# USING A CHOICE EXPERIMENT TO UNDERSTAND THE PRICE DIFFERENTIAL BETWEEN GEO AND N-GEO CARBON OFFSETS FUTURES CONTRACTS

A Thesis

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Master of Science in Applied Economics and Management

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ABSTRACT

In this study we elicit participants’ preferences for a variety of attributes when choosing between different carbon offsets. Using a discrete choice experiment, we make students compare and decide between different types of carbon offsets based on various attributes. Results show that respondents obtain an increased marginal utility for carbon offsets of projects (i) sourced from ”biodiversity conservation and regeneration”, “manufacturing companies that replace traditional sources of energy for renewable sources of energy (i.e., solar and wind)”, “forestry conservation and regeneration”, and “sustainable agriculture practices”, (ii) verified by “a non-profit organization” and “a government entity”, (iii) originated in “a regulated market”, and (iv) “near their home location (assuming they are based in the US)”, followed by the option “in a developing country”. We find that concrete differences in the willingness to pay for the attributes provide substantiating argument for a behavioral component that explains why the price of the Nature-Based Global Emissions Offset futures contract is higher than the Global Emissions Offset futures contract, when the underlying asset or deliverable is the same for both: 1,000 environmental offsets, each representing 1 Mt CO2e. Given that voluntary carbon markets are a complementary tool to policy development on environmental markets, these results might be useful to consider when establishing the rules for compliance carbon markets.

## BIOGRAPHICAL SKETCH

Raised and educated in a rural area in Buenos Aires, Argentina, Josefina Uranga is a second-year graduate student pursuing a Master of Science in Applied Economics and Management at Cornell University, with a minor in Food and Agricultural Economics. She is also a Graduate Research Assistant at the Cornell Atkinson Center for Sustainability, working on a research-to-action project focused on developing innovative financial solutions for regenerative agriculture systems in the Great Lakes region of North America.

Prior to Cornell, she was a Corporate Strategy Associate Intern at Cargill during the summer of 2022 based in Minneapolis. Prior to starting her master degree, Josefina worked in the banking industry in Buenos Aires, Argentina. Her last position was as Associate in the Corporate Finance and M&A team at Rabobank, after starting as an Analyst in the Corporate and Investment Banking team at ICBC.

Josefina obtained her bachelor’s degree in Economics from Universidad de San Andrés in Buenos Aires, Argentina. Her research interests focus on conservation finance, sustainability, agriculture, and commodity markets.

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## DECLARATIONS

*Conflict of interest* The author declares to have no conflict of interest.

*Ethical approval* This study went through, and was approved, by the human subjects Internal Review Board (IRB), Cornell University. IRB approval no. IRB0009137.

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## 1. Introduction

"Getting to net zero carbon emissions is going to require a revolution in the production of everything we produce, and a revolution in everything we consume. The process of creating fuel, food, and construction materials, with all the needs that we have as humanity, it all has to be reinvented"–Larry Fink, CEO and Chairman of BlackRock, stated at the Middle East Green Initiative Summit in Riyadh, Saudi Arabia, in October 2021.[1] Back then, he argued that addressing climate change should be the focus of investors given the huge opportunity this area presents for new businesses, finance, and innovation. Similarly, Bill Gates, co-founder Microsoft, invests in clean tech through his firm Breakthrough Energy Ventures, which also counts Amazon founder Jeff Bezos, Michael Bloomberg and Ray Dalio as investors. This is not only a trend that private investors or philanthropy are following; currently, there is tremendous market momentum for the conservation space that is gaining attention from all active players in an economy, including policy makers, consumers, non-profit organizations, investors, and corporations.

More and more companies are taking actions on ESG, making sustainability a top priority at the corporate and executive levels for a variety of likely reasons: they genuinely think it is the best action to take, or because they must comply with policies and regulations, or because private investors and the media are forcing it upon them. Regardless of the specific reason, significant commitments have been made towards improving supply chain resiliency and reducing business' footprint on the environment, to achieve the ultimate goal of climate change mitigation. During the past two decades, corporations have released climate change pledges to be aligned with the 2016 Paris Agreement that calls, among many other things, to achieve net zero emissions by 2050. The concept of net zero emissions implies that greenhouse gas (GHG) emissions to the atmosphere

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[1] CNBC, https://www.cnbc.com/2021/10/25/blackrock-ceo-larry-fink-next-1000-unicorns-will-be-in-climatetech.html#:~:text=%E2%80%9CGetting%20to%20net%20zero%20carbon,be%20reinvented%2C%E2%80%9D%20Fink%20said.

are balanced by removals, both actions happening during the same period of time (Robin Matthews, 2018).

More recently, through the Business Ambition for 1.5°C pledge in 2021 and other wide set of initiatives, these commitments were expanded to include a greater variety of resources such as water and land. For GHG accounting and reporting purposes, the GHG Protocol Corporate Standard (Ranganathan et al., 2004) established the definition of Scope 1, or direct emissions of anthropogenic greenhouse gases from all sources owned or controlled by a company, and Scope 2 emissions, or electricity indirect GHG emissions that are those purchased by the company from the grid. Moreover, Scope 3, or all other indirect emissions that occur in a company's value chain, is an optional reporting category in the GHG Protocol Corporate Standard but is a required one to comply with the GHG Protocol Scope 3 Standard (Bhatia et al., 2011).

Cargill, for example, is committed to reduce 10% of its Scope 1 and 2 GHG emissions by 2025. In addition, the company has a target to reduce global GHG emissions from the global supply chain (Scope 3) by 30% by 2030, measured per ton of product.[2] Similarly, Danone is committed to reducing absolute Scope 1 and 2 GHG emissions by 47.2% by 2030, and absolute Scope 3 GHG emissions by 42% by 2030.[3] PepsiCo also plans to reduce Scope 1 and 2 emissions by 75% and Scope 3 emissions by 40% by 2030 (2015 baseline). Moreover, the corporation has committed to achieve net zero emissions by 2040.[4] Walmart, as well, has set the goal of achieving zero emissions across global operations by 2040.[5] And these are just a few examples on the corporate side.

Climate has also become a very important topic shaping policy agenda. Back in February 2022 USDA announced an investment of $1 billion to finance projects in agriculture and forestry that implement innovative, cost-effective ways to measure and verify GHG benefits.[6] The funding for Partnerships for Climate-Smart Commodities initiative was later expanded to more than $3.1

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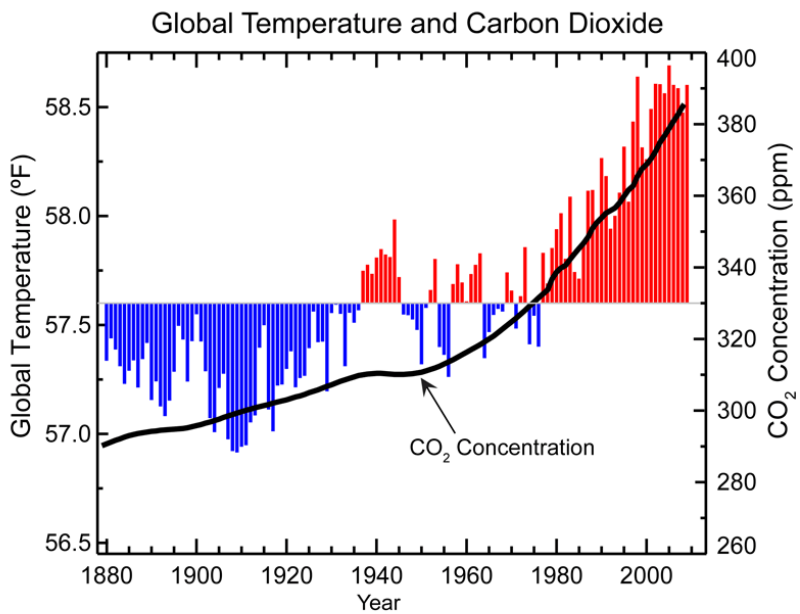
[2] Cargill, https://www.cargill.com/sustainability/esg-scorecard.
[3] Danone, https://www.danone.com/impact/planet/climate-actions.html.
[4] PepsiCo, https://www.pepsico.com/our-impact/esg-topics-a-z/climate-change.
[5] Walmart, https://corporate.walmart.com/esgreport/environmental/climate-change.
[6] USDA, https://www.usda.gov/media/press-releases/2022/02/07/usda-invest-1-billion-climate-smart-commodities-expanding-markets.

billion in what is considered a historic investment of USDA to support farmers, ranchers, and forest landowners, in the United States of America.[7] The USDA Partnership for Climate-Smart Commodities together with the Inflation Reduction Act of 2022 will enhance the development of voluntary carbon markets to contribute to the goal of reducing US emissions by 40 percent by 2030. Over $20 billion will be devoted to agriculture during the next five years to promote the adoption of conservation practices (Plastina, 2023).

These examples clearly illustrate that climate change is now part of the agenda for corporations, governments, and individuals, all taking concrete actions to tackle this problem. As we can observe in **Figure 1** below, there is a positive correlation between increased global temperature and carbon dioxide levels in the atmosphere from 1880 until 2021, as both variables have been increasing throughout the years.[8]

***Figure 1.*** *Global temperature and carbon dioxide (1880-2021).*



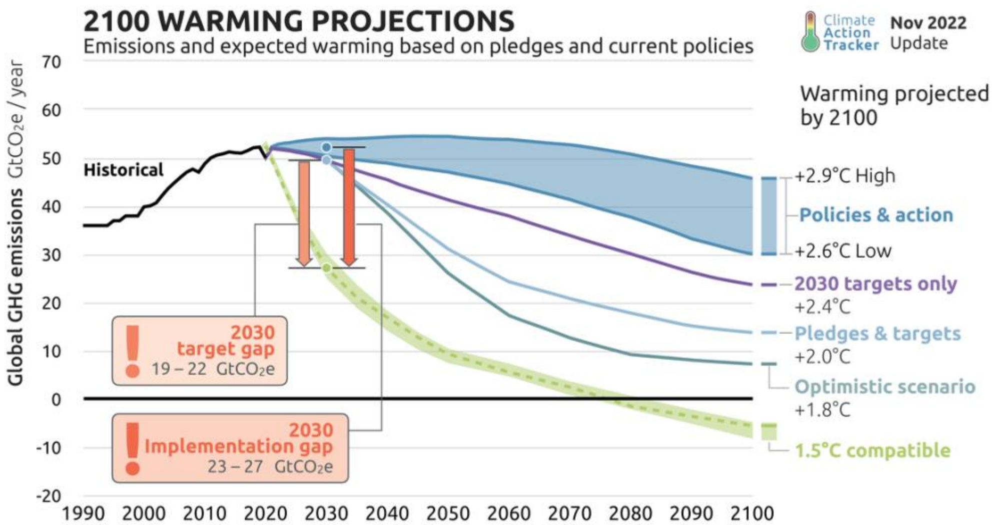

*Source: NOAA/NCDC. NASA's Goddard Institute for Space Studies (GIS), the U.S. National Climatic Data Center, and the University of East Anglia, UK.*

[7] USDA, https://www.usda.gov/climate-solutions/climate-smart-commodities#:~:text=On%20September%2014%2C%202022%2C%20Secretary,Climate%2DSmart%20Commodities%20funding%20opportunity.

[8] Global Change, https://nca2009.globalchange.gov/global-temperature-and-carbon-dioxide/index.html and https://www.isws.illinois.edu/statecli/climate-change/gtrends.htm.

According to the Climate Action Tracker, addressing climate change and particularly GHG emissions will require significant innovation if we want to achieve net zero GHG emissions in the second half of this century, as we can observe in **Figure 2**.[9]

***Figure 2.*** *2100 warming projections.*



*Source: Climate Action Tracker*

At a first glance, this information represents a heavy burden. However, on second glance, it presents a huge opportunity. McKinsey estimates that capital expenditures for energy and land-based systems needed to achieve net zero emissions by 2050 is $9.2 trillion per year on average (Krishnan et al., 2022). These estimates are in line with a recent publication indicating that funds devoted to climate financing amounted to $850-940 billion during 2021 (Naran et al., 2022). This is a significant amount of capital to be deployed in investments and new businesses. There will be a huge potential to develop ideas and projects that deliver creative and innovative solutions, and it will also generate a very important need for novel and tailor-made financial tools to enable the risk transfer from nature to other sectors in the economy.

As explained by Tobin-de la Puente and Mitchell (2021), before exploring mechanisms to scale up nature financing, or biodiversity specifically, we must first understand what the active mechanisms currently financing conservation are; these include (i) debt products such as transition loans, equipment financing, and sustainability-linked loans, (ii) equity solutions from accelerators,

[9] Climate Action Tracker, https://climateactiontracker.org/global/temperatures/.

VCs, and impacting investing sources, (iii) hybrid financing mechanisms such as blended finance and pay-for-success models, (iv) philanthropic capital and grants, (v) crop insurance, and (vi) environmental marketplaces. With water, carbon, and nutrient marketplaces, corporations and other entities can reduce their environmental footprint.

Specifically, carbon markets have been able to successfully expand and attract different types of investors and clients, including but not limited to corporations and individuals. The World Bank's Carbon Pricing Dashboard (2022) lists 70 carbon pricing initiatives implemented around the world, covering 23.17% of GHG emissions worldwide with a total value of $277 billion.[10]

Compliance markets are driven by government regulations and policies whereas voluntary markets are driven by social responsibility, moral suasion, and customer or shareholder advocacy. A practical example of this difference is the existence of carbon credits from certain agricultural practices, such as cover cropping and fertilizer use reductions, that cannot be used to comply with emission targets in mandatory United States carbon markets. Thus, the demand for carbon credits generated from agriculture and traded in voluntary markets is expected to originate mainly from the implementation of net zero initiatives by more than 1,500 companies and 120 nations (Black et al., 2021).

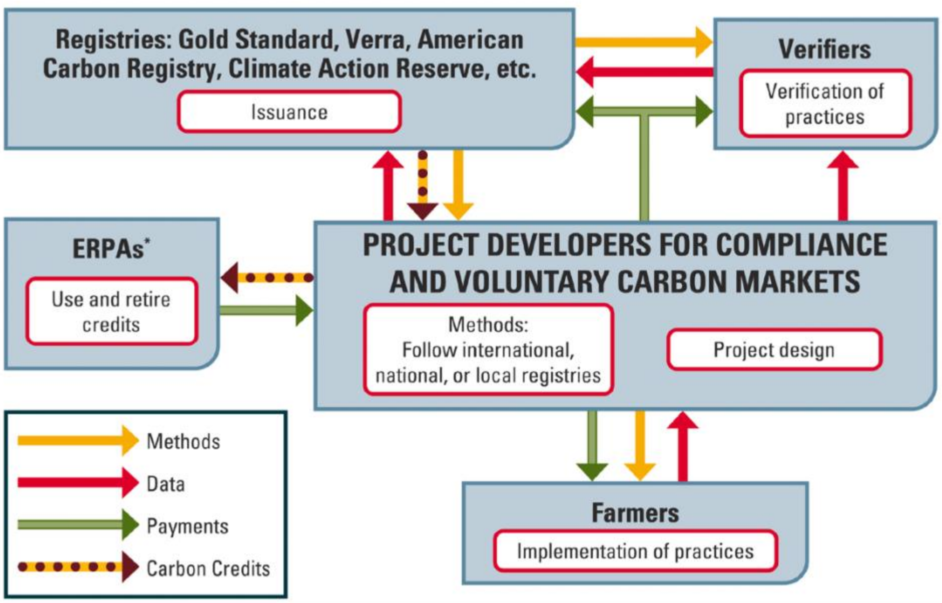
Voluntary carbon offset markets provide a market-based mechanism that allows hedging climate change through carbon offsets or other related GHG effects, wherein those who can reduce or remove carbon emissions sell the offsets to those who are not able to do it, but still have the willingness to reduce their carbon footprint by offsetting their emissions. Carbon offsets are represented by validated certificates and are sold by several organizations that enumerate the amount of carbon reduced by one party and act as clearinghouse to sell to a counterparty. A carbon offset is "a top-quality token for 1 Mt CO2e removed through practices that adhere to trusted protocols ensuring additionality and permanence, which are verified by an independent third party,

[10] The World Bank Group, https://carbonpricingdashboard.worldbank.org/map_data.

certified, and registered with a unique serial number into a secure ledger called the registry" (Schulte Moore and Jordahl, 2022).

The following diagram in **Figure 3** (Plastina, 2021) shows how a carbon offset is generated from a project that incentivizes the implementation of conservation practices in agriculture, including the flow and structure of payments, data, and practices. For detailed descriptions of how real-world carbon programs work, see Plastina and Wongpiyabovorn (2021), who thoroughly analyze examples such Bayer, Nori, and Nutrien, among others.

***Figure 3.*** *Carbon offset generation from an agricultural project.*




Thus, the carbon spot market is made up of buyers and sellers of carbon credits. Carbon spot markets are volatile with CO2e prices rising and falling randomly. Until 2020, this randomness was unhedged. Corporations and other types of clients may now purchase carbon offsets into the future as a permanent offset to their current level of pollution, or as an interim strategy while changing technologies and retrofitting facilities, among others.

The Global Emission Offset™, or GEO[11], is a way of trading carbon that provides companies with the means to meet compliance and voluntary carbon objectives and to manage future price risk.

[11] CME Group - CBL Global Emissions Offset, https://www.cmegroup.com/markets/energy/emissions/cbl-global-emissions-offset.html.

GEO spot and futures markets enable market participants to buy carbon offsets. Underlying every GEO contract is a carbon offset that meets the eligibility criteria defined by the International Civil Aviation Organization, a United Nations specialized agency, for Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA). The settlement method for the GEO spot contract is physical delivery of CORSIA eligible voluntary carbon offset credits from three different possible registries: Verified Carbon Standard (VCS), American Carbon Registry (ACR), and Climate Action Reserve (CAR). The GEO spot contracts are traded on the CBL exchange and GEO futures on the New York Mercantile Exchange (NYMEX) that is a Designated Contract market (DCM) of the CME Group. The Nature-Based Global Emissions Offset™, or N-GEO[12], offers buyers offsets sourced exclusively from Agriculture, Forestry, and Other Land Use (AFOLU) projects. The N-GEO enables purchasers nature-based offsets generated from projects that address climate change, support local communities and smallholders, and conserve biodiversity following the eligibility criteria defined by Verra's Climate, Community, and Biodiversity (CCB) Standards. Like the GEO, the N-GEO spot contract is traded on the CBL exchange, and the futures contract on the NYMEX. A comparison between GEO and N-GEO contract specifications can be seen in **Table 1**.

[12] CME Group – CBL Nature-Based Global Emissions Offset, https://www.cmegroup.com/markets/energy/emissions/cbl-nature-based-global-emissions-offset.html.

**Table 1**
GEO and N-GEO Specifications

| | GEO | NGO |
|---|---|---|
| Contract unit | 1,000 environmental offsets (each representing 1 mtCO2e) | 1,000 environmental offsets (each representing 1 mtCO2e) |
| Price quotation | U.S. dollars and cents per environmental offset | U.S. dollars and cents per environmental offset |
| Trading hours | (i) CME Globex: Sunday 5:00 p.m. - Friday - 4:00 p.m. CT with a 60-minute break each day beginning at 4:00 p.m. CT, and<br>(ii) CME ClearPort: Sunday 5:00 p.m. - Friday 4:00 p.m. CT with no reporting Monday - Thursday from 4:00 p.m. – 5:00 p.m. CT | (i) CME Globex: Sunday 5:00 p.m. - Friday - 4:00 p.m. CT with a 60-minute break each day beginning at 4:00 p.m. CT, and<br>(ii) CME ClearPort: Sunday 5:00 p.m. - Friday 4:00 p.m. CT with no reporting Monday - Thursday from 4:00 p.m. – 5:00 p.m. CT |
| Minimum price fluctuation | 0.01 per environmental offset = $10.00 | 0.01 per environmental offset = $10.00 |
| Product code | (i) CME Globex: GEO,<br>(ii) CME ClearPort: GEO, and<br>(iii) Clearing: GEO | (i) CME Globex: NGO,<br>(ii) CME ClearPort: NGO, and<br>(iii) Clearing: NGO |
| Listed contracts | Monthly contracts listed for the current year and the next 3 calendar years. List monthly contracts for a new calendar year following the termination of trading in the December contract of the current year. | Monthly contracts listed for the current year and the next 3 calendar years. List monthly contracts for a new calendar year following the termination of trading in the December contract of the current year. |
| Settlement method | Deliverable | Deliverable |
| Floating price | The floating price is equal to CBL Global Emissions Offset spot price | The floating price is equal to CBL Nature-Based Global Emissions Offset spot price |
| Termination of trading | Trading terminates 3 business days prior to the last business day of the contract month | Trading terminates 3 business days prior to the last business day of the contract month |
| Position limits | NYMEX Position Limits | NYMEX Position Limits |

One essential aspect of these contracts is that they both use the settlement method of delivery at maturity, which means that after contract expiration, the purchaser receives an offset credit from a registry and that offset is retired, so that it can no longer be traded. Both contracts provide liquidity, transparent price discovery, risk transference mechanisms, and a reliable benchmark for the global carbon market. The underlying asset for both types of contracts is the same amount of carbon dioxide, but there is a convenience-type preference for N-GEO derived exclusively from AFOLU projects, for which buyers are willing to accept a higher price for N-GEO than for GEO carbon futures contracts. So, why in a transparent market are these two prices different?

Following the concept of an efficient market originally used in finance that can be applied to commodity markets, given that the information on the underlying assets, on the terms and conditions of the contracts, and on prices is available, accessible, and visible, there should be no sources of price differentiation between N-GEO and GEO futures contracts. Instead, given that for both types of contracts consumers receive an offset certificate for the same amount of carbon dioxide, both prices should converge. This was not the case when we started this study back in December 2021.

The existing literature explores various factors affecting willingness to pay for carbon offsets using different empirical methods. Brouwer et al. (2008) find a positive WTP for mandatory carbon tax for airplane passengers, using the contingent valuation method through a survey at Schiphol airport. Early on, they suggest that people's willingness to finance climate change mitigation may be greater than what it is generally assumed. Furthermore, previous literature reveals that we all have a socially responsible self-image individually (Brekke et al., 2003) and that the perceived responsibility to act in a pro-social way, and to offset specifically, greatly varies with external factors (Brekke et al., 2010; Schwirplies et al., 2019). Moreover, that feeling of responsibility is highly influential in triggering CO2e offsetting behavior and other climate change mitigation options (Lange and Ziegler, 2012). Ziegler et al. (2012) find that there is a positive correlation between previous knowledge in offsetting CO2e emissions from fuel consumption and the purchase of carbon offsets. In line with this, MacKerron et al. (2009) use the results of an online survey to show that projects with co-benefits such as human development, environmental protection and biodiversity, and technology and market development, increase the willingness to pay, when these are clearly communicated and emphasized to purchasers. Moreover, Blasch and Farsi (2014) suggest that individuals prefer offsetting projects in developing countries that are initiated by nongovernmental organizations and certified by the government. The authors conduct an online survey in Switzerland and find that there is greater propensity to offset in low-cost situations and obtain higher willingness to pay estimates in emission-intensive contexts, such as airplane flights. On the contrary, Schwirplies et al. (2019) reveal that the willingness to pay for carbon offsets produced by bus trips is higher when compared to planes, the latter being the most emission intensive. Using data collected from an online survey in Germany, they show that re-/afforestation projects are preferred to renewable energies projects or projects that improve energy efficiency, and that participants prefer projects carried out in their region, when compared to other European countries or in developing countries.

Given the potential and relevance of this market, as according to the Green Business Bureau, the voluntary carbon offset market is projected to reach $700.5 million by 2027[13], in this thesis we try to understand why there is a price difference between N-GEO and GEO carbon offset futures contracts. We expanded upon previous studies in that we conduct a discrete choice experiment and include a broad variety of levels for the different attributes to be considered, particularly for the type of project from the carbon offset is sourced. In this context, we implemented a Discrete Choice Experiment (DCE) at Cornell University located in Ithaca, Tompkins County NY, during November and December 2022 with participants from Cornell's community that had to choose from different types of carbon offsets presented, based on varying attributes. Our results show that people have an emotional difference towards carbon offsets generated from AFOLU projects, which could be the reason why there is a wedge between the prices of both contracts in the market. We find that, although respondents' preferences are heterogeneous, there is an increased marginal utility from carbon offsets (i) generated in "biodiversity conservation and regeneration" and "forestry conservation and regeneration", "manufacturing companies moving to renewable sources of energy", and "sustainable agriculture practices"; (ii) verified by "a non-profit organization" followed by verification performed by "a government entity"; (iii) originated in "a regulated market"; and (iv) located "near their home location (assuming they are based in the US)".

The remainder of the thesis is structured as follows: Section 2 presents the data and methodology implemented to pursue this study and Section 3, the econometric model used to estimate participant's willingness to pay for carbon offsets futures contracts considering different attributes. We continue by presenting the results obtained from the choice experiment in Section 4. In Section 5 we discuss the limitations of the study and potential extensions of the work presented. Lastly, we conclude this thesis in Section 6.

[13] Green Business Bureau, https://greenbusinessbureau.com/topics/carbon-accounting/carbon-offsets-vs-carbon-credits/.

## 2. Data and methodology

In an attempt to close the gap between the price of the GEO and N-GEO carbon futures contracts, we conducted a discrete choice experiment to assess the willingness to pay of individuals for different offsets contracts with varying attributes. Population behavior can be modeled from observing choices at the individual level as utility maximization behavior and rationality can be assumed for the choice experiments, both characteristics derived from the Random Utility Maximization model (Luce, 1959; Marschak, 1960; McFadden, 1973). Thus, economics and the different fields that comprise it, frequently use choice experiments to estimate willingness to pay. These methods have been mainly used in Agricultural Economics in topics related to risk assessment and insurance (Hennessy and Marsh, 2021; Fu et al., 2022; Fu et al., 2021; Kong et al., 2021) and to perform cost benefit analysis for Environmental Economics as an input for Contingent Valuation Methods (Whitehead and Haab, 2013). This study adds to previous results in applying the discrete choice experiment methodology to the area of conservation finance.

The experiment was conducted at the Cornell University campus located in Ithaca, Tompkins County NY in late November and beginning of December 2022. Both S.C. Johnson Graduate School of Management and Charles H. Dyson School of Applied Economics and Management have laboratories devoted to performing behavioral research to study economic and psychological phenomena, the Business Simulation Lab and Lab for Experimental Economics & Decision Research, respectively. The experiment was published on both laboratories' websites and emails were sent to individuals who had an existing account, notifying that the experiment was posted. Subscribers were able to sign up for the experiment by choosing an available time slot and had to assist for an in-person session that included maximum of 22 people. See **Appendix A** for sample photographs of what an experimental session looked like.

The final sample contains 272 respondents that attended the 28 different sessions (10 in BSL and 18 in LEEDR). As can be seen in **Table 2**, 69% of respondents are Female and 27% Male, with 1% being Nonbinary and 3% that did not answer. Moreover, regarding nationality, 53% of respondents are American and 11% Indian, being the largest groups, as none of the rest have over 10% of nationality concentration. In addition, 80% of our sample are students.

Before the start of each session, the person responsible for the experiment briefly introduced the project, the researcher, and stated the fact that no previous knowledge was needed to perform the study.

**Table 2**
Descriptive statistics of the sample

| | N | Percent |
|---|---|---|
| *Gender* | | |
| Female | 188 | 69% |
| Male | 74 | 27% |
| Non binary | 2 | 1% |
| Blank | 8 | 3% |
| *Nationality* | | |
| Asia | 5 | 2% |
| Bangladesh | 1 | 0% |
| Brazil | 1 | 0% |
| Chile | 2 | 1% |
| China | 15 | 6% |
| Colombia | 7 | 3% |
| Congo | 1 | 0% |
| France | 2 | 1% |
| Germany | 2 | 1% |
| Hispanic | 2 | 1% |
| India | 31 | 11% |
| Indonesia | 5 | 2% |
| Italy | 1 | 0% |
| Korea | 1 | 0% |
| Lebanon | 1 | 0% |
| Malaysia | 2 | 1% |
| Mexico | 5 | 2% |
| Nepal | 1 | 0% |
| Other | 10 | 4% |
| Peru | 1 | 0% |
| Portugal | 1 | 0% |
| Spain | 1 | 0% |
| Taiwan | 4 | 1% |
| UK | 1 | 0% |
| United States of America | 143 | 53% |
| United States of America and | 12 | 4% |
| Zimbabwe | 1 | 0% |
| Blank | 13 | 5% |
| *Occupation* | | |
| Student | 217 | 80% |
| Employed | 43 | 16% |
| Retired | 3 | 1% |
| Blank | 9 | 3% |

For the choice experiment design, we used the D-optimal approach, as a fully orthogonal model would have required 756 combinations considering the different attributes and their levels, that are described later in this section. Instead, the D-optimal design allowed us to limit the options to create six blocks, with nine cards per block, and three options from which individuals had to choose in each of the cards. Previous literature has not established a "one size fits all" approach when it comes to experimental design, so we used one that has worked in similar environments and in pursuit of comparable outcomes. Moreover, we took into account Johnson and Orme (1996) results that show that the number of choice tasks and sample size can be traded off, which means that doubling the number of tasks per respondent is as beneficial as doubling the sample size.

Each participant was randomly assigned one of the six blocks available and had to decide nine consecutive times. Each choice was recorded using a 1 and a 0 was used for the two non-selected options in each card. At the end of the experiment, each respondent had to answer a survey. An example of what a card looked like can be seen in **Figure 4** and **Figure 5**, and the survey can be found in **Appendix B**.

***Figure 4.*** *Card 1 in Block 1 presented to an individual to choose from the three options of Carbon Offset.*

**B1C1**

| | **Carbon offset 1** | **Carbon offset 2** | **Carbon offset 3** |
|---|---|---|---|
| **Price** *Price of a carbon offset is* | $17 | $2 | $11 |
| **Sourcing** *Carbon offset is sourced from* | Sustainable agriculture practices | Biodiversity conservation and regeneration | Forestry conservation and regeneration |
| **Verification** *Carbon offset verification is performed by* | A private company | A non-profit organization | A government entity |
| **Market origination type** *Carbon offset is generated in* | A regulated market | A non-regulated market | A non-regulated market |
| **Geographic location** *The project that generated the carbon offset is located* | In a developing country | Near your home location (assuming you are based in the US) | In another developed country |

***Figure 5.*** *Card 4 in Block 6 presented to an individual to choose from the three options of Carbon Offset*

**B6C4**

| | **Carbon offset 1** | **Carbon offset 2** | **Carbon offset 3** |
|---|---|---|---|
| **Price** *Price of a carbon offset is* | $11 | $17 | $8 |
| **Sourcing** *Carbon offset is sourced from* | Other land conservation uses | Transportation fleets that make investments in their trucks so that these burn less fuel and in a more efficient way | Manufacturing companies that replace traditional sources of energy for renewable sources of energy (i.e. solar and wind) |
| **Verification** *Carbon offset verification is performed by* | A government entity | A private company | A non-profit organization |
| **Market origination type** *Carbon offset is generated in* | A non-regulated market | A regulated market | A regulated market |
| **Geographic location** *The project that generated the carbon offset is located* | Near your home location (assuming you are based in the US) | In another developed country | In a developing country |

Previous studies included an opt out clause because authors didn't believe that the market was well enough developed and therefore that people simply would not want to participate. It is our belief that including an opt out option creates a discontinuity or non-convexity in the demand structure and that without knowing why someone opted out, we cannot draw conclusions about their demand preferences. On the one hand, people knew that the topic of this study was carbon offsets as it was advertised ahead of time and, on the other hand, we included in the preamble an explanation of what a carbon offset is. Thus, we decided not to include an opt out option in the cards.

As we knew that respondents would be people who could or could not have previous knowledge in the subject, we decided that the experiment approach would be from the perspective of an individual willing to offset the emissions of a recently bought car, through the purchase of carbon offset units. Though we know from previous literature that the framing context highly influences the willingness to pay for people to contribute to public goods (Cason and Raymond, 2011; Huber et al., 2018; Shogren et al., 2010), we chose a car purchase as the event to include in the preamble because average car ownership in Ithaca is two units per household[14], over 80% of vehicle registrations in Tomkins County are personal vehicles, and drive alone represents over 60% of Tompkins County means of transportation to work (Linde et al., 2019). Both factors make the hypothetical situation representative of the population and easily relatable to participants. So, the following preamble was included on the top of each card:

"<u>Preamble</u>

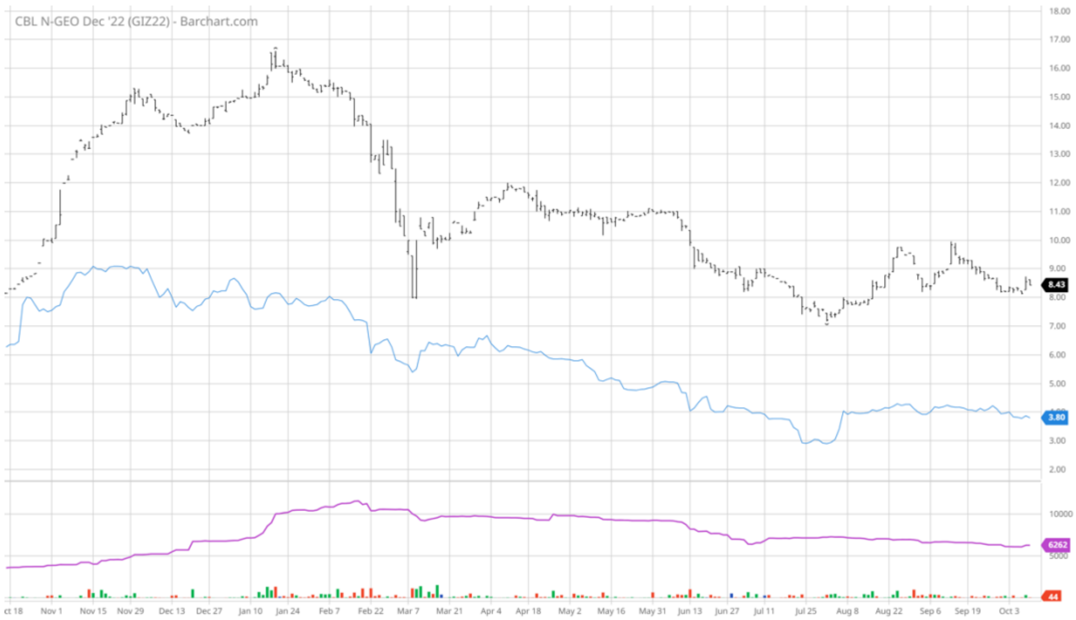
**Suppose you are an individual who is buying a new car (conventional gas engine with a fuel tank). To offset Greenhouse Gas (GHG) emissions of using your new car, you want to buy carbon offsets. Which type of carbon offsets would you buy?**

*Carbon offsets are transferrable instruments certified to represent Greenhouse Gas (GHG) emissions reductions, or an increase in carbon storage, that are sold to compensate for emissions that occur elsewhere."*

To determine which variables should be included in the study, we first took "Price" as the key factor to understand the willingness to pay and the main question around which this thesis originated. We started by taking the maximum and minimum prices of the GEO and N-GEO December 2022 contracts, that were $8.89 on November 23, 2021, and $1.92 on April 15, 2021, for the GEO contract, and $15.89 on January 18, 2022 and $5.35 on August 3, 2021 for the N-GEO contract. Please see in **Figure 6** the price evolution of the N-GEO (black line) and GEO (blue line) December 2022 futures contracts.

[14] Data USA, https://datausa.io/profile/geo/ithaca-ny-31000US27060.

***Figure 6.*** *N-GEO (black line) and GEO (blue line) December 2022 futures contracts.*




*Source: Barchart.com*

By taking the maximum price difference, we established six different levels for the "Price" attribute getting (i) $2, (ii) $5, (iii) $8, (iv) $11, (v) $14, and (vi) $17 as options, which represent the approximate range of prices charged in the actual market.

We then went through the attributes of carbon credits currently traded. From these, we took that the type of project from which carbon offset was sourced, was also a very relevant aspect to focus on, as it is the clearest distinction between GEO and N-GEO. For this reason, we established the levels within the "Sourcing" attribute to be: (i) aviation industry that transitions from the use of traditional fuel to sustainable aviation fuel, (ii) biodiversity conservation and regeneration, (iii) forestry conservation and regeneration, (iv) manufacturing companies that replace traditional sources of energy for renewable sources of energy (i.e. solar and wind), (v) other land conservation uses, (vi) sustainable agriculture practices, and (vii) transportation fleets that make investments in their trucks so that these burn less fuel and in a more efficient way.

Another important attribute we wanted to focus on was "Verification". Currently, verification is done by private companies, so we thought it was important to understand people's preference to make this study useful for future market developments and policy. The levels we included of this attribute were the following: (i) a government entity, (ii) a non-profit organization, and (iii) a private company.

Furthermore, though in reality we are only dealing with voluntary carbon markets, we wanted to assess if there is a preference for the offset originated in (i) a non-regulated market or in (ii) a regulated market, so we established these two possibilities for the attribute “Market origination type”.

Lastly, we stress tested the attributes to be included with the corresponding specific levels with professionals currently working as Traders in Voluntary Carbon Markets team of a large corporation in the industry, and they suggested to include “Geographic location”. It is a relevant item that comes up frequently in the discussions on whether carbon offset markets will be able to scale, as it could become an opportunity to have the freedom to generate the carbon offset anywhere and trade it at the highest price, no matter where the market is, or it could be a limitation if this is not the case. So, we included this fifth attribute considering the options (i) in a developing country, (ii) in another developed country, and (iii) near your home location (assuming you are based in the US).

Each card had a total of five attributes, which is below the maximum number of ten established by the literature to allow a reasonable processing workload from participants (Deshazo and Fermo, 2002). In addition, randomized design given by JMP Software, in which we input the number of blocks (9), cards per block (6), and choices per card (3), and automatically generated the combinations of the different levels of attributes to be included in each of the cards. We also used these three input numbers to obtain the minimum sample size using the following formula:

$$N \geq 500 \; x \; (I^* / S \; x \; J)$$

Where $I^*$ is the largest number of levels of any of the attributes, which in our case is seven levels for “Sourcing” attribute. $S$ is the number of choice tasks presented to each respondent, nine cards in this DCE, and $J$ is the number of alternatives per choice task, three options of Carbon Offset per card. This is the method that is generally used to calculate the minimum sample size in choice experiments (Johnson and Orme, 2003; Orme, 2019; Rose and Bliemer, 2013). The result was $N$

$\geq 130$ and thus our final number of participants 272, is in compliance with the minimum sample size.

## 3. Econometric model

Discrete choice models are a very popular method used by economists to calculate willingness to pay (McFadden, 2001). In this case, we are applying it to understand the willingness to accept a differential in the price of N-GEO with respect to that of GEO contracts, considering that the underlying traded asset is the same; 1,000 environmental offsets (each representing 1 Mt CO2e). To analyze the data gathered during the experiment, we used three specific types of discrete choice models: traditional logit, conditional and two different mixed logit models. Given that the results across the four models were consistent and significant, we will hereby focus on the application of conditional and mixed logit models that allow for more direct interpretation of the data.

### *4.1 Conditional logit model*

Based on random utility theory, the conditional logit model assumes homogeneous preferences among respondents (McFadden, 1973). Each respondent $i$ faces $J$ alternative specific carbon offset options from which the individual obtains a utility $U_{ij}$, where $j$ will be chosen if and only if

$$U_{ij} > U_{ik} \;\; \forall j \neq k$$

The theory assumes that the utility of respondent $U_{ij}$ has two components. The first one is the indirect utility $V_{ij}$ that is observable to the researcher through alternative specific attributes $X'_{ij}$ and estimated preference parameters $\beta$. Under the conditional logit model, participants are assumed to have homogeneous preferences, so $\beta$ does not vary among individuals. The second component of the utility function is an unknown term $\varepsilon_{ij}$ that considers all the characteristics of participants that the model is not able to capture and is treated as a random error. Thus, the underlying utility function is:

$$U_{ij} = V_{ij} + \varepsilon_{ij} = X'_{ij}\beta + \varepsilon_{ij}$$

The conditional logit model assumes that the random error term $\varepsilon_{ij}$ is independently, identically distributed and follows an extreme value type I distribution. The probability that an individual $i$ will chose alternative $j$ among $J$ choices can be derived from the following closed form expression (McFadden, 1973):

$$P_{ij}= \frac{exp\left(X_{ij}^{'}\beta\right)}{\sum_{k=1}^{k=J} exp\left(X_{ik}^{'}\beta\right)} \tag{1}$$

The estimator for the conditional logit model using the maximum likelihood estimator can be derived as:

$$\widehat{\beta}_{MLE}= \underset{\beta}{argmax} \sum_{i=1}^{i=N} \sum_{j=1}^{j=3} y_{ij} ln \left[\frac{1}{R} \sum_{r=1}^{r=R} \frac{exp\left(X_{ij}^{'}\beta\right)}{\sum_{k=1}^{k=3} exp\left(X_{ik}^{'}\beta\right)}\right] \tag{2}$$

For the choice experiment developed in this thesis, the latent utility for individual *i* to choose Carbon Offset *j* (*j* = 1, 2, 3) is:

$$U_{ij}=b_1 Price_{ij}+b_2 Sourcing_{ij}+b_3 Verification_{ij}+b_4 MarketOriginationType_{ij}+b_5 GeographicLocation_{ij}+\varepsilon_{ij} \tag{3}$$

Thus, the logit probability for individual *i* to choose Carbon Offset *j* (*j* = 1, 2, 3) is:

$$P_{ij}=\frac{exp\left(\beta_1 Price_{ij}+\beta_2 Sourcing_{ij}+\beta_3 Verification_{ij}+\beta_4 MarketOriginationType_{ij}+\beta_5 GeographicLocation_{ij}\right)}{\sum_{k=1}^{k=J} exp\left(\beta_1 Price_{ij}+\beta_2 Sourcing_{ij}+\beta_3 Verification_{ij}+\beta_4 MarketOriginationType_{ij}+\beta_5 GeographicLocation_{ij}\right)} \tag{4}$$

The utility values and logit probabilities are not observable, so we only observe the choice indicators $y_i = j\ (j = 1, 2, 3),\ if\ U_{ij} > U_{ik}\ \forall j \neq k$. and as each respondent had three choices per card, we generate three binary choice indicators:

$$y_{ij}=\begin{cases} 1, & U_{ij} > U_{ik}\ \forall j \neq k \\ 0, & if\ not \end{cases} \tag{5}$$

The conditional logit model evaluates alternative-specific variations among attributes, assuming that there are no individual-specific variations, attributing variations in the estimates solely to varies the attributes.

*4.2 Mixed logit model*

Instead, the mixed logit model is implemented to capture preference heterogeneity among respondents. The mixed logit model is a more flexible one (when compared to the conditional logit model) in overcoming the limitations of the latter to proportionate non-restricted substitution patterns, to allow random test variations, and to the correction in unobserved factors over time (McFadden and Train, 2000). Consequently, the mixed logit model does not impose the independence of irrelevant alternatives axiom.

Moreover, the underlying utility function in the mixed logit model also has two components, just as in the conditional logit model: an observable and an unobservable one. On the one hand, individual-specific coefficients $\beta_i$ are now added to the observable part of the utility $V_{ij}$. On the other hand, as preferences are allowed to vary across individuals, the error component has now a mean $\bar{\beta}$ and a deviation around that mean that varies across individuals $\xi_i$.

$$U_{ij} = V_{ij} + \varepsilon_{ij} = X'_{ij}\,\bar{\beta} + X'_{ij}\,\xi_i + \varepsilon_{ij}$$

$$U_{ij} = X'_{ij}\left(\bar{\beta} + \xi_i\right) + \varepsilon_{ij}$$

$$U_{ij} = X'_{ij}\beta_i + \varepsilon_{ij} \tag{6}$$

In this model, $\varepsilon_{ij}$ is still assumed to be independently, identically distributed. Instead, $\xi_i$ can be correlated across individuals so that the probability of respondent $i$ choosing alternative $j$ being conditioned on knowing $\beta_i$ is:

$$P_{ij|\beta_i} = \frac{exp\left(X'_{ij}(\bar{\beta} + \xi_i)\right)}{\sum_{k=1}^{k=J} exp\left(X'_{ik}(\bar{\beta} + \xi_i)\right)} \tag{7}$$

In contrast to the conditional logit model probability, that can be solved analytically, we cannot do this for the mixed logit model probability because of randomness. Instead, a statistical software (STATA) was used to approximate the probability through the maximum likelihood estimator simulation method:

$$\hat{\theta}_{SMLE} = \underset{\theta}{argmax} \sum_{i=1}^{i=N} \sum_{j=1}^{j=3} y_{ij} ln \left[ \frac{1}{R} \sum_{r=1}^{r=R} \frac{exp\left(X'_{ij}\beta_i^r\right)}{\sum_{l=1}^{l=J} exp\left(X'_{ik}\beta_i^r\right)} \right] \tag{8}$$

*4.3 Willingness to pay*

From the results obtained by running the conditional and mixed logit model, we calculated the willingness to pay. In this case, we interpret it as willingness to accept the price difference between the N-GEO and GEO futures contracts price, or derived marginal increase in utility a participant in the green market obtains from purchasing the N-GEO in comparison to the GEO futures contract. Thus, the WTP for the *k*th attribute is:

$$WTP_k = -\frac{\frac{\partial U_{ij}}{\partial X_{ijk}}}{\frac{\partial U_{ij}}{\partial Price_{ijk}}} = -\frac{\widehat{\beta}_k}{\widehat{\beta}_p},\ k=1,\ldots,5 \text{ for } k \neq p \tag{9}$$

Where $\widehat{\beta_k}$ is the kth attribute estimator, and $\widehat{\beta_p}$ is the estimator for “Price” attribute.

## 4. Results

The results for the traditional logit, conditional and mixed logit models are presented in **Table 3**.

**Table 3**
STATA Results

| | LOGIT | CONDITIONAL | MIXED 1 | | MIXED 2 | |
|---|---|---|---|---|---|---|
| VARIABLES | Response Indicator | Response Indicator | Mean | SD | Mean | SD |
| Price | -0.0899*** | -0.0805*** | -0.0974*** | 0.130*** | -0.119*** | 0.152*** |
| | (0.00552) | (0.00528) | (0.0102) | (0.0110) | (0.0123) | (0.0123) |
| sourceAVI | 0.0128 | 0.0704 | 0.0747 | | 0.127 | -0.682*** |
| | (0.102) | (0.0994) | (0.107) | | (0.136) | (0.214) |
| sourceBIO | 0.870*** | 0.589*** | 0.654*** | | 0.786*** | 0.710*** |
| | (0.106) | (0.0974) | (0.106) | | (0.138) | (0.221) |
| sourceFOR | 0.597*** | 0.561*** | 0.595*** | | 0.670*** | 0.489** |
| | (0.0974) | (0.0903) | (0.0963) | | (0.120) | (0.212) |
| sourceMAN | 0.590*** | 0.538*** | 0.615*** | | 0.721*** | 0.420* |
| | (0.0971) | (0.0929) | (0.0985) | | (0.121) | (0.232) |
| sourceAGR | 0.415*** | 0.398*** | 0.429*** | | 0.500*** | -0.523** |
| | (0.101) | (0.0954) | (0.102) | | (0.127) | (0.238) |
| sourceTRA | 0.199** | 0.269*** | 0.322*** | | 0.321** | 0.730*** |
| | (0.0972) | (0.0986) | (0.106) | | (0.140) | (0.176) |
| verifyGOV | 0.386*** | 0.412*** | 0.451*** | | 0.593*** | -0.610*** |
| | (0.0697) | (0.0714) | (0.0756) | | (0.0994) | (0.170) |
| verifyNON | 0.598*** | 0.552*** | 0.584*** | | 0.699*** | 0.795*** |
| | (0.0628) | (0.0592) | (0.0633) | | (0.0913) | (0.119) |
| marketREG | 0.561*** | 0.634*** | 0.681*** | | 0.933*** | 0.870*** |
| | (0.0537) | (0.0600) | (0.0640) | | (0.0994) | (0.130) |
| geographyDEV | 0.158** | 0.0494 | 0.00406 | | 0.0233 | -0.971*** |
| | (0.0708) | (0.0686) | (0.0748) | | (0.111) | (0.142) |
| geographyHOM | 0.297*** | 0.308*** | 0.366*** | | 0.431*** | 0.721*** |
| | (0.0602) | (0.0564) | (0.0606) | | (0.0834) | (0.112) |
| Constant | -1.062*** | | | | | |
| | (0.104) | | | | | |
| Observations | 7,143 | 7,143 | 7,143 | 7,143 | 7,143 | 7,143 |
| N | 7143 | 7143 | 7143 | 7143 | 7143 | 7143 |
| AIC | 8490 | 4683 | 4531 | 4531 | 4531 | 4531 |
| BIC | 8579 | 4752 | 4621 | 4621 | 4621 | 4621 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The logit results in Table 3 can be interpreted as measures of utility in a probabilistic (logit distribution) scale. The results are best interpreted in terms of 'willingness to pay' which follows, but in their totality the results indicate strong conformity with each other without contradictions, and strong significance in our selection of attributes and levels. The results suggest robustness with regards to different econometric approaches. As mentioned, the ability of the mixed logit model

(2) which accounts for respondent heterogeneity and thus is not subject to the independence of irrelevant alternatives axiom imposed by the conditional logit model, makes it the stronger of the four models provided.

Interestingly, the only negative coefficient is price, which conforms to a downward sloping demand for offset credits, suggesting with statistical significance, that there might be limits to buying in the offset market as prices of carbon offsets rise. Our approach is unable to determine whether the demand is inelastic or elastic, however the positive influences of the remaining attributes suggest that the effects of carbon offset price increases can be moderated by marketing hedonic attributes.

Using the coefficients obtained, we have calculated the willingness to pay of individuals for the different attributes of carbon offsets futures contracts. Strictly, the calculations lead us to the definition of willingness to pay because it is denominated in dollars, and it is also a reference of increases and decreases in marginal utility. Thus, we have interpreted the results as utility, drawn from the hedonic utility function, or the Lancastrian view of utility as being a mix of goods, or in this case a mix of affects, that we believe is more accurate for the purpose of this thesis. We have interpreted the willingness to pay as a reflection of the increase in the marginal utility derived from that attribute, and consequently the willingness to accept the higher price for the N-GEO futures contract in comparison to the GEO futures contract.

Conditional logit assumes homogeneity among respondents and that, on average, all results converge to the mean leading to some model limitations such as IIA (Independence of irrelevant alternatives) and taste variation. People do converge to the mean but results for the mixed logit model show that participants are different, they have heterogeneous preferences, and the model is able to account for them. This is why we ran two mixed logit models: in the first one, we made the variable “Price” bear the heterogeneous effect among people; in the second one, we added all the variables, so all the different levels of the attributes could account for heterogeneous effect.

Results, and thus the interpretation storyline, hold for all the four different models we have used to test the data: logit, conditional logit, and two different mixed logit models. No matter what kind of approach we take, the results are consistent and statistically significant. Based on the rules that the smaller Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are, the better fit that model gives, we decide to choose the mixed logit model.

Moreover, it is important to note as mentioned before that there is preference heterogeneity among individuals for the different levels of attributes, as the reported standard deviation is significant. For this reason, we have chosen to report the different models, but we base our analysis in the mixed logit model 2.

To be able to run the regression, we created a reference definition as a baseline case to which we compared the results obtained for each of the different levels of attributes. Dropping one level of each attribute also contributed to the avoidance of multicollinearity. This reference definition includes "other land conservation" uses as "Sourcing", "Verification" performed by "a private company", "a non-regulated market" as "Market origination type", and "in another developed country" as the "Geographic location" where the carbon reduction and removal takes place.

**Table 4**
Willingness to pay estimates

| | LOGIT | CONDITIONAL | MIXED 1 | MIXED 2 |
|---|---|---|---|---|
| VARIABLES | | UTILITY | | |
| sourceAVI | 0.14238 | 0.87453 | 0.76694 | 1.06723 |
| sourceBIO | 9.67742 | 7.31677 | 6.71458 | 6.60504 |
| sourceFOR | 6.64071 | 6.96894 | 6.10883 | 5.63025 |
| sourceMAN | 6.56285 | 6.68323 | 6.31417 | 6.05882 |
| sourceAGR | 4.61624 | 4.94410 | 4.40452 | 4.20168 |
| sourceTRA | 2.21357 | 3.34161 | 3.30595 | 2.69748 |
| verifyGOV | 4.29366 | 5.11801 | 4.63039 | 4.98319 |
| verifyNON | 6.65184 | 6.85714 | 5.99589 | 5.87395 |
| marketREG | 6.24027 | 7.87578 | 6.99179 | 7.84034 |
| geographyDEV | 1.75751 | 0.61366 | 0.04107 | 0.19580 |
| geographyHOM | 3.30367 | 3.82609 | 3.75770 | 3.62185 |

Results in **Table 4** show that, among the different "Sourcing" options that were presented to respondents, "biodiversity conservation and regeneration" is the type of project that provides the greatest utility (6.605), when compared to "other land conservation uses". Participants valued "manufacturing companies that replace traditional sources of energy for renewable sources of energy (i.e. solar and wind)" (6.059) higher than "forestry conservation and regeneration" (5.630). "Sustainable agriculture practices" follows in fourth place (4.202). These results are comparable to those obtained by MacKerron et al. (2019) who find that conservation and biodiversity related projects yield the highest implicit price when compared to human development and technology and market development. On the contrary, Schwirplies et al. (2019) show that re-/afforestation projects are preferred to renewable energies projects or projects to improve energy efficiency, and Conte and Kotchen (2010) reveal that forestry-based offsets sell for lower prices than offsets of other types, such as biomass methane, hydropower, solar, and wind. This may be attributed to public knowledge and familiarity, as well as concerns about additionality and permanence for this type of projects. Furthermore, there is a lower marginal preference for transportation sector in general and the improvements that can be done to "transportation fleets that make investments in their trucks so that these burn less fuel and in a more efficient way" (2.697), and "aviation industry that transitions from the use of traditional fuel to sustainable aviation fuel" (1.067).

Moreover, results suggest that from the increased utility derived from carbon offsets verified by "a non-profit organization", participants are willing to validate a premium (5.874), followed by the option of verification performed by "a government entity" (4.983), taking verification by "a private company" as the baseline scenario. In line with most of the previous literature, verification has a positive correlation to carbon offset demand. The difference arises with the verifying entity, as previous studies find that government certification is preferred in countries such as Germany, Switzerland, and UK, when governments are credible and trustworthy, but it is not the same case in developing nations (Blasch and Farsi, 2012; Conte and Kotchen, 2010; MacKerron et al., 2019), or in the US.

Regarding the "Market origination type", though in reality we are nowadays mainly dealing with voluntary carbon markets, the model suggests an agent enjoys a marginal increase in utility (7.840) if the carbon offset was originated in "a regulated market", rather than in "a non-regulated market". Lastly, it is clear from the results that respondents experience a higher utility from a carbon offset project that reduces or removes carbon dioxide in the atmosphere "near their home location (assuming they are based in the US)" (3.622), followed by the option "in a developing country" (0.196), when compared to "in another developed country". The latter is in line with results from Schwirplies et al. (2019) who showed that projects located in a participant's region are preferred to projects carried out in other European or developing countries and agrees with discussions held with industry professionals who indicated that individuals willing to trade in this market preferred projects close to the place where they were generating the emissions. This also indicates that projects more distant to the home location are discounted significantly more, which aligns with the theory of "Spatial discounting" (Hannon, 2005). In addition, though Conte and Kotchen (2010) suggest that location of projects generating carbon offsets have a significant effect on price, their empirical results show higher prices in non-industrialized nations, which is different from what we herein obtained.

With these results, the model suggests that there is reason to believe that consumers in the carbon offsets market do have an affect for the N-GEO in comparison to the GEO, which translates in an increased utility derived from one contract over the other, respectively, that justifies the existing premium. If we add up all the highest levels' coefficients in the different attributes (23.941) this result is higher than the maximum historic difference between the two contracts, and though it is not proven that people would pay that exact amount of dollars, it is strong proof that the attributes are relevant and that people weigh them higher, picking on that affective feeling of consumers that justifies for a higher price of N-GEO over GEO.

Though not strictly required in our case, as the results and their standard deviations were significant in most of the cases, we have also calculated the probability that, given the mean and standard deviation, under the assumption that we are working with a normal distribution for each of the attributes, the number is negative under the bell curve. Please refer to results in **Table 5**. These results illustrate the heterogeneity of the sample respondent. For example althout the WTP for sourceAVI is positive at $1.067/MT the marginal utility for approximately 43% of respondents was negative, or at least reflecting lower-than-average utility. There was much stronger agreement when the offset was to be used for biodiversity, manufacturing, forestry and agriculture, in which only 13%, 9%, 4% and 17% indicated a negative or weak utility resoponse to carbon offsets being put to those uses.

**Table 5**
Normal distribution probabilities

| | MIXED 2 | NORMAL DISTRIBUTION |
|---|---|---|
| VARIABLES | UTILITY | P (x<0) |
| sourceAVI | 1.067 | 43% |
| sourceBIO | 6.605 | 13% |
| sourceFOR | 5.630 | 9% |
| sourceMAN | 6.059 | 4% |
| sourceAGR | 4.202 | 17% |
| sourceTRA | 2.697 | 33% |
| verifyGOV | 4.983 | 17% |
| verifyNON | 5.874 | 19% |
| marketREG | 7.840 | 14% |
| geographyDEV | 0.196 | 49% |
| geographyHOM | 3.622 | 27% |

## 5. Limitations

Although the study has shown clear results for willingness to pay or, as we have preferred to interpret the results, derived utility from certain types of attributes, the thesis is not free from biases.

First, all participants are related or belong to the Cornell University community. Either students, faculty, alumni, or family of these groups, which makes this a limited representation of the world and the potential different types of people willing to participate in the open market to offset their carbon emissions.

Moreover, there is a bias of representation when analyzing the demographic information from the sample pool, as most respondents are female, originally from the United States of America, and students by occupation. These three characteristics imply a significant representation bias in our group of respondents.

In addition, though the mixed logit results suggest that respondents are more heterogeneous than homogeneous, the fact that people had to sign up for the experiment, might also create a self-selection bias of participants that are interested and knowledgeable in the subject, or at least have a previous strong opinion.

Furthermore, the way in which we outlined the experiment, having participants place themselves in the hypothetical case of offsetting emissions of a newly bought car, implies a bias, as it has been shown by previous literature that willingness to offset carbon emissions significantly varies with the framing of the experiment.

Another aspect of the study that might potentially limit the extrapolation of our results is that we have only explored five specific attributes, and different levels within them, and there could be others that people have in mind that are not included in the analysis. However, by design, the choice and inclusion of the attributes was limited to the characteristics of the two GEO and N-GEO futures contracts, and stress tested with professionals currently working as Traders in Voluntary Carbon Market team of a large corporation in the industry. This creates an opportunity for future research to explore other attributes of carbon offsets and the contracts not captured in this work, such as their duration and vintage, or even different levels within a specific attribute, for example other types of projects for "Sourcing".

A natural extension of this work could be to analyze the results in light of the survey conducted at the end of the experiment. Making both data sets interact might bring different observations or make the results even more robust, as people were asked to elicit their preferences for the different attributes in a scale from 1 to 5.

Moreover, at the beginning of the thesis process, the aim was to perform the experiment in Argentina and China to be able to compare the results between the three geographies. Though we performed the experiment in a similar university environment in Argentina, participation was voluntary and not paid, and we did not get enough survey results to make the comparison statistically significant. This is why we believe that obtaining results from different countries would be very interesting.

Finally, in this study we explored the difference in price between GEO and N-GEO as these were the two tradable futures contracts available when we initiated this research, but there is also a third type of contract CBL Core Global Emissions Offset (C-GEO)[15] futures contract that is publicly traded in the market and was launched in January 2022. These types of futures contracts track carbon offset projects across energy, renewables, and other technology-based offsets from the Verra registry. There is a clear opportunity to expand the study to include this third type of contracts to do a more holistic comparison of the price and their attributes.

[15] CME Group – CBL Core Global Emissions Offset https://www.cmegroup.com/markets/energy/emissions/cbl-core-global-emissions-offset-c-geo.html.

## 6. Conclusions

The primary objective of this research was to investigate why a spread between two offsets futures contracts delivering the same amount of CO2e could be differentiated in market price when the source of the carbon offsets come from different types of projects, N-GEO based on AFOLU and GEO based on different projects.

The proposition put forth was that individuals trading in the market must have greater affect for land-based offsets than aviation-based offsets. This study sought to investigate this proposition by developing a DCE. Results from the choice experiment verified that there is a greater utility derived from "biodiversity conservation and regeneration", "manufacturing companies that replace traditional sources of energy for renewable sources of energy (i.e., solar and wind)", "forestry conservation and regeneration", and "sustainable agriculture practices".

What originally motivated the study was the idea that, a priori and just by observing the phenomenon, one would assume that markets and market efficiency would drive N-GEO and GEO futures contracts to a similar price; but there appears to be a behavioral component that explains why individuals have a greater affect and are thus willing to accept a higher price for the carbon generated from certain types of projects, than others.

Moreover, climate change mitigation requires that individual voluntary contributions be complemented by policy enforcement to establish clear rules and certainty conditions for companies. Generally, GEO contracts can be used as indicators to policy makers as to how carbon offsets should be priced for public projects or public private partnerships. The price differential defined by "Sourcing" type seems to be supported in terms of demand characteristics. This information, including that derived from the other attributes such as the fact that people prefer offsets generated from projects located near where they are located, is key for policy makers to consider when shaping these markets and creating compliance rules.

Also, having transparent prices for carbon offsets in a regulated marketplace provides opportunities to incorporate futures contracts into green finance initiatives, for example carbon linked bonds, and other types of land conservation securities. Lastly, regulated marketplaces with greater reach to the general public will provide project executives with the opportunity to lock in a price for carbon offsets to secure their cash flows for their ESG projects.

In the end carbon, it ain’t no. 2 yellow corn.

# Appendix

## Appendix A

LEEDR Lab experiment session

BSL experiment session

**Appendix B**

Survey following the cards

Now please fill out the survey. Thank you!

Age:

Gender:

Nationality:

Were you raised in an urban or rural background?

Major (if applicable):

Occupation (student, employed/unemployed):

Level of study achieved or in progress, if currently studying (Undergraduate, Graduate or PhD.):

Now please answer the following questions. Thank you!

How would you rate your knowledge of carbon offset markets?

| | | | | |
|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 |

That the aviation industry transitions from the use of traditional fuel to sustainable aviation fuel is important to me

| Strongly disagree | Disagree | Neutral | Agree | Strongly agree |
|---|---|---|---|---|

That transportation fleets make investments in their trucks so that these burn less fuel and in a more efficient way is important to me

| Strongly disagree | Disagree | Neutral | Agree | Strongly agree |
|---|---|---|---|---|

That manufacturing companies replace traditional sources of energy for renewable sources of energy (i.e. solar and wind) is important to me

| Strongly disagree | Disagree | Neutral | Agree | Strongly agree |
|---|---|---|---|---|

Sustainable agriculture practices are important to me

| Strongly disagree | Disagree | Neutral | Agree | Strongly agree |
|---|---|---|---|---|

Forestry conservation and regeneration is important to me

| Strongly disagree | Disagree | Neutral | Agree | Strongly agree |
|---|---|---|---|---|

Other land conservation uses are important to me

| Strongly disagree | Disagree | Neutral | Agree | Strongly agree |
|---|---|---|---|---|

Biodiversity conservation and regeneration is important to me

| Strongly disagree | Disagree | Neutral | Agree | Strongly agree |
|---|---|---|---|---|

I would pay more for a carbon offset if it is sourced from the aviation industry that transitions from the use of traditional fuel to sustainable aviation fuel

| | | | | |
|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 |

I would pay more for a carbon offset if it is sourced from transportation fleets that make investments in their trucks so that these burn less fuel and in a more efficient way

| | | | | |
|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 |

I would pay more for a carbon offset if it is sourced from manufacturing companies that replace traditional sources of energy for renewable sources of energy (i.e. solar and wind)

| | | | | |
|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 |

I would pay more for a carbon offset if it is sourced from sustainable agriculture practices

| | | | | |
|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 |

I would pay more for a carbon offset if it is sourced from forestry conservation and regeneration

| | | | | |
|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 |

I would pay more for a carbon offset if it is sourced from land conservation uses

| | | | | |
|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 |

I would pay more for a carbon offset if it is sourced from biodiversity conservation regeneration

| | | | | |
|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 |

I believe that climate change is going to worsen in the next five years

| | | | | |
|---|---|---|---|---|
| Strongly disagree | Disagree | I'm not sure | Agree | Strongly agree |

I believe that Greenhouse Gas (GHG) emissions contribute to climate change

| | | | | |
|---|---|---|---|---|
| Strongly disagree | Disagree | I'm not sure | Agree | Strongly agree |

Given that carbon offsets are used to offset Greenhouse Gas (GHG) emissions, I believe that carbon offset price in the next five years will

| | | |
|---|---|---|
| Decrease | Stay the same | Increase |

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