$2.5 Model Using the Original Dataset (Step 1)

```

-----
Price_250 | Coefficient Std. err.   z   P>|z|   [95% conf. interval]
-----+-----
Ukraine | .0182815   .13016   0.14  0.888   -.2368274   .2733904
Disaster | .0921116   .1316436  0.70  0.484   -.1659052   .3501284
   _cons | .4948732   .091994  5.38  0.000   .3145683   .675178
-----

```

```

-----
Model |      N ll(null) ll(model)   df    AIC    BIC
-----+-----
. |    608 -370.2116 -369.9383    3  745.8766  759.1071
-----

```

Probit Regression and AIC/BIC value for Gas Price at \$2.5 Model Using the Original Dataset (Step 2)

```

-----
Price_250 | Coefficient Std. err.   z   P>|z|   [95% conf. interval]
-----+-----
Ukraine | .0166958   .1304364  0.13  0.898   -.2389548   .2723463
Disaster | .0924578   .1325354  0.70  0.485   -.1673069   .3522224
Proportionofincomeo~250 | -3.047233  1.471577  -2.07  0.038   -5.93147   -.1629946
   _cons | .5830341   .1017801  5.73  0.000   .3835488   .7825194
-----

```

```

-----
Model |      N ll(null) ll(model)   df    AIC    BIC
-----+-----
. |    606 -368.6459 -366.2049    4  740.4097  758.0373
-----

```

Probit Regression and AIC/BIC value for Gas Price at \$2.5 Model Using the Original Dataset (Step 3)

```

-----
Price_250 | Coefficient Std. err. z P>|z| [95% conf. interval]
-----+-----
Ukraine | .0174115 .1315572 0.13 0.895 -.2404359 .2752589
Disaster | .0835705 .1335764 0.63 0.532 -.1782343 .3453754
Proportionofincomeo~250 | -2.967767 1.474598 -2.01 0.044 -5.857927 -.0776079
hhsizesize | .1330956 .0384286 3.46 0.001 .0577769 .2084144
_cons | .2179468 .1456859 1.50 0.135 -.0675922 .5034859
-----

```

```

-----
Model | N ll(null) ll(model) df AIC BIC
-----+-----
. | 606 -368.6459 -360.0106 5 730.0212 752.0556
-----

```

Probit Regression and AIC/BIC value for Gas Price at \$2.5 Model Using the Original Dataset (Step 4)

```

-----
Price_250 | Coefficient Std. err. z P>|z| [95% conf. interval]
-----+-----
Ukraine | .019613 .1318333 0.15 0.882 -.2387755 .2780016
Disaster | .0995861 .1342854 0.74 0.458 -.1636084 .3627807
Proportionofincomeo~250 | -2.604154 1.486427 -1.75 0.080 -5.517498 .3091897
hhsizesize | .1304981 .038629 3.38 0.001 .0547867 .2062096
democrat | .2482421 .1142139 2.17 0.030 .024387 .4720972
_cons | .1176501 .1535771 0.77 0.444 -.1833556 .4186558
-----

```

```

-----
Model | N ll(null) ll(model) df AIC BIC
-----+-----
. | 606 -368.6459 -357.629 6 727.2579 753.6992
-----

```

-----  
 Probit Regression and AIC/BIC value for Gas Price at \$2.5 Model Using the Original Dataset  
 (Step 5)  
 -----

Price_250	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
Ukraine	.0239949	.1320345	0.18	0.856	-.234788	.2827778
Disaster	.1007679	.1344164	0.75	0.453	-.1626833	.3642191
Proportionofincomeo~250	-2.599674	1.483068	-1.75	0.080	-5.506434	.307087
hhsiz	.1227688	.039071	3.14	0.002	.046191	.1993466
democrat	.236737	.1146708	2.06	0.039	.0119864	.4614877
RiskHealth	.0272049	.0213428	1.27	0.202	-.0146262	.069036
_cons	.0010249	.1787408	0.01	0.995	-.3493007	.3513506

Model	N	ll(null)	ll(model)	df	AIC	BIC
.	606	-368.6459	-356.815	7	727.6301	758.4783

-----  
 Probit Regression and AIC/BIC value for Gas Price at \$2.5 Model Using the Original Dataset  
 (Step 5)  
 -----

Price_250	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
Ukraine	.026275	.1342076	0.20	0.845	-.236767	.2893171
Disaster	.0629664	.1370327	0.46	0.646	-.2056127	.3315455
Proportionofincomeo~250	-2.759808	1.493394	-1.85	0.065	-5.686806	.1671903
hhsiz	.1194028	.0395476	3.02	0.003	.041891	.1969147
democrat	.1482569	.1174276	1.26	0.207	-.081897	.3784109
RiskHealth	-.0076077	.0227544	-0.33	0.738	-.0522054	.03699
GWharm	.2840739	.0534779	5.31	0.000	.1792592	.3888887
_cons	-.4863198	.2034315	-2.39	0.017	-.8850383	-.0876013

Model	N	ll(null)	ll(model)	df	AIC	BIC
.	606	-368.6459	-342.4065	8	700.8129	736.068

Probit Regression and AIC/BIC value for Gas Price at \$2.5 Model Using the Original Dataset (Step 6)

Price_250	Coefficient	Std. err.	z	P> z	[95% conf. interval]
Ukraine	.0183688	.134642	0.14	0.891	-.2455246 .2822622
Disaster	.0570976	.1371697	0.42	0.677	-.2117501 .3259454
Proportionofincomeo~250	-2.8008	1.495124	-1.87	0.061	-5.731189 .1295883
hhsiz	.1257082	.0398613	3.15	0.002	.0475815 .2038349
democrat	.1873002	.1200867	1.56	0.119	-.0480654 .4226658
RiskHealth	-.0031824	.0229226	-0.14	0.890	-.0481099 .0417451
GWharm	.2897068	.0535276	5.41	0.000	.1847946 .3946189
urban	-.2047581	.1229309	-1.67	0.096	-.4456983 .036182
_cons	-.4808865	.2039205	-2.36	0.018	-.8805634 -.0812096

Model	N	ll(null)	ll(model)	df	AIC	BIC
.	606	-368.6459	-341.0203	9	700.0406	739.7025

Probit Regression and AIC/BIC value for Gas Price at \$2.5 Model Using the Original Dataset (Step 7)

Price_250	Coefficient	Std. err.	z	P> z	[95% conf. interval]
Ukraine	.019168	.1346608	0.14	0.887	-.2447623 .2830984
Disaster	.0567675	.137189	0.41	0.679	-.2121179 .3256529

```

Proportionofincomeo~250 | -2.842801  1.500435  -1.89  0.058  -5.7836  .0979974
      hhsiz | .1253031  .0398825   3.14  0.002   .0471349  .2034714
      democrat | .1898152  .1203911   1.58  0.115  -.046147  .4257775
      RiskHealth | -.0035144  .0229516  -0.15  0.878  -.0484987  .0414698
      GWharm | .2900947  .0535452   5.42  0.000   .185148  .3950413
      urban | -.2045961  .1229375  -1.66  0.096  -.4455492  .0363571
      natgas | -.0354683  .114849  -0.31  0.757  -.2605681  .1896316
      _cons | -.4652257  .2100602  -2.21  0.027  -.8769361  -.0535153

```

```

-----
-----
      Model |      N ll(null) ll(model)  df   AIC   BIC
-----+-----
      . |      606 -368.6459 -340.9726   10  701.9453  746.0141
-----

```

APPENDIX F

PROBIT USING DIFFERENT RISK VARIABLES WITH THE GP\_2.5 (1) MODEL (ORIGINAL DATASET)

Probit Regression and AIC/BIC value for \$2.5 Price Gas Model Using the Risk family variable (Original Dataset)

```

-----
Price_250 | Coefficient Std. err. z P>|z| [95% conf. interval]
-----+-----
Ukraine | .0193833 .134659 0.14 0.886 -.2445436 .2833102
Disaster | .0587061 .1372068 0.43 0.669 -.2102142 .3276264
Proportionofincomeo~250 | -2.78402 1.503034 -1.85 0.064 -5.729913 .1618726
hhsiz | .1265888 .0397354 3.19 0.001 .0487089 .2044688
democrat | .1940174 .1206266 1.61 0.108 -.0424063 .4304411
RiskFamily | -.0122795 .0202021 -0.61 0.543 -.051875 .0273159
GWharm | .2941704 .0524906 5.60 0.000 .1912908 .3970501
urban | -.2003531 .122525 -1.64 0.102 -.4404978 .0397916
natgas | -.0382074 .1149042 -0.33 0.740 -.2634155 .1870008
_cons | -.4390836 .2080084 -2.11 0.035 -.8467726 -.0313945
-----

```

```

-----
Model | N ll(null) ll(model) df AIC BIC
-----+-----
. | 606 -368.6459 -340.7995 10 701.5991 745.6679
-----

```

Probit Regression and AIC/BIC value for \$2.5 Price Gas Model Using the Risk financial variable (Original Dataset)

```

-----
Price_250 | Coefficient Std. err. z P>|z| [95% conf. interval]
-----+-----
Ukraine | .0212616 .1347822 0.16 0.875 -.2429067 .2854299
Disaster | .0579674 .1371784 0.42 0.673 -.2108973 .326832
Proportionofincomeo~250 | -2.843548 1.499712 -1.90 0.058 -5.78293 .0958344
-----

```

```

hhsize | .1259807 .0399117 3.16 0.002 .0477551 .2042062
democrat | .1919714 .1206968 1.59 0.112 -.04459 .4285329
RiskFinancial | -.0064769 .0231132 -0.28 0.779 -.051778 .0388243
GWharm | .2910136 .0526835 5.52 0.000 .1877559 .3942713
urban | -.2043827 .1223953 -1.67 0.095 -.444273 .0355076
natgas | -.0347483 .1147317 -0.30 0.762 -.2596183 .1901218
_cons | -.4551675 .2119577 -2.15 0.032 -.8705969 -.0397381

```

```

-----
-----
Model |      N ll(null) ll(model)  df    AIC    BIC
-----+-----
. |    606 -368.6459 -340.9451   10  701.8902  745.959
-----

```

Probit Regression and AIC/BIC value for \$2.5 Price Gas Model Using the Risk Car variable (Original Dataset)

```

-----
Price_250 | Coefficient Std. err.  z  P>|z|  [95% conf. interval]
-----+-----
Ukraine | .0217992 .1347416 0.16 0.871  -.2422896 .2858879
Disaster | .0568327 .1371475 0.41 0.679  -.2119714 .3256368
Proportionofincomeo~250 | -2.823043 1.5 -1.88 0.060  -5.76299 .1169031
hhsize | .1266092 .0398627 3.18 0.001 .0484798 .2047386
democrat | .1930239 .1206545 1.60 0.110  -.0434547 .4295024
RiskCar | -.0096227 .0224908 -0.43 0.669  -.0537039 .0344584
GWharm | .2919012 .0523069 5.58 0.000 .1893816 .3944208
urban | -.2038319 .1222843 -1.67 0.096  -.4435048 .035841
natgas | -.035299 .1147562 -0.31 0.758  -.260217 .1896191
_cons | -.4471306 .2099464 -2.13 0.033  -.858618 -.0356433

```

```

-----
-----
Model |      N ll(null) ll(model)  df    AIC    BIC
-----+-----

```

```
.|    606 -368.6459 -340.8928   10 701.7856 745.8544
```

-----  
**Probit Regression and AIC/BIC value for \$2.5 Price Gas Model Using the Risk Sports variable (Original Dataset)**  
 -----

```
Price_250 | Coefficient Std. err.   z  P>|z|  [95% conf. interval]
-----+-----
Ukraine | .0246931 .1348157   0.18 0.855  -.2395408 .288927
Disaster | .0629277 .13744   0.46 0.647  -.2064498 .3323053
Proportionofincomeo~250 | -2.740337 1.50387  -1.82 0.068  -5.687868 .2071941
hhszise | .1198417 .0397545   3.01 0.003  .0419244 .1977591
democrat | .1743788 .1211926   1.44 0.150  -.0631544 .411912
RiskSports | .0277363 .0237527   1.17 0.243  -.0188181 .0742908
GWharm | .2763772 .0523909   5.28 0.000  .173693 .3790615
urban | -.2200781 .1227123  -1.79 0.073  -.4605899 .0204336
natgas | -.0319904 .1149207  -0.28 0.781  -.257231 .1932501
_cons | -.5761611 .2177202  -2.65 0.008  -1.002885 -.1494372
```

```
-----
-----
Model |      N ll(null) ll(model)  df   AIC   BIC
```

```
.|    606 -368.6459 -340.3024   10 700.6047 744.6735
```

-----  
**Probit Regression and AIC/BIC value for \$2.5 Price Gas Model Using the Risk Job variable (Original Dataset)**  
 -----

```
Price_250 | Coefficient Std. err.   z  P>|z|  [95% conf. interval]
-----+-----
Ukraine | .0190436 .134675   0.14 0.888  -.2449146 .2830019
Disaster | .0581444 .1372347   0.42 0.672  -.2108307 .3271195
Proportionofincomeo~250 | -2.836187 1.500243  -1.89 0.059  -5.776609 .104234
hhszise | .1235763 .0398453   3.10 0.002  .0454809 .2016717
```

democrat	.1894717	.120394	1.57	0.116	-.0464961	.4254396
RiskJob	.0047401	.0235554	0.20	0.841	-.0414276	.0509078
GWharm	.2851058	.0531643	5.36	0.000	.1809058	.3893059
urban	-.2093694	.1227869	-1.71	0.088	-.4500273	.0312886
natgas	-.0344621	.1147336	-0.30	0.764	-.2593358	.1904115
_cons	-.4914093	.2148035	-2.29	0.022	-.9124165	-.0704021

-----

-----

Model	N	ll(null)	ll(model)	df	AIC	BIC
-------	---	----------	-----------	----	-----	-----

-----+

.	606	-368.6459	-340.9641	10	701.9283	745.9971
---	-----	-----------	-----------	----	----------	----------

---

## APPENDIX G

### PROBIT ANALYSIS FOR CURRENT GAS PRICE USING THE CLEANED DATASET

#### Stepwise Entry of the variables

#### Probit Regression and AIC/BIC value of CGP against Ukraine and Disaster variable (Step 1) (Cleaned Dataset)

```

-----
Price_Current | Coefficient Std. err.   z   P>|z|   [95% conf. interval]
-----+-----
    Ukraine |   .1558834   .1293502   1.21  0.228   -.0976384   .4094052
    Disaster |   .0677802   .1300706   0.52  0.602   -.1871534   .3227138
      _cons |  -.2149745   .092179   -2.33  0.020   -.395642   -.0343069
-----

```

```

-----
Model |      N ll(null) ll(model)   df    AIC    BIC
-----+-----
. |    567 -389.5072 -388.7754    3  783.5509  796.5719
-----

```

#### Step 2 of the Probit Regression and AIC/BIC value at Current Price (Cleaned Dataset)

```

-----
Price_Current | Coefficient Std. err.   z   P>|z|   [95% conf. interval]
-----+-----
    Ukraine |   .1578799   .130012   1.21  0.225   -.096939   .4126987
    Disaster |   .0493387   .1308318   0.38  0.706   -.2070869   .3057642
Proportionofincomeong~P | -2.49772   .9487089   -2.63  0.008   -4.357155   -.6382846
      _cons |  -.0904787   .1032974   -0.88  0.381   -.2929378   .1119805
-----

```

```

-----
Model |      N ll(null) ll(model)   df    AIC    BIC
-----+-----
. |    566 -388.6952 -384.2541    4  776.5082  793.8626
-----

```

Step 3 of the Probit Regression and AIC/BIC value at Current Price (Cleaned Dataset)

```

-----
Price_Current | Coefficient Std. err.   z   P>|z|   [95% conf. interval]
-----+-----
Ukraine | .1734343 .1309781   1.32  0.185   -.083278 .4301467
Disaster | .0502421 .131642   0.38  0.703   -.2077714 .3082556
Proportionofincomeong~P | -2.450722 .9591148  -2.56  0.011   -4.330553 -.5708917
hhsized | .1217587 .0361221   3.37  0.001   .0509607 .1925568
_cons | -.4441833 .1476685  -3.01  0.003   -.7336082 -.1547584
-----

```

```

-----
Model |      N ll(null) ll(model)   df   AIC   BIC
-----+-----
. |    566 -388.6952 -378.5103    5  767.0205  788.7135
-----

```

Step 4 of the Probit Regression and AIC/BIC value at Current Price (Cleaned Dataset)

```

-----
Price_Current | Coefficient Std. err.   z   P>|z|   [95% conf. interval]
-----+-----
Ukraine | .1831698 .1318415   1.39  0.165   -.0752348 .4415745
Disaster | .0682746 .1328892   0.51  0.607   -.1921835 .3287327
Proportionofincomeong~P | -2.237726 .9710845  -2.30  0.021   -4.141017 -.3344354
hhsized | .1208102 .036429   3.32  0.001   .0494106 .1922098
democrat | .4234988 .1107998   3.82  0.000   .2063352 .6406623
_cons | -.6246276 .1563895  -3.99  0.000   -.9311453 -.3181099
-----

```

```

-----
Model |      N ll(null) ll(model)   df   AIC   BIC
-----+-----
. |    566 -388.6952 -371.1689    6  754.3378  780.3693
-----

```

Step 5 of the Probit Regression and AIC/BIC value at Current Price (Cleaned Dataset)

```

-----
Price_Current | Coefficient Std. err.   z   P>|z|   [95% conf. interval]
-----+-----
Ukraine | .1991422 .1337306   1.49  0.136   -.0629649 .4612494
Disaster | .0801414 .1345709   0.60  0.551   -.1836127 .3438956
Proportionofincomeong~P | -2.546048 1.011542  -2.52  0.012   -4.528635 -.5634616
hhsizesize | .0949306 .0371076   2.56  0.011   .022201 .1676601
democrat | .3809249 .1125004   3.39  0.001   .1604281 .6014216
RiskHealth | .1035476 .0213534   4.85  0.000   .0616956 .1453995
_cons | -1.072263 .1842254  -5.82  0.000   -1.433338 -.7111881
-----

```

```

-----
Model |      N ll(null) ll(model)   df    AIC    BIC
-----+-----
. |    566 -388.6952 -359.1803    7  732.3605  762.7307
-----

```

Step 6 of the Probit Regression and AIC/BIC value at Current Price (Cleaned Dataset)

```

-----
Price_Current | Coefficient Std. err.   z   P>|z|   [95% conf. interval]
-----+-----
Ukraine | .1903692 .1374133   1.39  0.166   -.078956 .4596944
Disaster | -.0083488 .1385465  -0.06  0.952   -.279895 .2631975
Proportionofincomeong~P | -2.81102 1.025321  -2.74  0.006   -4.820613 -.8014282
hhsizesize | .0835529 .0377387   2.21  0.027   .0095865 .1575193
democrat | .2919899 .1155637   2.53  0.012   .0654893 .5184905
RiskHealth | .0670601 .022495   2.98  0.003   .0229707 .1111496
GWharm | .3747876 .0581813   6.44  0.000   .2607544 .4888209
_cons | -1.782745 .2219267  -8.03  0.000   -2.217714 -1.347777
-----

```

Model	N	ll(null)	ll(model)	df	AIC	BIC
.	566	-388.6952	-336.9735	8	689.9471	724.6558

Step 7 of the Probit Regression and AIC/BIC value at Current Price (Cleaned Dataset)

Price_Current	Coefficient	Std. err.	z	P> z	[95% conf. interval]
Ukraine	.2087939	.1379866	1.51	0.130	-.0616548 .4792427
Disaster	-.0016155	.1390869	-0.01	0.991	-.2742209 .2709898
Proportionofincomeong~P	-2.745883	1.023809	-2.68	0.007	-4.752512 -.7392535
hhsize	.0777565	.0378879	2.05	0.040	.0034976 .1520154
democrat	.2493394	.1177332	2.12	0.034	.0185866 .4800922
RiskHealth	.0623932	.0226467	2.76	0.006	.0180065 .1067798
GWharm	.3678632	.058426	6.30	0.000	.2533503 .4823761
urban	.2448086	.123525	1.98	0.047	.002704 .4869131
_cons	-1.798538	.2224871	-8.08	0.000	-2.234605 -1.362471

Model	N	ll(null)	ll(model)	df	AIC	BIC
.	566	-388.6952	-335.011	9	688.022	727.0693

Step 8 of the Probit Regression and AIC/BIC value at Current Price (Cleaned Dataset)

Price_Current	Coefficient	Std. err.	z	P> z	[95% conf. interval]
Ukraine	.2241839	.1387439	1.62	0.106	-.0477491 .4961168
Disaster	-.0020964	.1395544	-0.02	0.988	-.275618 .2714252
Proportionofincomeong~P	-2.969378	1.043972	-2.84	0.004	-5.015526 -.9232295

hhsz		.0789459	.0379834	2.08	0.038	.0044999	.1533919
democrat		.2629252	.1183452	2.22	0.026	.0309729	.4948775
RiskHealth		.0624426	.0227187	2.75	0.006	.0179148	.1069703
GWharm		.3721191	.0586668	6.34	0.000	.2571344	.4871039
urban		.2375112	.1239909	1.92	0.055	-.0055065	.480529
natgas		-.2534066	.1168491	-2.17	0.030	-.4824265	-.0243866
_cons		-1.711497	.2265969	-7.55	0.000	-2.155619	-1.267375

-----

-----

Model		N	ll(null)	ll(model)	df	AIC	BIC
.		566	-388.6952	-332.6457	10	685.2914	728.6774

-----

APPENDIX H

PROBIT USING DIFFERENT RISK VARIABLES WITH THE CGP (1) MODEL (CLEANED DATASET)

Probit Regression using Risk family and AIC/BIC value at Current Price (Cleaned Dataset)

```

-----
Price_Current | Coefficient Std. err. z P>|z| [95% conf. interval]
-----+-----
Ukraine | .2239527 .1390971 1.61 0.107 -.0486726 .4965779
Disaster | -.021793 .1399523 -0.16 0.876 -.2960946 .2525085
Proportionofincomeong~P | -3.230414 1.05174 -3.07 0.002 -5.291786 -1.169042
hhsizesize | .0843993 .0379351 2.22 0.026 .0100478 .1587508
democrat | .2429847 .1188642 2.04 0.041 .0100151 .4759542
RiskFamily | .0673451 .0204121 3.30 0.001 .0273382 .107352
GWWharm | .3785111 .0577529 6.55 0.000 .2653175 .4917047
urban | .2335548 .124332 1.88 0.060 -.0101314 .4772409
natgas | -.2472712 .1169928 -2.11 0.035 -.4765728 -.0179696
_cons | -1.730019 .2251918 -7.68 0.000 -2.171387 -1.288651
-----

```

```

-----
Model | N ll(null) ll(model) df AIC BIC
-----+-----
. | 566 -388.6952 -330.9721 10 681.9443 725.3302
-----

```

Probit Regression using Risk financial and AIC/BIC value at Current Price (Cleaned Dataset)

```

-----
Price_Current | Coefficient Std. err. z P>|z| [95% conf. interval]
-----+-----
Ukraine | .2120721 .138444 1.53 0.126 -.0592732 .4834174
Disaster | -.0114286 .1392589 -0.08 0.935 -.2843709 .2615138
-----

```

```

Proportionofincomeong~P | -2.905482  1.03628  -2.80  0.005  -4.936554  -.8744095
    hhsiz | .0818065  .0379534  2.16  0.031  .0074191  .1561938
    democrat | .2548226  .1182122  2.16  0.031  .023131  .4865142
    RiskFinancial | .0457778  .0228529  2.00  0.045  .000987  .0905687
    GWharm | .3878032  .0578557  6.70  0.000  .274408  .5011983
    urban | .2538955  .1234281  2.06  0.040  .0119808  .4958101
    natgas | -.2561591  .1164837  -2.20  0.028  -.484463  -.0278552
    _cons | -1.678298  .2282844  -7.35  0.000  -2.125727  -1.230869

```

```

-----
-----
Model |      N ll(null) ll(model)  df    AIC    BIC
-----+-----
. |    566 -388.6952 -334.4347   10  688.8695  732.2554
-----

```

Probit Regression using Risk care and AIC/BIC value at Current Price (Cleaned Dataset)

```

-----
Price_Current | Coefficient Std. err.  z  P>|z|  [95% conf. interval]
-----+-----
    Ukraine | .2231609  .1384136  1.61  0.107  -.0481248  .4944465
    Disaster | -.0005081  .1394601  -0.00  0.997  -.2738448  .2728286
Proportionofincomeong~P | -3.070542  1.044769  -2.94  0.003  -5.118251  -1.022832
    hhsiz | .0806303  .038034  2.12  0.034  .006085  .1551756
    democrat | .2452572  .1185475  2.07  0.039  .0129084  .4776059
    RiskCar | .0506138  .0225572  2.24  0.025  .0064025  .0948252
    GWharm | .3867864  .0576672  6.71  0.000  .2737607  .4998121
    urban | .2576531  .1233796  2.09  0.037  .0158335  .4994726
    natgas | -.2542965  .1165816  -2.18  0.029  -.4827922  -.0258007
    _cons | -1.671371  .2249286  -7.43  0.000  -2.112223  -1.230519

```

```

-----
-----
Model |      N ll(null) ll(model)  df    AIC    BIC
-----+-----

```

```
-----+-----
. |    566 -388.6952 -333.9223    10 687.8446 731.2305
-----
```

Probit Regression using Risk Sports and AIC/BIC value at Current Price (Cleaned Dataset)

```
-----+-----
Price_Current | Coefficient Std. err.    z  P>|z|  [95% conf. interval]
-----+-----
Ukraine | .2291262 .1383074    1.66 0.098  -.0419514  .5002038
Disaster | -.0031119 .139288    -0.02 0.982  -.2761113  .2698874
Proportionofincomeong~P | -2.787448 1.025192    -2.72 0.007  -4.796788  -.778108
hhsizel | .0853088 .0377786    2.26 0.024  .011264  .1593535
democrat | .24296 .1188859    2.04 0.041  .0099479  .4759721
RiskSports | .0389404 .0231572    1.68 0.093  -.0064469  .0843276
GWharm | .3934125 .0576467    6.82 0.000  .2804269  .506398
urban | .2606022 .1230759    2.12 0.034  .0193779  .5018266
natgas | -.2573511 .1164761    -2.21 0.027  -.4856401  -.0290621
_cons | -1.67509 .2323391    -7.21 0.000  -2.130466  -1.219714
-----
```

```
-----+-----
Model |      N ll(null) ll(model)  df    AIC    BIC
-----+-----
. |    566 -388.6952 -335.0283    10 690.0566 733.4425
-----
```

Probit Regression using Risk Job and AIC/BIC value at Current Price (Cleaned Dataset)

```
-----+-----
Price_Current | Coefficient Std. err.    z  P>|z|  [95% conf. interval]
-----+-----
Ukraine | .2111369 .1391486    1.52 0.129  -.0615894  .4838632
Disaster | .0058003 .1401499    0.04 0.967  -.2688884  .280489
Proportionofincomeong~P | -2.943536 1.030549    -2.86 0.004  -4.963376  -.9236961
hhsizel | .0766725 .038203    2.01 0.045  .001796  .151549
-----
```

democrat		.2586247	.1188003	2.18	0.029	.0257804	.491469
RiskJob		.0820522	.0236088	3.48	0.001	.0357798	.1283246
GWharm		.3703581	.0583513	6.35	0.000	.2559917	.4847245
urban		.2272012	.1245379	1.82	0.068	-.0168886	.4712911
natgas		-.2681865	.1173177	-2.29	0.022	-.4981249	-.0382481
_cons		-1.820015	.2342718	-7.77	0.000	-2.279179	-1.36085

-----

-----

Model		N	ll(null)	ll(model)	df	AIC	BIC
-------	--	---	----------	-----------	----	-----	-----

-----+

.		566	-388.6952	-330.354	10	680.7079	724.0939
---	--	-----	-----------	----------	----	----------	----------

-----

APPENDIX I

PROBIT ANALYSIS FOR GAS PRICE AT \$2.5 USING THE CLEANED DATASET

Stepwise entry of all variables

Probit Regression and AIC/BIC value for \$2.5 Price Gas Model Using the Cleaned Dataset variable (Step 1)

```

-----
Price_250 | Coefficient Std. err.   z   P>|z|   [95% conf. interval]
-----+-----
Ukraine | -.0038087   .139352   -0.03  0.978   -.2769337   .2693162
Disaster | .0852134   .141549   0.60  0.547   -.1922175   .3626443
_cons | .6578441   .0989715   6.65  0.000   .4638635   .8518247
-----

```

```

-----
Model |      N ll(null) ll(model)   df   AIC   BIC
-----+-----
. |    567 -316.907 -316.6542    3  639.3084  652.3294
-----

```

Probit Regression and AIC/BIC value for \$2.5 Price Gas Model Using the Cleaned Dataset variable (Step 2)

```

-----
Price_250 | Coefficient Std. err.   z   P>|z|   [95% conf. interval]
-----+-----
Ukraine | -.0041778   .1397062   -0.03  0.976   -.277997   .2696414
Disaster | .0680316   .1421974   0.48  0.632   -.2106701   .3467334
Proportionofincomeo~250 | -2.731172   1.542214   -1.77  0.077   -5.753855   .2915123
_cons | .7383438   .1094446   6.75  0.000   .5238364   .9528513
-----

```

```

-----
Model |      N ll(null) ll(model)   df   AIC   BIC
-----+-----
. |    566 -316.6231 -314.8458    4  637.6916  655.0459
-----

```

-----  
**Probit Regression and AIC/BIC value for \$2.5 Price Gas Model Using the Cleaned Dataset variable (Step 3)**  
 -----

Price_250	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
Ukraine	.0070907	.1416161	0.05	0.960	-.2704719	.2846532
Disaster	.0558547	.1437951	0.39	0.698	-.2259786	.337688
Proportionofincomeo~250	-2.583562	1.548961	-1.67	0.095	-5.619469	.4523447
hhsiz	.1598518	.0413753	3.86	0.000	.0787577	.2409458
_cons	.3029474	.1557358	1.95	0.052	-.0022893	.608184

Model	N	ll(null)	ll(model)	df	AIC	BIC
.	566	-316.6231	-307.0148	5	624.0296	645.7226

-----  
**Probit Regression and AIC/BIC value for \$2.5 Price Gas Model Using the Cleaned Dataset variable (Step 4)**  
 -----

Price_250	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
Ukraine	.0111449	.1424626	0.08	0.938	-.2680767	.2903665
Disaster	.0791449	.1452171	0.55	0.586	-.2054754	.3637651
Proportionofincomeo~250	-2.087349	1.563112	-1.34	0.182	-5.150992	.9762942
hhsiz	.1618705	.0419289	3.86	0.000	.0796913	.2440497
democrat	.3747011	.1255551	2.98	0.003	.1286177	.6207846
_cons	.1448741	.1660491	0.87	0.383	-.1805762	.4703243

Model	N	ll(null)	ll(model)	df	AIC	BIC
.	566	-316.6231	-307.0148	5	624.0296	645.7226

```
.|    566 -316.6231 -302.4644    6 616.9287 642.9603
```

-----  
**Probit Regression and AIC/BIC value for \$2.5 Price Gas Model Using the Cleaned Dataset variable (Step 5)**  
 -----

```
Price_250 | Coefficient Std. err.    z  P>|z|  [95% conf. interval]
-----+-----
Ukraine | .0154493 .1430031    0.11 0.914  -.2648316  .2957303
Disaster | .0850692 .1458915    0.58 0.560  -.200873  .3710114
Proportionofincomeo~250 | -2.067408 1.558401  -1.33 0.185  -5.121818  .9870021
hhsizesize | .1487051 .042364    3.51 0.000  .0656732  .2317369
democrat | .3504846 .1264696    2.77 0.006  .1026088  .5983603
RiskHealth | .0504961 .0227115    2.22 0.026  .0059823  .0950098
    _cons | -.0675689 .1917973   -0.35 0.725  -.4434846  .3083468
```

```
-----
Model |    N ll(null) ll(model)  df    AIC    BIC
-----+-----
.|    566 -316.6231 -299.9752    7 613.9504 644.3205
```

-----  
**Probit Regression and AIC/BIC value for \$2.5 Price Gas Model Using the Cleaned Dataset variable (Step 6)**  
 -----

```
Price_250 | Coefficient Std. err.    z  P>|z|  [95% conf. interval]
-----+-----
Ukraine | .0153762 .1463522    0.11 0.916  -.2714688  .3022211
Disaster | .0152985 .1497008    0.10 0.919  -.2781097  .3087067
Proportionofincomeo~250 | -2.368882 1.572824  -1.51 0.132  -5.45156  .7137965
hhsizesize | .1431158 .0429824    3.33 0.001  .0588718  .2273598
democrat | .2578618 .1298158    1.99 0.047  .0034276  .5122961
RiskHealth | .0101748 .0243881    0.42 0.677  -.037625  .0579747
```

```

GWharm | .3067711 .0570204 5.38 0.000 .1950131 .418529
_cons | -.5555625 .2154783 -2.58 0.010 -.9778922 -.1332329

```

---



---

Model	N	ll(null)	ll(model)	df	AIC	BIC
.	566	-316.6231	-285.1447	8	586.2893	620.9981

---

Probit Regression and AIC/BIC value for \$2.5 Price Gas Model Using the Cleaned Dataset variable (Step 7)

---

Price_250	Coefficient	Std. err.	z	P> z	[95% conf. interval]
Ukraine	.0054083	.1469063	0.04	0.971	-.2825228 .2933394
Disaster	.0071717	.1499164	0.05	0.962	-.286659 .3010023
Proportionofincomeo~250	-2.389019	1.573345	-1.52	0.129	-5.472719 .694681
hhsize	.1472581	.0432548	3.40	0.001	.0624802 .2320359
democrat	.2903658	.1335783	2.17	0.030	.0285571 .5521744
RiskHealth	.0125927	.0244884	0.51	0.607	-.0354037 .0605891
GWharm	.3107722	.0570771	5.44	0.000	.1989031 .4226413
urban	-.1478392	.1362373	-1.09	0.278	-.4148594 .1191811
_cons	-.5468058	.2158518	-2.53	0.011	-.9698676 -.1237439

---



---



---

Model	N	ll(null)	ll(model)	df	AIC	BIC
.	566	-316.6231	-284.5573	9	587.1145	626.1619

---

Probit Regression and AIC/BIC value for \$2.5 Price Gas Model Using the Cleaned Dataset variable (Step 8)

---

Price_250	Coefficient	Std. err.	z	P> z	[95% conf. interval]
-----------	-------------	-----------	---	------	----------------------

```

-----+-----
      Ukraine | .0070522 .1469527  0.05  0.962  -.2809697  .2950741
      Disaster | .0049533 .1500178  0.03  0.974  -.2890761  .2989828
Proportionofincomeo~250 | -2.487743  1.577781  -1.58  0.115  -5.580136  .60465
      hhsizel | .1462128 .0432944  3.38  0.001  .0613573  .2310683
      democrat | .2968985 .1340592  2.21  0.027  .0341473  .5596497
      RiskHealth | .012201 .0245106  0.50  0.619  -.035839  .0602409
      GWharm | .3119144 .0571275  5.46  0.000  .1999467  .4238822
      urban | -.1500568 .1363103  -1.10  0.271  -.4172201  .1171064
      natgas | -.0862093 .124136  -0.69  0.487  -.3295113  .1570927
      _cons | -.509235 .2223492  -2.29  0.022  -.9450314  -.0734385
-----

```

```

-----
Model |      N ll(null) ll(model)  df    AIC    BIC
-----+-----
. |    566 -316.6231 -284.3164   10  588.6329  632.0188
-----

```

APPENDIX J

PROBIT USING DIFFERENT RISK VARIABLES WITH THE GP\_2.5 (1) MODEL (CLEANED DATASET)

Probit Regression and AIC/BIC value for \$2.5 Price Gas Model Using the Risk family variable (Cleaned Dataset)

```

-----
Price_250 | Coefficient Std. err. z P>|z| [95% conf. interval]
-----+-----
Ukraine | .0048678 .1470508 0.03 0.974 -.2833464 .2930821
Disaster | -.0012148 .1500554 -0.01 0.994 -.2953181 .2928884
Proportionofincomeo~250 | -2.578354 1.582991 -1.63 0.103 -5.680958 .5242505
hhsiz | .146994 .0431106 3.41 0.001 .0624987 .2314893
democrat | .292709 .1343119 2.18 0.029 .0294626 .5559554
RiskFamily | .0149686 .0215798 0.69 0.488 -.027327 .0572642
GWharm | .3131723 .0555413 5.64 0.000 .2043133 .4220312
urban | -.1510386 .1362221 -1.11 0.268 -.4180291 .1159519
natgas | -.0851773 .1241814 -0.69 0.493 -.3285683 .1582137
_cons | -.5192091 .2211422 -2.35 0.019 -.9526398 -.0857784
-----

```

```

-----
Model | N ll(null) ll(model) df AIC BIC
-----+-----
. | 566 -316.6231 -284.1996 10 588.3991 631.785
-----

```

Probit Regression and AIC/BIC value for \$2.5 Price Gas Model Using the Risk financial variable (Cleaned Dataset)

```

-----
Price_250 | Coefficient Std. err. z P>|z| [95% conf. interval]
-----+-----

```

```

Ukraine | .0057309 .1471671 0.04 0.969 -.2827114 .2941732
Disaster | .0019399 .1498945 0.01 0.990 -.291848 .2957278
Proportionofincomeo~250 | -2.496983 1.579491 -1.58 0.114 -5.592728 .5987621
hhsiz | .1478172 .0434133 3.40 0.001 .0627286 .2329057
democrat | .2970796 .1342916 2.21 0.027 .033873 .5602863
RiskFinancial | .0033385 .024488 0.14 0.892 -.0446571 .0513341
GWharm | .3187077 .0560255 5.69 0.000 .2088997 .4285156
urban | -.144785 .135842 -1.07 0.286 -.4110303 .1214604
natgas | -.0878262 .1240927 -0.71 0.479 -.3310433 .1553909
_cons | -.4858864 .2240286 -2.17 0.030 -.9249745 -.0467984

```

```

-----
-----
Model |      N ll(null) ll(model)  df    AIC    BIC
-----+-----
. |    566 -316.6231 -284.431   10  588.862  632.248
-----

```

Probit Regression and AIC/BIC value for \$2.5 Price Gas Model Using the Risk care variable (Cleaned Dataset)

```

-----
Price_250 | Coefficient Std. err.  z  P>|z|  [95% conf. interval]
-----+-----
Ukraine | .0046554 .1470564 0.03 0.975 -.2835698 .2928806
Disaster | .0037775 .1499826 0.03 0.980 -.290183 .297738
Proportionofincomeo~250 | -2.522463 1.58034 -1.60 0.110 -5.619874 .574947
hhsiz | .1463826 .043305 3.38 0.001 .0615064 .2312587
democrat | .293506 .1344229 2.18 0.029 .030042 .55697
RiskCar | .0112846 .0238906 0.47 0.637 -.0355401 .0581094
GWharm | .315809 .0554146 5.70 0.000 .2071983 .4244196
urban | -.1459629 .1358016 -1.07 0.282 -.4121291 .1202034
natgas | -.0873927 .1241 -0.70 0.481 -.3306243 .1558388
_cons | -.5092249 .2234179 -2.28 0.023 -.9471159 -.071334
-----

```

Model	N	ll(null)	ll(model)	df	AIC	BIC
.	566	-316.6231	-284.3287	10	588.6575	632.0434

Probit Regression and AIC/BIC value for \$2.5 Price Gas Model Using the Risk sports variable (Cleaned Dataset)

Price_250	Coefficient	Std. err.	z	P> z	[95% conf. interval]
Ukraine	.0130736	.1472532	0.09	0.929	-.2755375 .3016846
Disaster	.0160835	.1506855	0.11	0.915	-.2792546 .3114215
Proportionofincomeo~250	-2.316692	1.586839	-1.46	0.144	-5.42684 .7934548
hhsiz	.1416068	.0432307	3.28	0.001	.0568761 .2263374
democrat	.2653669	.1354377	1.96	0.050	-.0000861 .53082
RiskSports	.0465828	.0250002	1.86	0.062	-.0024167 .0955824
GWharm	.3018713	.0555343	5.44	0.000	.1930261 .4107166
urban	-.1591398	.136253	-1.17	0.243	-.4261907 .1079111
natgas	-.0833391	.1246044	-0.67	0.504	-.3275593 .160881
_cons	-.6458749	.2317247	-2.79	0.005	-1.100047 -.1917029

Model	N	ll(null)	ll(model)	df	AIC	BIC
.	566	-316.6231	-282.7003	10	585.4007	628.7866

Probit Regression and AIC/BIC value for \$2.5 Price Gas Model Using the Risk Job (Cleaned Dataset)

Price_250	Coefficient	Std. err.	z	P> z	[95% conf. interval]
Ukraine	.0021194	.1471197	0.01	0.989	-.2862299 .2904688

```

Disaster | .0097676 .1501901 0.07 0.948 -.2845995 .3041347
Proportionofincomeo~250 | -2.4675 1.581475 -1.56 0.119 -5.567134 .6321335
hhsizel | .1434166 .0433183 3.31 0.001 .0585142 .228319
democrat | .296027 .1341725 2.21 0.027 .0330538 .5590003
RiskJob | .0260712 .0249402 1.05 0.296 -.0228107 .074953
GWharm | .3054107 .0564108 5.41 0.000 .1948477 .4159738
urban | -.156114 .1364009 -1.14 0.252 -.4234548 .1112267
natgas | -.0887241 .1242144 -0.71 0.475 -.3321799 .1547318
_cons | -.5611356 .2276154 -2.47 0.014 -1.007254 -.1150176

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Model	N	ll(null)	ll(model)	df	AIC	BIC
.	566	-316.6231	-283.8943	10	587.7886	631.1745

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APPENDIX K:

MARGINAL EFFECTS OF ALL VARIABLES IN CGP (1) MODEL (ORIGINAL DATASET)

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	Delta-method					
	dy/dx	std. err.	z	P> z	[95% conf. interval]	
Ukraine	.0660324	.0448041	1.47	0.141	-.0217821	.1538468
Disaster	.0069278	.0451214	0.15	0.878	-.0815086	.0953641
ProportionofincomeongasCP	-.7978884	.3182189	-2.51	0.012	-1.421586	-.1741907
hhsiz	.0286308	.0124542	2.30	0.022	.004221	.0530406
democrat	.0819774	.038194	2.15	0.032	.0071187	.1568362
RiskHealth	.024587	.0072712	3.38	0.001	.0103356	.0388383
GWharm	.1164466	.0170587	6.83	0.000	.0830123	.149881
urban	.0972615	.0395643	2.46	0.014	.0197169	.1748062
natgas	-.0931747	.0375635	-2.48	0.013	-.1667979	-.0195515

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APPENDIX L

MARGINAL EFFECTS OF ALL VARIABLES IN CGP (1) MODEL (CLEANED DATASET)

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-----
|      Delta-method
|  dy/dx  std. err.   z   P>|z|   [95% conf. interval]
-----+-----
Ukraine | .0747532 .0459981   1.63  0.104   -.0154013   .1649078
Disaster | -.000699 .0465333  -0.02  0.988   -.0919026   .0905045
ProportionofincomeongasCP | -.9901274 .3408596  -2.90  0.004   -1.6582   -.3220549
hhsizex | .0263242 .0125346   2.10  0.036   .0017569   .0508915
democrat | .0876714 .0389058   2.25  0.024   .0114175   .1639253
RiskHealth | .0208212 .0074209   2.81  0.005   .0062766   .0353659
GWharm | .1240817 .0174578   7.11  0.000   .0898651   .1582983
urban | .0791972 .0409363   1.93  0.053   -.0010365   .1594309
natgas | -.0844974 .0384875  -2.20  0.028   -.1599315   -.0090633

```

## APPENDIX M

### SUMMARY STATISTICS OF THE 41 ILLOGICAL RESPONSES

<b>Variable</b>	<b>N</b>	<b>Mean</b>	<b>SD</b>	<b>Max</b>	<b>Min</b>
Bid	41	0.26	0.12	0.45	0.05
Age	41	31.88	11.80	74	9
Male	41	0.46	0.51	1	0
Education	41	14.49	2.56	20	10
Income	41	67,682.93	46,601.34	175,000	12,500
Gas Price	41	4.92	1.21	7.61	1.94
Global Warming Harm	41	2.71	0.87	4	0
Fossil tax.	41	2.56	0.87	4	0
General Risk attitude	41	5.95	1.38	9	3
Risk attitude on Health	41	6.05	1.76	10	1
Bidgas	41	0.06	0.03	0.122	0
GasExp	41	227.71	117.27	467	12
GasTax	41	13.04	9.52	37.64	0.90
Urban	41	0.49	0.51	1	0
Rural	41	0.29	0.46	1	0
Suburban	41	0.22	0.42	1	0

## APPENDIX N

### PROBIT ANALYSIS OF THE PREFERRED MODELS WITH REGIONS USING THE ORIGINAL DATASET AT THE CURRENT GAS PRICE AND AT \$2.50 PER GALLON

Price_Current	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
ProportionofincomeongasCP	-2.310418	.9603175	-2.41	0.016	-4.192605 - .4282299	
hhsiz	.0894626	.0376233	2.38	0.017	.0157223 .1632029	
democrat	.2395074	.1152851	2.08	0.038	.0135527 .4654621	
RiskHealth	.0672112	.0224148	3.00	0.003	.023279 .1111434	
GWharm	.3322654	.0560842	5.92	0.000	.2223424 .4421884	
urban	.2674905	.1204627	2.22	0.026	.031388 .503593	
natgas	-.2506344	.1138039	-2.20	0.028	-.473686 -.0275827	
region_dummy1	-.1661788	.1643516	-1.01	0.312	-.488302 .1559445	
region_dummy2	-.3633012	.1807091	-2.01	0.044	-.7174846 -.0091178	
region_dummy3	-.0851235	.1991645	-0.43	0.669	-.4754787 .3052318	
region_dummy4	-.1722031	.3858378	-0.45	0.655	-.9284312 .584025	
_cons	-1.343234	.2579759	-5.21	0.000	-1.848858 -.8376108	
Model	N	ll(null)	ll(model)	df	AIC	BIC
.	598	-413.9366	-355.0211	12	734.0421	786.7652

Price_250	Coefficient	Std. err.	z	P> z	[95% conf. interval]
Proportionofincomeongas250	-2.718816	1.514021	-1.80	0.073	-5.686242 .248611
hhsiz	.1248199	.0407107	3.07	0.002	.0450283 .2046114
democrat	.1745589	.1222945	1.43	0.153	-.0651338 .4142517
RiskHealth	-.005729	.0233769	-0.25	0.806	-.0515469 .0400889
GWharm	.2772735	.0539843	5.14	0.000	.1714662 .3830808
urban	-.2215438	.1261257	-1.76	0.079	-.4687457 .0256581
natgas	-.0152647	.1173373	-0.13	0.896	-.2452415 .2147122
region_dummy1	-.2601382	.1796295	-1.45	0.148	-.6122057 .0919292
region_dummy2	-.4923692	.1911683	-2.58	0.010	-.8670522 -.1176862
region_dummy3	-.1406215	.2149597	-0.65	0.513	-.5619348 .2806918

region_dummy4		.5335833	.5443996	0.98	0.327	-.5334203	1.600587
_cons		-.141567	.2580139	-0.55	0.583	-.6472649	.364131
Model		N	ll(null)	ll(model)	df	AIC	BIC
.		598	-364.1028	-331.0311	12	686.0622	738.7853

APPENDIX O

PROBIT ANALYSIS OF THE PREFERRED MODELS WITH REGIONS USING THE  
CLEANED DATASET AT THE CURRENT GAS PRICE AND \$2.50 PER GALLON

Price_Current	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
ProportionofincomeongasCP	-4.166724	1.756813	-2.37	0.018	-7.610015	-.7234339
hhsz	.0832047	.0382371	2.18	0.030	.0082614	.1581481
democrat	.2412443	.119729	2.01	0.044	.0065797	.4759089
RiskHealth	.0573709	.0229591	2.50	0.012	.012372	.1023699
GWharm	.3420917	.0578162	5.92	0.000	.228774	.4554093
urban	.2039197	.1258287	1.62	0.105	-.0427	.4505395
natgas	-.2339096	.1178655	-1.98	0.047	-.4649216	-.0028975
region_dummy1	-.2438596	.1678882	-1.45	0.146	-.5729144	.0851952
region_dummy2	-.4429249	.1871608	-2.37	0.018	-.8097533	-.0760964
region_dummy3	-.1430054	.2044218	-0.70	0.484	-.5436648	.2576541
region_dummy4	-.2857677	.4003343	-0.71	0.475	-1.070409	.4988731
_cons	-1.329087	.2627177	-5.06	0.000	-1.844005	-.8141701
Model	N	ll(null)	ll(model)	df	AIC	BIC
.	560	-384.2641	-328.9844	12	681.9687	733.904

Price_250	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
Proportionofincomeongas25	-.8944494	.9334619	-0.96	0.338	-2.724001	.9351024
hhsz	.1499416	.0443022	3.38	0.001	.0631109	.2367723
democrat	.2995032	.136746	2.19	0.029	.0314859	.5675204
RiskHealth	.0138039	.0248974	0.55	0.579	-.034994	.0626018
GWharm	.2870762	.0569769	5.04	0.000	.1754036	.3987489
urban	-.1528135	.1399272	-1.09	0.275	-.4270657	.1214387
natgas	-.0656982	.1270734	-0.52	0.605	-.3147575	.1833611
region_dummy1	-.2266415	.1963867	-1.15	0.248	-.6115523	.1582693
region_dummy2	-.4347302	.2084737	-2.09	0.037	-.8433311	-.0261292
region_dummy3	-.0603232	.236631	-0.25	0.799	-.5241116	.4034651

```

region_dummy4 |      0 (omitted)
      _cons | -.2823406 .2764897 -1.02 0.307 -.8242505 .2595692
Model |      N ll(null) ll(model)  df    AIC    BIC
. |      547 -310.0446 -276.3374  11  574.6749  622.0238

```