Demand for carbon-neutral products*

Stefano Carattini[†‡§], Fabian Dvorak[¶‖ **], Ivana Logar[‖], and Begüm Özdemir Oluk[¶‖]

January 25, 2024

*We thank Pascal Bärtschi, Durronjae Boothe, Gil Eris, Mahta Ghafarianghadim, Oliver Hegi, Arseniy Khovanskiy, Sandra Lettu, Leon Nissen, Jannis Portmann, and Elto Wolde for their outstanding research assistance. Carattini and Logar acknowledge support from the Swiss Federal Institute of Aquatic Science and Technology (Eawag). Carattini acknowledges support from the Swiss National Science Foundation, grant number PZ00P1_180006/1.

[†]Department of Economics, Andrew Young School of Policy Studies, Georgia State University

[‡]CESifo

[§]SIAW-HSG and Department of Economics, University of St. Gallen

[¶]Eawag, Swiss Federal Institute of Aquatic Science and Technology

[‖]Department of Economics, University of Konstanz

[**]Thurgau Institute of Economics

Abstract

Corporate social responsibility and the private provision of (global) public goods are of key interest to economists and policymakers alike. Increasingly, private companies are making their operations carbon neutral, often leading their own products to also be certified accordingly. It is an empirical question how consumers value carbon-neutral products and how informed they are about them, which we address as follows. First, we provide a meta-analysis of the literature analyzing demand for products with carbon-neutral labels, based on an overall sample of 27,241 participants. In this analysis, the focus is on average willingness to pay for carbon reductions as well as on the characteristics of the underlying literature, including the use of stated preferences and population samples, and their association with willingness to pay. Second, we leverage information on prices and product characteristics from one of the largest online marketplaces, Amazon's, to infer from revealed preferences on consumers' valuation of carbon-neutral products, through a hedonic approach. The staggered process of carbon-neutral certification leads to a series of quasi-natural experiments, which we use for identification purposes. We find that the literature, which is mainly based on survey studies, suggests a positive willingness to pay for carbon neutrality of products that exceeds most estimates of the social cost of carbon. However, this finding is not supported by the hedonic approach, which is based on market prices, where we do not find evidence for a positive willingness to pay for carbon neutrality for a wide range of products sold on Amazon.

Keywords corporate social responsibility; pro-social behavior; stated and revealed preferences; hedonic analysis; carbon neutrality

JEL codes C83; D12; D22; H23; H41; Q50

1 Introduction

An important question in economics relates to why people engage in pro-social behavior and to what extent society can rely on people's private motivations to ensure the provision of public goods. Climate change mitigation is such a (global) public good. While climate policy gradually reaches the level of stringency required in an attempt to avoid severe interference with the climate system, private behavior by individuals and firms can contribute to accelerating the transition towards a cleaner economy. Over the last few years, more and more firms have decided or announced plans to make their operations, or at least part of them, carbon neutral (Rogelj et al., 2021). The main driver of these decisions is likely pressure from investors and company boards to prepare firms for a low-carbon future (Kim and Lyon, 2011). Yet, it is an open empirical question whether consumers are willing to pay more for carbon-neutral labels, assuming that they are aware of such feature.

This paper aims to address this question. It does so as follows. First, it collects evidence on consumers' willingness to pay (WTP) for the carbon-neutrality of products (sometimes along with other characteristics) from a set of studies using population samples, which apply either stated or revealed preference methods, and sometimes a combination of both, to gauge what premium, if any, consumers are willing to pay for products that are labeled carbon neutral or that are produced with lower emissions than usual. The literature that we cover includes 37 studies, providing 129 observations, and an overall sample of 27,241 participants. From this body of evidence, it is possible to estimate average WTP across studies, contexts, and samples, and compare it with the range of estimates that economists have provided for the social cost of carbon to understand at what level, if any, consumers privately internalize the climate externality, if we were to take the estimates of the literature at face value. Further, with the tools of meta-analysis, it is possible to determine, at least correlationally, the study features that may lead to higher or lower WTP for carbon-neutral labels, including the key methodological difference between stated and revealed preferences.

Second, this paper uses hedonic difference in differences to complement the previous analysis, which as described are based on surveys and experiments with population samples, with a real-world assessment. In particular, we use publicly-available information on prices and product characteristics from the Amazon marketplace covering a wide range of products, tracked over several months to estimate WTP for the carbon neutrality of products in a hedonic framework. Amazon is by far the most important online marketplace in the US, where many products have been recently certified carbon neutral.[1] From an empirical standpoint, the emergence of these certifications creates a multitude of quasi-natural experiments, which we leverage to causally identify consumers' WTP for the carbon neutrality of products. Between March 2023 and December 2023, we retrieved the data of over 38,000 products on Amazon on a weekly basis. Using this data, we identify 230 treated products that received a carbon-neutral certification in the period of observation and 24,932 control products without such certification during our data collection. Given the staggered property of these certifications, we rely on recent advances in the difference in differences literature, and in particular on Callaway and Sant'Anna (2021), to address potential biases in two-way fixed-effect estimations. While doing so, we also examine closely pre-trends, to ensure that certifications happen, if not entirely at random, in ways consistent with the methodology used and the goal of deriving causal inference.

Preliminary results from the meta-analysis point to a positive WTP for carbon-

[1] Of the 122 million households in the United States, more than a half possess an Amazon Prime subscription. Further, in a month there are about 224 million unique visitors to Amazon's marketplace, as of April 2022 (https://www.statista.com/statistics/861060/total-number-of-households-amazon-prime-subscription-usa/ and https://www.statista.com/topics/4076/amazon-prime/, last accessed on July 21, 2022).

neutral labels, where at USD 1993 per ton of CO_2, WTP largely exceeds the distribution of current carbon prices and many estimates of the social cost of carbon. Furthermore, we find a positive and significant association between the amount of CO_2 reductions and WTP, which may indicate that respondents are sensitive to the amount of carbon reduction. Higher product prices are associated with a higher WTP, suggesting that the relative cost of carbon reductions may matter as well. Moreover, studies conducted in Europe show a higher WTP compared to other regions, even when controlling for GDP per capita. Lastly, stated preference methods are associated with higher WTP, possibly indicating hypothetical bias. Other features of the underlying literature are examined as well.

Based on the hedonic difference in differences approach, we find no evidence for a causal relationship between carbon-neutral labeling and product prices. A comparison between the WTP observed in the extensive literature covered by the meta-analysis and estimates derived from hedonic analysis suggests that the substantial WTP for the carbon neutrality of products reported in the literature is not reflected in the prices of products sold on the major online marketplace in the United States.

This paper contributes to the following strands of literature. First, a body of work examining the role of corporate social responsibility (e.g. Fehr et al., 1993; Shleifer, 2004; Besley and Ghatak, 2007; Falk and Szech, 2013; Bartling et al., 2015; see also Bénabou and Tirole, 2010, and Kitzmueller and Shimshack, 2012), including with respect to reductions in carbon emissions (e.g. Kim and Lyon, 2011; Doda et al., 2016). Second, a broad literature on the adoption of pro-social behavior (e.g. Dawes and Thaler, 1988; Fehr et al., 1993; Fehr and Schmidt, 1999; Bénabou and Tirole, 2006; Ellingsen and Johannesson, Ellingsen and Johannesson; Andreoni and Bernheim, 2009; Ariely et al., 2009), including a recent focus on the adoption of non-normative pro-social behavior (e.g. Sparkman and Walton, 2017; Kraft-Todd et al., 2018; Bicchieri and Dimant, 2019; Mortensen et al., 2019; Carattini and Blasch, 2020; Spencer et al., 2019; Andreoni et al., 2020; Carattini et al., 2022). Third, analyses of people's cooperativeness in a global social dilemma such as climate change mitigation (see Carattini et al., 2019 for a review), including private demand for carbon offsets (Kotchen, 2009; Jacobsen, 2011; Kesternich et al., 2016). Fourth, a varied scholarship estimating WTP precisely for labeled products, including carbon-neutral labels (e.g. Akaichi et al., 2017; Birkenberg et al., 2021; Muller et al., 2019), as well as studies assessing the role for overlapping labels (e.g. Fischer and Lyon, 2014; Brécard, 2017; Heyes and Martin, 2018; Poret, 2019; Fischer and Lyon, 2019). Fifth, a strand of literature comparing stated and revealed preference methods and their ability to uncover actual preferences, including WTP (e.g. Arrow et al., 1993; Adamowicz et al., 1994; Bateman et al., 2002; Johnston et al., 2017). Sixth, an established literature applying hedonic methods to a wide range of questions in environmental economics and beyond (e.g. Rosen, 1974; Smith and Desvousges, 1986; Chay and Greenstone, 2005; Muehlenbachs et al., 2015; Banzhaf, 2020, 2021).

In terms of policy implications, assessing the demand for carbon-neutral products may contribute to understanding the potential for expanding the market for carbon-neutral products beyond niche, thus achieving additional voluntary carbon reductions in the private sector, while ambitious climate policy gradually ramps up. While large, publicly-traded firms have been pledging to become carbon neutral largely in response to investors' pressure in expectation of future policy tightening, there may be a rationale for many other firms as well to turn to carbon neutrality, if there is a demand to be met.

2 Data and empirical approach

2.1 Meta analysis

This section describes shortly the data and empirical approach used for the meta-analysis, pointing the reader to a set of sections in the Appendix providing more detailed information. The underlying literature and derivation procedure of WTP for reductions in CO_2 emissions is described in Section A.1 in the Appendix. In our main analyses we have in total 129 observations across 37 studies, using a variety of methodologies, including four contingent valuation (CV) surveys, 29 discrete choice experiments (DCEs) based on stated preferences, two lab experiments, one field experiment inferring from revealed preferences, as well as one study that leverages both a DCE and a field experiment. The underlying sample comprises 27,241 participants.

Our database comprises studies that value various forms of CO_2 reductions, through either real or hypothetical product purchases. To ensure that the observations in meta-analyses represent comparable concepts (Smith and Pattanayak, 2002; Nelson and Kennedy, 2009), we include only studies from which we can derive WTP estimates for CO_2 reductions. Our focus is only on the marginal value of CO_2 reductions via climate labels, excluding the cost of the product. The studies in our database focus on a variety of products, which we categorize as dairy, fruits and vegetables, meat, non-food items, oil and grain, snacks, and water and drinks. In our database, we not only have observations of reductions in CO_2 emissions, but also reductions in greenhouse gas emissions expressed as CO_2 equivalents, and we treat these equally. Additionally, we consider the term "CO_2 reduction" in a broad sense, encompassing actual carbon reductions, offsets, and carbon capture. We elaborate more on these concepts in Section A.1.3 of the Appendix.

We define four WTP measures. First, the measure WTP_{NS} refers to the non-standardized WTP for CO_2 reductions which may vary both between and within studies. This value is either directly obtained or derived from studies and is normalized to 2020 USD. To standardize WTP estimates for easier comparison with our results from the hedonic approach, we also define three additional measures. WTP_{kg} represents the WTP per 1 kg of CO_2 reduction, calculated by dividing WTP_{NS} by the CO_2 reduction in kilograms, and is expressed in USD. When comparing with estimates for the social cost of carbon, we easily convert this measure into USD per ton of CO_2. WTP_{CN} denotes the WTP for achieving carbon neutrality. It is computed by multiplying WTP_{kg} by the baseline CO_2 emissions of the product, and is also expressed in USD. Finally, $WTP_{CN\%}$ represents WTP_{CN} normalized by product price. In other words, it is the proportion of a product's price that consumers would be willing to pay extra for carbon neutrality and calculated by dividing WTP_{CN} by the price of the product.

First, we highlight one of our main descriptive findings by presenting the average WTP_{kg} of study averages in Section 3.1. The distribution of WTP_{NS} and WTP_{kg} across studies, along with the magnitude of product carbon emissions, is plotted in Section 3.1, in Figure 1. Similarly, the distributions of WTP_{CN} and $WTP_{CN\%}$ are plotted in Figure A.1 in Appendix Section A.2. In the figures, a logarithmic x-axis is used for a better representation of the distribution of observations. Further details, including a breakdown of average WTP measures across different product categories, can be found in Section A.2 in the Appendix. Next, for the purpose of regression analyses, our outcome variable, WTP_{NS}, is transformed using the inverse hyperbolic sine function to account for negative values, which make up less than 5% of the sample.

Our independent variables include the following items: the amount of CO_2 reduction, to understand whether study participants value greater contributions to climate mitigation; and product price, which is z-scored, to assess the proportionality of WTP to product price. Methodological variables include a dummy variable for stated preference methods, to account for potential biases such as hypothetical bias that may arise in survey studies compared to revealed preference studies, as well as a dummy variable for in-person studies to account for differences relative to computer-based or online studies. Contextual controls include study year, which is z-scored, to account for potential secular trends in public awareness regarding climate change and climate labels; gross domestic product (GDP) per capita, which is z-scored, to account for the economic situation of consumers in the study country; and a dummy variable for studies conducted in Europe to control for geography-specific effects, including potential variation in environmentally-friendly lifestyles. Additionally, we also have a dummy variable for unpublished studies to account for potential biases in comparison to published studies. Finally, we control for observations requiring assumptions about CO_2 reductions, and for observations we derived from studies ourselves (as opposed to those directly reported by the authors), to account for the need to interpret the results from the original findings. As a robustness check, we also include dummy variables for colored labels, which are used in the literature to distinguish between high and low carbon options, as well as for distinguishing labels with carbon-neutral certifications from labels associated with carbon reductions.

To understand the factors associated with $\mathrm{WTP}_{\mathrm{NS}}$ estimates, we leverage three models: Ordinary Least Squares (OLS), mixed effects, and weighted mixed effects. The OLS model serves as a baseline for comparison with the mixed effects models we use, using contextual and methodological factors as independent variables and clustering standard errors across studies. Second, the mixed effect models account for random effects for studies and product categories, which implicitly adjust the standard errors to account for study- and product-specific heterogeneity (Cameron and Trivedi, 2005). Lastly, for the weighted mixed effects model, we assign weights based on the inverse of the number of observations from each study to equally weight studies in the analysis.

Our analyses also include a battery of robustness tests: excluding observations requiring CO_2 reduction assumptions or WTP derivations, including variables for carbon neutral and colored labels, using sample size as a weight factor, incorporating country random effects, and using different functional forms of dependent variable and CO_2 reduction variable.

2.2 Hedonic model

This section describes the data used for the hedonic analyses as well as the corresponding empirical approach, while also pointing the reader to additional information in the Appendix. The goal of the hedonic model is to provide empirical evidence from revealed preferences, to be compared with the evidence, mostly from stated preference studies and population samples, covered by the meta-analysis. To ensure comparability with the data from the meta-analysis, and for reasons of external validity, we cover a wide range of products from a large online marketplace with global coverage, Amazon's. Amazon's marketplace provides detailed information about product characteristics, including prices, as well as customer reviews, which may point to carbon neutrality (or carbon reductions) as a valuable feature. Further, over the years, Amazon has given increasing importance to carbon neutrality, among other environmental aspects, collaborating with several organizations providing labels for carbon-neutral or carbon reduced products. More than 50 different sustainability labels certifications are currently displayed on Amazon's marketplace, to which Amazon refers as "Climate Pledge Friendly" certifications. Among them are 4 carbon neutral and carbon reduced labels certified by various entities, as described in Appendix B.

Our hedonic analysis is based on a weekly panel of products sold on Amazon's U.S. marketplace. We employ the following strategy to construct the panel. First, we identify a list of several thousand products with carbon-neutral labels based on special collections of carbon-neutral products available on Amazon.com. Next, we identify the category nodes of the carbon-neutral products that are used by Amazon to tag products of the same product category. For each category node we identify, we scrape several untreated products without carbon labels. This process ensures that for each treated product, we obtain several control units from the same product category.

The benefits of this product selection strategy are twofold. First, selecting products to be monitored from categories that already contain treated products ensures that it is in principle possible to make such products carbon neutral and label them accordingly. Second, it also implies that there is some incentive for manufacturers to make these products carbon neutral in the near future to catch up with competitors, thereby increasing the likelihood of treatment within the time horizon of our study. Third, it allows us to estimate the dynamic effect of treatment by controlling for the category-specific price trend of untreated products in the same category.

Our product selection strategy results in a set of 39,161 products from 468 different product categories. Starting in March 2023, we scrape the same set of product information for all these products each week, as displayed on Amazon.com for IP addresses from the United States. We collect data for 42 weeks until December 25, 2023. Most importantly, we retrieve information about the price of the product and the treatment status of the product, which allows us to perform a staggered difference in differences analysis. The staggered adoption of carbon-neutral labels by products sold on Amazon.com provides the ideal features of a quasi-natural experiment. Here, a product changes treatment status when it receives one of the abovementioned carbon-neutral labels. Control units are represented by arguably comparable products with the same product category assigned by Amazon.

The main underlying assumption of this exercise is that the prices observed on Amazon's marketplace are equilibrium prices. It is well known that Amazon uses dynamic pricing for its own products and offers its in-house dynamic pricing engine to all sellers. As a result, the prices displayed on the website automatically adjust to changes in demand, in principle quickly approaching equilibrium prices. As Amazon's often uses its own products in a similar way to attract customers to different parts of the marketplace, we exclude Amazon's own products from the hedonic analysis. Another underlying assumption is that products advertised on Amazon's marketplace are eventually sold to customers. We assume this condition to be met on Amazon's marketplace, in general. While we do not have access to information on the number of times a product has been sold on Amazon's marketplace, we control for the number of reviews written by customers with verified purchases, as a proxy for sale numbers. We also consider sales, still proxied by reviews, as an endogenous equilibrium variable.

From a hedonic perspective, it is also important to determine whether people are aware of the fact that some products are certified carbon neutral and whether they care about it. We assume that the labels make people aware of the products' carbon-neutral status. Appendix Section B.1 Figure B.1 provides an example of a carbon-neutral product on Amazon.com.

From a causal perspective, we estimate the treatment effect of carbon neutrality based on difference in differences. We assume that the timing at which products get treated is plausibly random and treatment is irreversible, leading to a difference in difference setup with random staggered treatment assignment. Our setting is also such that only a small share of products receive the treatment, so that economically meaningful general equilibrium effects are unlikely.

For the difference in difference analysis, we focus on a subset of 38,968 products for which product information could be scraped repeatedly during the observation period. We drop 9,392 products from the panel for which price information is unavailable in more than 75% of the weekly waves, which suggests that they are not available for purchase. We also drop 2,901 products that are treated in the first wave of the panel and therefore cannot be used for the difference in differences analysis, as well as 243 products for which the treatment status is unclear (because labels switch on and off several times in the observed period).[2] After data cleaning, we have 26,432 untreated candidate products without a carbon-neutral label at the beginning of our time frame in March 2023. To account for the fact that some products have more than one climate pledge friendly label during the observation period, we restrict our main analysis to a subset of 25,162 products that have either a carbon neutral-label or no label at all. We perform a robustness analysis that includes all products, including those with other climate pledge friendly labels.

To identify experiments, we require that a product had no carbon-neutral label for at least 3 consecutive weeks at the beginning of the panel and a carbon-neutral label in more than 90% of the scraped observations after treatment, allowing for some imprecision in the scraping approach. This yields 231 natural experiments treating as many products and 24,932 control products for the hedonic analysis. Table B.1 in Appendix B.2 provides a more detailed description of the experiments.

The canonical difference in difference model exploits the assumption that, without the treatment, the price of the treated products, i.e., those with a carbon-neutral label, would have evolved in parallel with the price of the untreated (unlabeled)

[2] For this small fraction of products we observe the labels switching on and off several times, likely because of technical issues on the marketplace, which calls for caution in using these observations.

products. However, this parallel-trend assumption is unlikely to hold when comparing products across different product categories, brands, and market segments. To address this problem, we use the staggered difference in difference model of Callaway and Sant'Anna (2021). This model only requires the parallel-trend assumption to hold after conditioning on observed covariates. This allows us to replace the parallel-trend assumption with the more plausible restriction that only prices of products from the same highest-level product category must follow a similar trend. As further variables to condition on we use the initial price of the product at panel onset, the initial number of ratings, and the average rating of the product as a proxy for sales and popularity.

Following Callaway and Sant'Anna (2021), the average effect of treatments is disaggregated into group-time average effects. These reflect the average treatment effects of, for instance, a carbon-neutral label at a specific point in time for a group of products that received the label in the same time period. The disaggregated effects can then be combined to an estimate for the average treatment effect that does not suffer from the interpretation problems of two-way fixed effects (Roth et al., 2022).

An appealing feature of group-time average treatment effects is that they can be partially aggregated to investigate heterogeneity in the effects of labels across different groups, time periods, and lengths of treatment exposure. Partially aggregating group-time average treatment effects for different lengths of treatment exposure allows us to study how the effect of labels varies over time since their introduction. This is particularly interesting in our setup to investigate how prices of products adjust after treatment.

3 Empirical evidence

3.1 Descriptive evidence from the meta analysis

In this section, we describe two main findings, of descriptive nature, related to the meta-analysis. The first finding focuses on the WTP for a reduction of 1 kg of CO_2 emissions (WTP_{kg}), as derived from the literature that the meta-analysis covers. We then compare the average WTP_{kg} with recent estimates of the social cost of carbon, taking the average WTP at face value and assessing at what level consumers are internalizing the climate externality in their provision of a global public good. We also report the average WTP_{CN}, which represents the WTP for reducing product emissions by 100%, or achieving carbon neutrality. The social cost of carbon is used to define the appropriate level at which carbon should be priced (Aldy et al., 2021) along with cost-effectiveness estimates, which are generally in a similar range (e.g. Stiglitz et al., 2017; IMF, 2019).

Second, we take a more critical approach and try to determine the main factors, including methodological, that may drive WTP for CO_2 reductions (WTP_{NS}). This analysis is correlational in spirit, yet informative to contribute to addressing our overarching question on the real-world demand for climate certifications, including carbon neutrality.

Figure 1 shows the distribution of WTP_{NS} and WTP_{kg} across studies. As illustrated in the figure, the average WTP_{kg} of study averages is approximately USD 1.99 per kg of CO_2 reduction, or USD 1993 per ton of CO_2. To put these estimates in comparison, the social cost of carbon during the Obama administration has been around USD 40 per ton of CO_2 (IWG on Social Cost of Carbon, 2010, 2013), while under the Biden administration has been at USD 51 per ton of CO_2 (IWG on Social Cost of Carbon, 2016; IWG on Social Cost of Greenhouse Gases, 2021) for several years before being raised to USD 190 per ton of CO_2 (Environmental Protection Agency, 2023). The economic literature points, however, to potentially larger values, with considerable dispersion in estimates (see e.g. Tol, 2011; Pindyck, 2013; Howarth et al., 2014; Pezzey, 2019; Aldy et al., 2021; National Academies of Sciences, Engineering, and Medicine, 2017; Rennert et al., 2022, for reviews and discussions). While some of these figures are in the thousands, most often they are in the low hundreds, much smaller than the average WTP that the meta-analysis provides. Carbon prices around the world also vary widely. They have generally kept increasing over the last few years, but only a few countries, such as Sweden and Switzerland, have carbon prices above USD 100 per ton of CO_2 (World Bank, 2023), about a twentieth of the average WTP derived from the literature that the meta-analysis covers.

Some interesting observations emerge from Figure 1. First, we observe substantial variation in WTP_{NS} and WTP_{kg} estimates, both between and within studies. Our regressions further explore potential sources of such variation, from a correlational perspective. Second, there seems to be a positive relationship between WTP_{NS} and the amount of CO_2 reductions. Third, based on Figure 1, meat products, which constitute 38% of our sample, seem to be related with a lower WTP_{kg} compared to other products. That is, study participants seem to be willing to pay less for a 1 kg CO_2 reduction in meat products compared to other products, such as water and drinks, which are responsible for less carbon emissions. For the breakdown of the remainder of our sample according to product categories, please refer to Appendix Section A.2.

Next, we turn to the drivers of WTP in the underlying studies covered in the meta-analysis. The drivers of WTP are discussed based on Table 1, which contains our main meta-analytical results providing associations between study characteristics and WTP for CO_2 reductions (WTP_{NS}), relying on the OLS, mixed effects, and weighted mixed effects models. Weighted mixed effects model is our preferred specification, as it more effectively handles heteroscedasticity, according to the Breusch-Pagan heteroscedasticity test provided in Table A.9, and residual plots provided in Figure A.5, both in Appendix Section A.2.

Table 1 shows that the significant coefficients remain largely unchanged across models. The coefficients confirm the positive and significant association between CO_2 reductions and WTP_{NS} showing participants are sensitive to the amount of CO_2 reductions implied by the climate labels. Other interesting associations also emerge. For instance, a higher product price is associated with a higher WTP. That is, comparable reductions in CO_2 emissions may be more easily accepted by study participants when the cost represents a smaller share of the overall product price, so that the relative price increase is more muted. Additionally, studies conducted in Europe (compared to America, Asia, and Africa) also seem to be associated with a higher WTP. Furthermore, we also observe a positive significant effect for stated preference methods at the 10% level in the weighted mixed effects model, potentially pointing to some hypothetical bias in stated preference studies.

We do not find any significant association of WTP with any of the following variables: in-person versus online or computer-assisted studies; potential biases in unpublished relative to published studies; year of study, which would account for trends in public awareness regarding climate labels; GDP per capita, to reflect the economic situations of consumers in the study country.

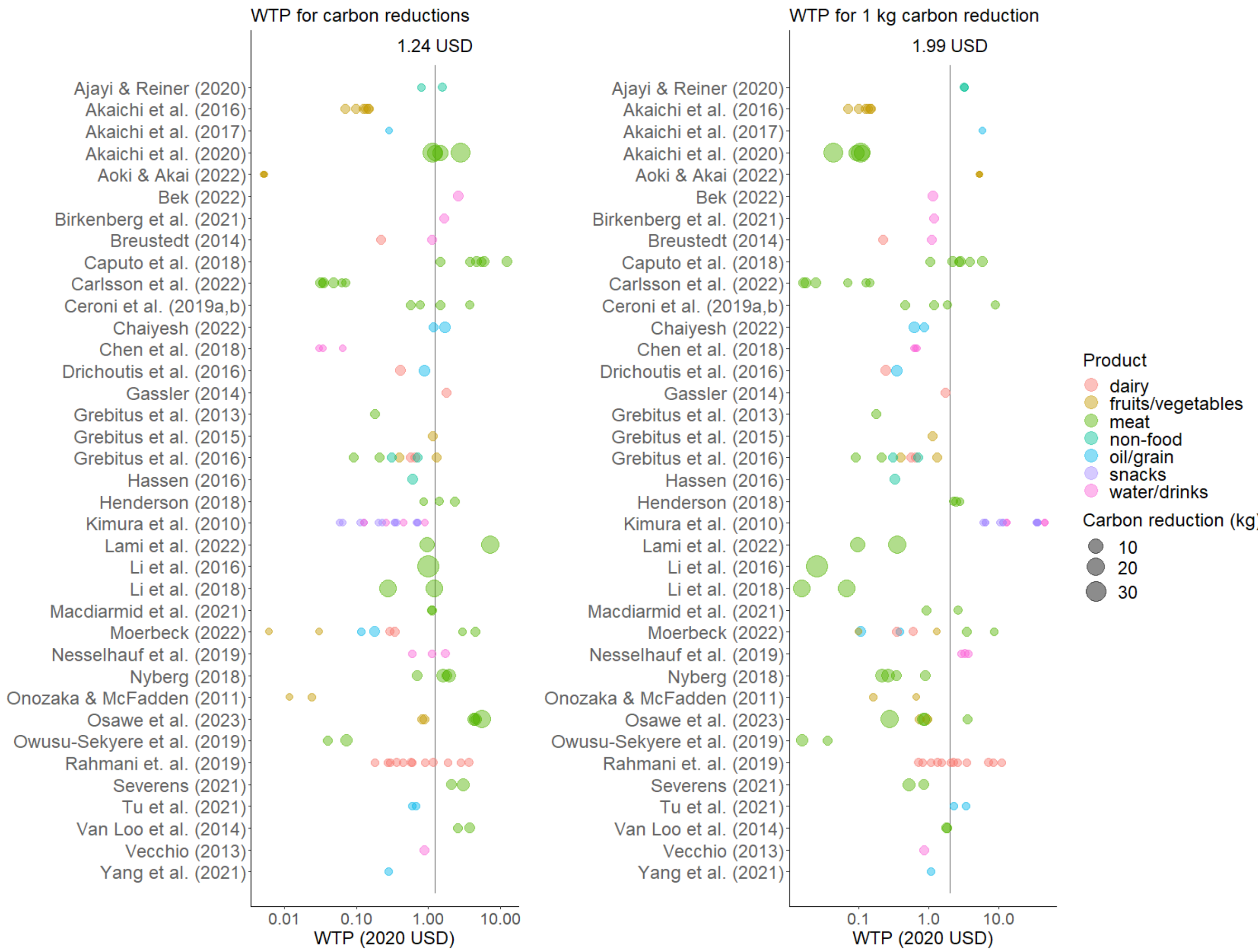


Figure 1: WTP for carbon reductions across studies

A logarithmic axis (base 10) is used to create this figure. The vertical lines represent the mean of study means. The left graph displays WTP_{NS} (non-standardized WTP for carbon reductions) across studies, where the size of each circle represents the amount of carbon reduction in kilograms. The right-hand graph shows WTP_{kg} (standardized WTP for 1 kg carbon reduction), which is calculated by dividing WTP_{NS} by the amount of carbon reduction.

Table 1: Factors associated with WTP for carbon reductions

	OLS	Mixed Effects	Weighted Mixed Effects
Intercept	0.47 (0.30)	-0.04 (0.34)	-0.18 (0.32)
CO_2 reduction	0.02** (0.01)	0.03** (0.01)	0.03*** (0.01)
Price	0.34*** (0.05)	0.33*** (0.06)	0.31*** (0.07)
Stated pref. method	-0.04 (0.25)	0.30 (0.28)	0.41* (0.24)
In-person	-0.08 (0.16)	0.05 (0.21)	0.06 (0.19)
Sample size	-0.05 (0.06)	-0.04 (0.09)	-0.06 (0.09)
Unpublished	0.03 (0.14)	0.18 (0.21)	0.23 (0.21)
Study year	-0.03 (0.07)	-0.02 (0.10)	-0.01 (0.09)
CO_2 reduction assump.	0.14 (0.14)	0.19 (0.19)	0.17 (0.18)
WTP Derivation	-0.07 (0.12)	0.05 (0.15)	0.06 (0.15)
GDP per capita	0.07 (0.05)	0.02 (0.07)	0.01 (0.07)
Europe	0.34** (0.14)	0.43** (0.17)	0.49*** (0.17)
Number of obs.	129	129	129
Var (study random effect)		0.14	0.18
Var (product random eff.)		0.00	0.02
AIC	216.72	242.87	253.25
BIC	251.04	285.76	296.14
Log Likelihood	-96.36	-106.43	-111.62

***$p<0.01$; **$p<0.05$; *$p<0.1$.

This table shows coefficient estimates and associated standard errors, which are indicated within parentheses. The standard errors for the OLS model are clustered by studies. We use a weighted mixed-effects model, incorporating product categories and studies as random effects. The weights correspond to the inverse of the number of observations from each study. The dependent variable is the unstandardized WTP for carbon emission reductions (WTP_{NS}), which is transformed using the inverse hyperbolic sine function. Price, sample size, study year, and GDP per capita variables are z-scored.

Appendix Section A.3 includes our battery of robustness tests. Table A.10 shows regressions with different subsets of the sample that exclude observations requiring CO_2 reduction assumptions, WTP derivations, or both. Table A.11 includes additional variables, namely carbon neutral certification and colored labels. Table A.12 uses sample size as a weight instead of the inverse number of observations. Table A.13 includes country random effects i.e. clusters standard errors by countries. Tables A.14, A.15, and A.16 show regressions with different functional forms of outcome variable and CO_2 reduction variable. Our main findings are robust to these additional sensitivity tests.

Overall, if taking the estimates in the literature at face value, the analysis provided in this section points to a very strong WTP for reductions in CO_2 emissions, potentially even an order of magnitude larger than estimates of the social cost of carbon and current levels of policy stringency.

3.2 Hedonic difference in differences

In this section we describe the main findings from the hedonic analyses. Then, we compare them with the findings from the meta-analysis. We start with the standard graphical representation for event studies. Figure 2 graphically illustrates the main result of the hedonic difference in difference analysis. It shows the effect of receiving a carbon neutral label on the price of the product in the months after treatment, allowing us to examine the dynamic effect of carbon neutrality. The y-axis indicates the relative price difference in percentage points to the product average price in March 2023. The dots to the left of the red vertical line show the effect of a carbon neutral label on the relative price of a product in the four months prior to treatment. The pre-treatment effects fluctuate around zero and are not statistically significant, except for the third month before treatment.

The dots to the right of the red line in figure 2 suggest that carbon neutrality does not have a consistent effect on the price of a product after treatment. The effect of a carbon neutral label is positive but very small in the first three months after the label is introduced. In the fourth month, the effect of carbon neutrality on the relative product price is negative and not statistically significant and remains negative until the eighth month after treatment. The average effect of a carbon-neutral label over the 8-month observation period is -0.01 (SE = 1.04) percentage points of the initial product price in March 2023, and not statistically significant from zero.

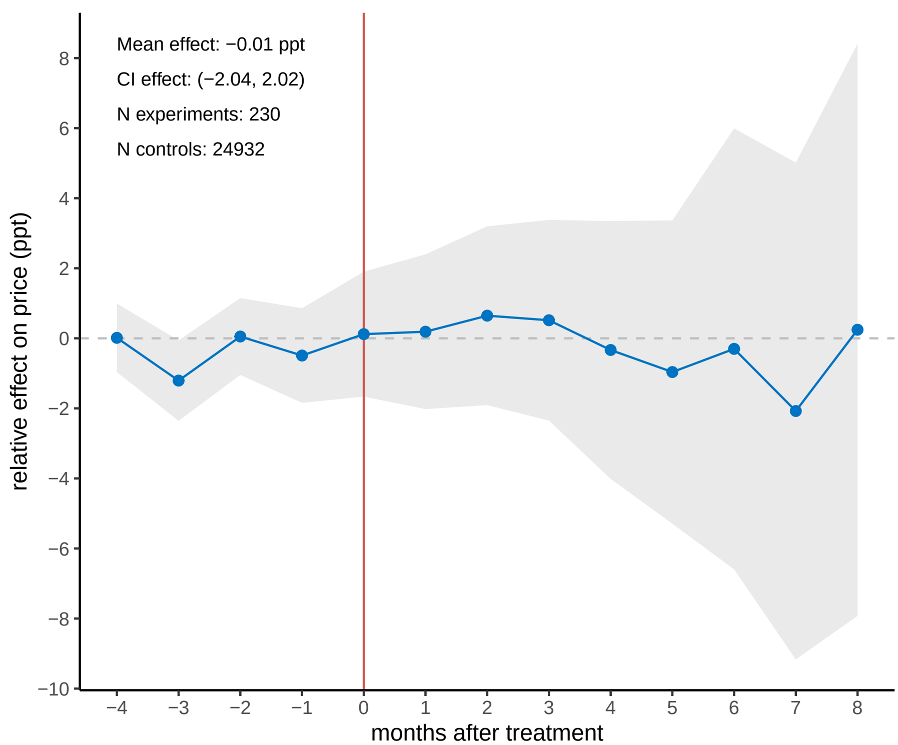


Figure 2: Effect of carbon-neutral label

Dynamic treatment effect in percentage points relative to the product's price in March 2023. Vertical red line marks treatment onset. Shaded area indicates 95% confidence interval of treatment effect based on 10,000 bootstrap samples that control for multiple hypothesis testing.

The depicted 95% confidence band of the dynamic treatment effect control for multiple hypothesis testing, as per default in the estimator. The confidence band always includes the zero line, which means that also no single treatment effect is statistically significant from zero. The confidence band becomes substantially wider over time. This pattern can be explained by the fact that the number of observations thins out as one moves towards the right hand side of the graph, due to the staggered nature of treatment assignment.

A similar result is obtained when using the absolute price as dependent variable of the hedonic analysis. The average effect of a carbon-neutral label on the absolute product price over the 8-month observation period is USD -0.16 (SE = 0.23, non significant). We also obtain comparable results when additionally including products that receive other climate pledge friendly labels during the observation period, with an average effect of -0.04 percentage points (SE = 1.00, n.s.). Finally, it should be noted that, because of the difference in differences analysis employed, the results reported in this section do not imply that the prices of products that received a carbon neutral label remained constant over the observation period. In fact, the average price of the treated products remained fairly stable and only slightly decreased from USD 42.35 in March 2023 to USD 41.74 in January 2024. During the same period, the average price of the control products also only slightly decreased, from USD 25.26 to USD 24.09.

4 Conclusions

Assessing the demand for carbon-neutral products is crucial to determine the potential for voluntary carbon reductions in the private sector. While carbon-neutral products are increasingly available, they still remain niche. Companies that make carbon-neutral products available often do so in response to broader efforts to decarbonize their operations, generally in response to expectations of future policy tightening as reflected in investors' pressure.

While ambitious climate policy gradually tightens up, understanding demand for carbon-neutral products can help highlighting areas of expansion for voluntary carbon reductions by the private sector, beyond what publicly-traded companies may do in response to investors' demands.

In this paper, we analyze demand for carbon-neutral products empirically. Our approach is twofold. First, we use a meta-analysis of studies in the literature assessing such demand, mostly with stated preference techniques and population samples. Second, we use a large online marketplace, Amazon's, and its staggered introduction of products certified carbon neutral, to estimate causally with the use of hedonics the willingness to pay associated with carbon-neutral products, leveraging the many quasi-natural experiments occurring on this market and leading new products to be certified carbon neutral.

Preliminary results indicate a large, positive willingness to pay for carbon neutral products in the literature covered by the meta-analysis. The WTP for carbon-neutral products reported in the literature largely exceeds the distribution of current carbon prices and many estimates of the social cost of carbon. While the results from the meta-analysis points to strong demand for carbon-neutral products among potential consumers, preliminary results from our hedonic model indicate no positive WTP for carbon neutrality for a wide range of products sold on Amazon.com.

References

Adalja, A., J. Hanson, C. Towe, and E. Tselepidakis (2015). An examination of consumer willingness to pay for local products. *Agricultural and Resource Economics Review 44*(3), 253–274.

Adamowicz, W., J. Louviere, and M. Williams (1994). Combining revealed and stated preference methods for valuing environmental amenities. *Journal of Environmental Economics and Management 26*(3), 271–292.

Ajayi, V. and D. Reiner (2020). Are consumers willing to pay for industrial decarbonisation? Evidence from a discrete choice experiment on green plastics. Cambridge Working Paper in Economics.

Akaichi, F., S. de Grauw, P. Darmon, and C. Revoredo-Giha (2016). Does fair trade compete with carbon footprint and organic attributes in the eyes of consumers? Results from a pilot study in Scotland, the Netherlands and France. *Journal of Agricultural and Environmental Ethics 29*(6), 969–984.

Akaichi, F., R. M. Nayga Jr, and L. L. Nalley (2017). Are there trade-offs in valuation with respect to greenhouse gas emissions, origin and food miles attributes? *European Review of Agricultural Economics 44*(1), 3–31.

Akaichi, F., C. Revoredo Giha, K. Glenk, and J. M. Gil (2020). How consumers in the UK and Spain value the coexistence of the claims low fat, local, organic and low greenhouse gas emissions. *Nutrients 12*(1), 120.

Aldy, J. E., M. J. Kotchen, R. N. Stavins, and J. H. Stock (2021). Keep climate policy focused on the social cost of carbon. *Science 373*(6557), 850–852.

Andreoni, J. and B. D. Bernheim (2009). Social image and the 50–50 norm: A theoretical and experimental analysis of audience effects. *Econometrica 77*(5), 1607–1636.

Andreoni, J., N. Nikiforakis, and S. Siegenthaler (2020). Predicting social tipping and norm change in controlled experiments. Working Paper 27310, National Bureau of Economic Research.

Aoki, K. and K. Akai (2022). Testing hypothetical bias in a choice experiment: An application to the value of the carbon footprint of mandarin oranges. *PLOS One 17*(1).

Ariely, D., A. Bracha, and S. Meier (2009). Doing good or doing well? Image motivation and monetary incentives in behaving prosocially. *American Economic Review 99*(1), 544–555.

Arrow, K., R. Solow, P. R. Portney, E. E. Leamer, R. Radner, and H. Schuman (1993). Report of the NOAA Panel on Contingent Valuation. Technical report, National Oceanic and Atmospheric Administration.

Asioli, D., C. Bazzani, and R. M. Nayga (2018). Consumers' valuation for lab produced meat: An investigation of naming effects.

Asioli, D., J. Fuentes-Pila, S. Alarcón, J. Han, J. Liu, J.-F. Hocquette, and R. M. Nayga (2022). Consumers' valuation of cultured beef burger: A multi-country investigation using choice experiments. *Food Policy 112*, 102376.

Asioli, D., X. Zhou, A. Halmemies-Beauchet-Filleau, A. Vanhatalo, D. I. Givens, A. Rondoni, and A. Turpeinen (2023). Consumers' valuation for low-carbon emission and low–saturated fat butter. *Food Quality and Preference 108*, 104859.

Banzhaf, H. S. (2020). Panel data hedonics: Rosen's first stage as a 'sufficient statistic'. *International Economic Review 61*(2), 973–1000.

Banzhaf, S. (2021). Difference-in-differences hedonics. *Journal of Political Economy*.

Bartling, B., R. A. Weber, and L. Yao (2015). Do markets erode social responsibility? *The Quarterly Journal of Economics 130*(1), 219–266.

Bateman, I., R. Carson, B. Day, M. Hanemann, N. Hanley, T. Hett, M. Jones-Lee, and G. Loomes (2002). *Economic Valuation with Stated Preference Techniques*. Edward Elgar Publishing.

Bek, U. (2022). Pricing sustainable shipping of coffee: Consumers' preferences and willingness to pay for emission reductions and offsets. *Junior Management Science 7*(3), 543–568.

Bénabou, R. and J. Tirole (2006). Incentives and prosocial behavior. *American Economic Review 96*(5), 1652–1678.

Bénabou, R. and J. Tirole (2010). Individual and corporate social responsibility. *Economica 77*(305), 1–19.

Besley, T. and M. Ghatak (2007). Retailing public goods: The economics of corporate social responsibility. *Journal of Public Economics 91*(9), 1645–1663.

Bicchieri, C. and E. Dimant (2019). Nudging with care: The risks and benefits of social information. *Public Choice*.

Birkenberg, A., M. E. Narjes, B. Weinmann, and R. Birner (2021). The potential of carbon neutral labeling to engage coffee consumers in climate change mitigation. *Journal of Cleaner Production 278*, 123621.

Boehm, R., H. Kitchel, S. Ahmed, A. Hall, C. M. Orians, J. R. Stepp, A. Robbat, Jr, T. S. Griffin, and S. B. Cash (2019). Is agricultural emissions mitigation on the menu for tea drinkers? *Sustainability 11*(18), 4883.

Boesch, I. and M. Weber (2012). Processor's preferences and basic differentiation strategies for potatoes, milk, and wheat in Switzerland. *Journal of Agricultural & Food Industrial Organization 10*(1).

Brécard, D. (2017). Consumer misperception of eco-labels, green market structure and welfare. *Journal of Regulatory Economics 51*, 340–364.

Breustedt, G. (2014). Demand for carbon-neutral food – evidence from a Discrete Choice Experiment for milk and apple juice. In *Proceedings of the 88th Annual Conference of the Agricultural Economics Society.*

Broeckhoven, I., W. Verbeke, J. Tur-Cardona, S. Speelman, and Y. Hung (2021). Consumer valuation of carbon labeled protein-enriched burgers in European older adults. *Food Quality and Preference 89*, 104114.

Callaway, B. and P. H. C. Sant'Anna (2021). Difference-in-Differences with multiple time periods. *Journal of Econometrics 225*(2), 200–230.

Cameron, A. C. and P. K. Trivedi (2005). *Microeconometrics: Methods and applications.* Cambridge UniversityPpress.

Caputo, V., R. M. Nayga Jr, and R. Scarpa (2013). Food miles or carbon emissions? Exploring labelling preference for food transport footprint with a stated choice study. *Australian Journal of Agricultural and Resource Economics 57*(4), 465–482.

Caputo, V., E. J. Van Loo, R. Scarpa, R. M. Nayga Jr, and W. Verbeke (2018). Comparing serial, and choice task stated and inferred attribute non-attendance methods in food choice experiments. *Journal of Agricultural Economics 69*(1), 35–57.

Carattini, S. and J. Blasch (2020). Nudging when the descriptive norm is low: Evidence from a carbon offsetting field experiment. Grantham Research Institute Working Paper Series 345, London School of Economics and Political Science.

Carattini, S., K. Gillingham, X. Meng, and E. Yoeli (2022). Peer-to-peer solar and social rewards: Evidence from a field experiment. Technical Report 10173, CESifo.

Carattini, S., S. Levin, and A. Tavoni (2019). Cooperation in the climate commons. *Review of Environmental Economics and Policy 13*(2), 227–247.

Carlsson, F., M. Kataria, E. Lampi, E. Nyberg, and T. Sterner (2022). Red, yellow, or green? Do consumers' choices of food products depend on the label design? *European Review of Agricultural Economics 49*(5), 1005–1026.

Carroll, K. A. (2018). *Three Papers on Consumer Food Choices: An Experimental Approach.* The University of Wisconsin-Madison.

Cerroni, S., V. Watson, D. Kalentakis, and J. I. Macdiarmid (2019a). Value-elicitation and value-formation properties of discrete choice experiment and experimental auctions. *European Review of Agricultural Economics*, Vol. 46, No. 1, pp. 3–27.

Cerroni, S., V. Watson, and J. I. Macdiarmid (2019b). Consumers' rationality and home-grown values for healthy and environmentally sustainable food. *Biobased and Applied Economics*, Vol. 8, No. 2, pp. 101–132.

Chaiyesh, T. (2022). Consumers' willingness to pay for healthiness, quality and carbon footprint reduction of bagged rice. *Global Business Review*, 1–13.

Chang, M.-Y., J.-C. Lin, and H.-S. Chen (2023). Consumer attitudes and preferences for healthy boxed meal attributes in Taiwan: Evidence from a choice experiment. *Nutrients 15*(4), 1032.

Chay, K. and M. Greenstone (2005). Does air quality matter? Evidence from the housing market. *Journal of Political Economy 113*(2), 376–424.

Chen, N., Z.-H. Zhang, S. Huang, and L. Zheng (2018). Chinese consumer responses to carbon labeling: Evidence from experimental auctions. *Journal of Environmental Planning and Management 61*(13), 2319–2337.

Colantuoni, F., G. Cicia, T. Del Giudice, D. Lass, F. Caracciolo, and P. Lombardi (2016). Heterogeneous preferences for domestic fresh produce: Evidence from German and Italian early potato markets. *Agribusiness 32*(4), 512–530.

Cubero Dudinskaya, E., S. Naspetti, G. Arsenos, E. Caramelle-Holtz, T. Latvala, D. Martin-Collado, S. Orsini, E. Ozturk, and R. Zanoli (2021). European consumers' willingness to pay for red meat labelling attributes. *Animals 11*(2), 556.

Cuong, O. Q., M. Connor, M. Demont, B. O. Sander, and K. Nelson (2022). How do rice consumers trade off sustainability and health labels? Evidence from Vietnam. *Frontiers in Sustainable Food Systems 6*, 1010161.

Dawes, R. M. and R. H. Thaler (1988). Anomalies: Cooperation. *Journal of Economic Perspectives 2*(3), 187–197.

De-Magistris, T., A. Gracia, and R. M. Nayga Jr (2013). On the use of honesty priming tasks to mitigate hypothetical bias in choice experiments. *American Journal of Agricultural Economics 95*(5), 1136–1154.

De Marchi, E., V. Caputo, R. M. Nayga Jr, and A. Banterle (2016). Time preferences and food choices: Evidence from a choice experiment. *Food Policy 62*, 99–109.

Doda, B., C. Gennaioli, A. Gouldson, D. Grover, and R. Sullivan (2016). Are corporate carbon management practices reducing corporate carbon emissions? *Corporate Social Responsibility and Environmental Management 23*(5), 257–270.

Drichoutis, A. C., J. L. Lusk, and V. Pappa (2016). Elicitation formats and the WTA/WTP gap: A study of climate neutral foods. *Food policy 61*, 141–155.

Dudinskaya, E. C., S. Naspetti, and R. Zanoli (2020). Using eye-tracking as an aid to design on-screen choice experiments. *Journal of Choice Modelling 36*, 100232.

Echeverría, R., V. H. Moreira, C. Sepúlveda, and C. Wittwer (2014). Willingness to pay for carbon footprint on foods. *British Food Journal*.

Ellingsen, T. and M. Johannesson. Pride and prejudice: The human side of incentive theory.

Environmental Protection Agency (2023). Report on the social cost of greenhouse gases: Estimates incorporating recent scientific advances. Technical report, U.S. Environmental Protection Agency.

Erraach, Y., S. Sayadi, and C. Parra-López (2017). Measuring preferences and willingness to pay for sustainability labels in olive oil: Evidence from Spanish consumers. In *XV EAAE Congress, Parma, Italy.*

Falk, A. and N. Szech (2013). Morals and markets. *Science 340*(6133), 707–711.

Fehr, E., G. Kirchsteiger, and A. Riedl (1993). Does fairness prevent market clearing? An experimental investigation. *The Quarterly Journal of Economics 108*(2), 437–459.

Fehr, E. and K. M. Schmidt (1999). A theory of fairness, competition, and cooperation. *The Quarterly Journal of Economics 114*(3), 817–868.

Feucht, Y. and K. Zander (2017). Consumers' attitudes on carbon footprint labelling: Results of the SUSDIET project. Technical report, Thünen Working Paper.

Feucht, Y. and K. Zander (2018). Consumers' preferences for carbon labels and the underlying reasoning. A mixed methods approach in 6 European countries. *Journal of Cleaner Production 178*, 740–748.

Fischer, C. and T. P. Lyon (2014). Competing environmental labels. *Journal of Economics & Management Strategy 23*(3), 692–716.

Fischer, C. and T. P. Lyon (2019). A theory of multitier ecolabel competition. *Journal of the Association of Environmental and Resource Economists 6*(3), 461–501.

Gassler, B. (2015). How green is your "Grüner"? Millennial wine consumers' preferences and willingness-to-pay for eco-labeled wine. *Jahrbuch der Österreichischen Gesellschaft für Agrarökonomie 24*, 131–140.

Grebitus, C., B. Steiner, and M. Veeman (2013). Personal values and decision making: Evidence from environmental footprint labeling in Canada. *American Journal of Agricultural Economics 95*(2), 397–403.

Grebitus, C., B. Steiner, and M. Veeman (2015). The roles of human values and generalized trust on stated preferences when food is labeled with environmental footprints: Insights from Germany. *Food Policy 52*, 84–91.

Grebitus, C., B. Steiner, and M. M. Veeman (2016). Paying for sustainability: A cross-cultural analysis of consumers' valuations of food and non-food products labeled for carbon and water footprints. *Journal of Behavioral and Experimental Economics 63*, 50–58.

Haab, T. C. and K. E. McConnell (2002). *Valuing Environmental and Natural Resources: The Econometrics of Non-market Valuation.* Edward Elgar Publishing.

Harrison, G. W. and J. A. List (2004). Field experiments. *Journal of Economic Literature 42*(4), 1009–1055.

Hassen, A. S. (2016). Consumers' willingness to pay for environmental attributes of a cut flower in Ethiopia: A choice experiment approach. *Yildiz Social Science Review 2*(1), 31–46.

Henderson, C. (2018). Consumer preferences for GM food labeling: A market segments analysis. Agricultural Economics and Agribusiness Undergraduate Honors Theses.

Heyes, A. and S. Martin (2018). Inefficient NGO labels: Strategic proliferation and fragmentation in the market for certification. *Journal of Economics & Management Strategy 27*(2), 206–220.

Howarth, R. B., M. D. Gerst, and M. E. Borsuk (2014). Risk mitigation and the social cost of carbon. *Global Environmental Change 24*, 123–131.

IMF (2019). Fiscal Monitor: How to mitigate climate change. Technical report, IMF, Washington, DC.

IWG on Social Cost of Carbon (2010). Technical support document: Social cost of carbon for regulatory impact analysis under Executive Order 12866. Technical report, Interagency Working Group on Social Cost of Carbon, Washington, DC.

IWG on Social Cost of Carbon (2013). Technical support document: Social cost of carbon for regulatory impact analysis under Executive Order 12866. Technical report, Interagency Working Group on Social Cost of Carbon, Washington, DC.

IWG on Social Cost of Carbon (2016). Technical support document: Technical update of the social cost of carbon for regulatory impact analysis under Executive Order 12866. Technical report, Interagency Working Group on Social Cost of Carbon, Washington, DC.

IWG on Social Cost of Greenhouse Gases (2021). Technical support document: Social cost of carbon, methane, and nitrous oxide interim estimates under Executive Order 13990. Technical report, Interagency Working Group on Social Cost of Greenhouse Gases, Washington, DC.

Jacobsen, G. D. (2011). The Al Gore effect: An Inconvenient Truth and voluntary carbon offsets. *Journal of Environmental Economics and Management 61*(1), 67–78.

Janßen, D. and N. Langen (2017). The bunch of sustainability labels - Do consumers differentiate? *Journal of Cleaner Production 143*, 1233–1245.

Johnston, R. J., K. J. Boyle, W. V. Adamowicz, J. Bennett, R. Brouwer, T. A. Cameron, W. M. Hanemann, N. Hanley, M. Ryan, R. Scarpa, R. Tourangeau, and C. A. Vossler (2017). Contemporary guidance for stated preference studies. *Journal of the Association of Environmental and Resource Economists 4*(2), 319–405.

Kesternich, M., A. Löschel, and D. Römer (2016). The long-term impact of matching and rebate subsidies when public goods are impure: Field experimental evidence from the carbon offsetting market. *Journal of Public Economics 137*(C), 70–78.

Kim, E.-H. and T. Lyon (2011). When does institutional investor activism increase shareholder value?: The Carbon Disclosure Project. *The B.E. Journal of Economic Analysis & Policy 11*(1).

Kim, H., L. A. House, and T.-K. Kim (2016). Consumer perceptions of climate change and Willingness to Pay for mandatory implementation of low carbon labels: The case of South Korea. *International Food and Agribusiness Management Review 19*(4), 129–144.

Kimura, A., Y. Wada, A. Kamada, T. Masuda, M. Okamoto, S.-i. Goto, D. Tsuzuki, D. Cai, T. Oka, and I. Dan (2010). Interactive effects of carbon footprint information and its accessibility on value and subjective qualities of food products. *Appetite 55*(2), 271–278.

Kitzmueller, M. and J. Shimshack (2012). Economic perspectives on corporate social responsibility. *Journal of Economic Literature 50*(1), 51–84.

Kotchen, M. J. (2009). Voluntary provision of public goods for bads: A theory of environmental offsets. *Economic Journal 119*(537), 883–899.

Kovalsky, K. L. and J. L. Lusk (2013). Do consumers really know how much they are willing to pay? *Journal of Consumer Affairs 47*(1), 98–127.

Kraft-Todd, G. T., B. Bollinger, K. Gillingham, S. Lamp, and D. G. Rand (2018). Credibility-enhancing displays promote the provision of non-normative public goods. *Nature 563*, 245–248.

Lami, O., F. J. Mesías, C. Balas, C. Díaz-Caro, M. Escribano, and A. Horrillo (2022). Does carbon footprint play a relevant role in food consumer behaviour? A focus on Spanish beef. *Foods 11*(23), 3899.

Li, X., K. L. Jensen, C. D. Clark, and D. M. Lambert (2016). Consumer willingness to pay for beef grown using climate friendly production practices. *Food Policy 64*, 93–106.

Li, X., K. L. Jensen, D. M. Lambert, and C. D. Clark (2018). Consequentiality beliefs and consumer valuation of extrinsic attributes in beef. *Journal of Agricultural and Applied Economics 50*(1), 1–26.

Lombardi, G. V., R. Berni, and B. Rocchi (2017). Environmental friendly food. Choice experiment to assess consumer's attitude toward "climate neutral" milk: The role of communication. *Journal of Cleaner Production 142*, 257–262.

Macdiarmid, J. I., S. Cerroni, D. Kalentakis, and C. Reynolds (2021). How important is healthiness, carbon footprint and meat content when purchasing a ready meal? Evidence from a non-hypothetical discrete choice experiment. *Journal of Cleaner Production 282*, 124510.

Magistris, T. d., A. Gracia, et al. (2014). Do consumers care about organic and distance labels? An empirical analysis in Spain. *International Journal of Consumer Studies 38*(6), 660–669.

Menapace, L. and R. Raffaelli (2017). Preferences for locally grown products: Evidence from a natural field experiment. *European Review of Agricultural Economics 44*(2), 255–284.

Meyerding, S. G., A.-L. Schaffmann, and M. Lehberger (2019). Consumer preferences for different designs of carbon footprint labelling on tomatoes in Germany - does design matter? *Sustainability 11*(6), 1587.

Michaud, C., D. Llerena, and I. Joly (2013). Willingness to pay for environmental attributes of non-food agricultural products: A real choice experiment. *European Review of Agricultural Economics 40*(2), 313–329.

Mōerbeck, S. (2022). Communicating sustainability in the food industry: The impact of carbon labels on the willingness to pay for food products. Master's thesis, Universidade Católica Portuguesa.

Moon, D., K. Lee, and C. Kim (2015). Measuring willingness to pay for CO2 information on consumption goods in Korea. Working Paper.

Mortensen, C. R., R. Neel, R. B. Cialdini, C. M. Jaeger, R. P. Jacobson, and M. M. Ringel (2019). Trending norms: A lever for encouraging behaviors performed by the minority. *Social Psychological and Personality Science 10*(2), 201–210.

Mostafa, M. M. (2016). Egyptian consumers' willingness to pay for carbon-labeled products: A contingent valuation analysis of socio-economic factors. *Journal of Cleaner Production 135*, 821–828.

Muehlenbachs, L., E. Spiller, and C. Timmins (2015). The housing market impacts of shale gas development. *American Economic Review 105*(12), 3633–3659.

Muller, L., A. Lacroix, and B. Ruffieux (2019). Environmental labelling and consumption changes: A food choice experiment. *Environmental and Resource Economics 73*(3), 871–897.

Nassivera, F., G. Gallenti, S. Troiano, F. Marangon, M. Cosmina, P. Bogoni, B. Campisi, and M. Carzedda (2020). Italian millennials' preferences for wine: An exploratory study. *British Food Journal 122*(8), 2403–2423.

National Academies of Sciences, Engineering, and Medicine (2017). *Valuing Climate*

Damages: Updating Estimation of the Social Cost of Carbon Dioxide. Washington, DC: The National Academies Press.

Nelson, J. P. and P. E. Kennedy (2009). The use (and abuse) of meta-analysis in environmental and natural resource economics: An assessment. *Environmental and Resource Economics 42*(3), 345–377.

Nesselhauf, L., R. Fleuchaus, and L. Theuvsen (2020). What about the environment? A choice-based conjoint study about wine from fungus-resistant grape varieties. *International Journal of Wine Business Research 32*(1), 96–121.

Nyberg, E. (2018). Meat production preferences among Swedish consumers: A choice experiment with lasagna.

Onozaka, Y. and D. T. McFadden (2011). Does local labeling complement or compete with other sustainable labels? A conjoint analysis of direct and joint values for fresh produce claim. *American Journal of Agricultural Economics 93*(3), 693–706.

Osawe, O. W., G. Grilli, and J. Curtis (2023). Examining food preferences in the face of environmental pressures. *Journal of Agriculture and Food Research 11*, 100476.

Owusu-Sekyere, E., Y. Mahlathi, and H. Jordaan (2019). Understanding South African consumers' preferences and market potential for products with low water and carbon footprints. *Agrekon 58*(3), 354–368.

Ozkan, M. (2011). Purchaser preferences on carbon labels: Conventional vs. organic milk.

Peschel, A. O., C. Grebitus, B. Steiner, and M. Veeman (2016). How does consumer knowledge affect environmentally sustainable choices? Evidence from a cross-country latent class analysis of food labels. *Appetite 106*, 78–91.

Pezzey, J. C. V. (2019). Why the social cost of carbon will always be disputed. *Wiley Interdisciplinary Reviews: Climate Change 10*(1), e558.

Pindyck, R. S. (2013). Climate change policy: What do the models tell us? *Journal of Economic Literature 51*(3), 860–872.

Poret, S. (2019). Label wars: Competition among NGOs as sustainability standard setters. *Journal of Economic Behavior & Organization 160*, 1–18.

Rahmani, D., Z. Kallas, M. Pappa, and J. M. Gil (2019). Are consumers' egg preferences influenced by animal-welfare conditions and environmental impacts? *Sustainability 11*(22), 6218.

Ratliff, E. L. (2021). *Consumer Preferences for Value Added Products: A Case Study for South Carolina.* Ph. D. thesis, Clemson University.

Rennert, K., F. Errickson, B. C. Prest, L. Rennels, R. G. Newell, W. Pizer, C. Kingdon, J. Wingenroth, R. Cooke, B. Parthum, et al. (2022). Comprehensive evidence implies a higher social cost of CO2. *Nature 610*(7933), 687–692.

Rogelj, J., O. Geden, A. Cowie, and A. Reisinger (2021). Net-zero emissions targets are vague: Three ways to fix. *Nature 591*(7850).

Rondoni, A. and S. Grasso (2021). Consumers behaviour towards carbon footprint labels on food: A review of the literature and discussion of industry implications. *Journal of Cleaner Production 301*, 127031.

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy 82*(1), 34–55.

Roth, J., P. H. C. Sant'Anna, A. Bilinski, and J. Poe (2022). What's trending in difference-in-differences? A Synthesis of the recent econometrics literature. Technical Report arXiv:2201.01194, arXiv.

Severens, F. (2021). Choice experiment amongst Dutch consumers: Willingness to pay for sustainability attributes of pork products.

Shleifer, A. (2004). Does competition destroy ethical behavior? *American Economic Review 94*(2), 414–418.

Smith, V. K. and W. H. Desvousges (1986). The value of avoiding a Lulu: Hazardous waste disposal sites. *The Review of Economics and Statistics 68*(2), 293–299.

Smith, V. K. and S. K. Pattanayak (2002). Is meta-analysis a Noah's ark for non-market valuation? *Environmental and Resource Economics 22*(1), 271–296.

Sonntag, W. I., D. Lemken, A. Spiller, and M. Schulze (2023). Welcome to the (label) jungle? Analyzing how consumers deal with intra-sustainability label trade-offs on food. *Food Quality and Preference 104*, 104746.

Sparkman, G. and G. M. Walton (2017). Dynamic norms promote sustainable behavior, even if it is counternormative. *Psychological Science 28*(11), 1663–1674.

Spencer, G., S. Carattini, and R. B. Howarth (2019). Short-term interventions for long-term change: Spreading stable green norms in networks. *Review of Behavioral Economics 6*(1), 53–93.

Sporleder, E. M., M. Kayser, N. Friedrich, and L. Theuvsen (2014). Consumer preferences for sustainably produced bananas: A discrete choice experiment. *International Food and Agribusiness Management Review 17*(1030-2016-82973), 59–82.

Staples, A. J., C. J. Reeling, N. J. O. Widmar, and J. L. Lusk (2020). Consumer willingness to pay for sustainability attributes in beer: A choice experiment using eco-labels. *Agribusiness 36*(4), 591–612.

Steiner, B. E., A. Peschel, and C. Grebitus (2017). Multi-product category choices labeled for ecological footprints: Exploring psychographics and evolved psychological biases for characterizing latent consumer classes. *Ecological Economics 140*, 251–264.

Stiglitz, J. E., N. Stern, M. Duan, O. Edenhofer, G. Giraud, G. Heal, E. L. la Rovere, A. Morris, E. Moyer, M. Pangestu, Y. Sokona, P. R. Shukla, and Winkler (2017). Report of the High-Level Commission on Carbon Prices. Technical report, Carbon Pricing Leadership Coalition.

Tait, P., C. Saunders, M. Guenther, P. Rutherford, and S. Miller (2016). Exploring the impacts of food label format on consumer willingness to pay for environmental sustainability: A choice experiment approach in the United Kingdom and Japan. *International Food Research Journal 23*(4).

Thøgersen, J. and K. S. Nielsen (2016). A better carbon footprint label. *Journal of Cleaner Production 125*, 86–94.

Tol, R. S. (2011). The social cost of carbon. *Annual Review of Resource Economics 3*(1), 419–443.

Tu, V. H., S. W. Kopp, N. T. Trang, A. Kontoleon, and M. Yabe (2021). Uk consumers' preferences for ethical attributes of floating rice: Implications for environmentally friendly agriculture in Vietnam. *Sustainability 13*(15), 8354.

Van Loo, E. J., V. Caputo, R. M. Nayga Jr, H.-S. Seo, B. Zhang, and W. Verbeke

(2015). Sustainability labels on coffee: Consumer preferences, willingness-to-pay and visual attention to attributes. *Ecological Economics 118*, 215–225.

Van Loo, E. J., V. Caputo, R. M. Nayga Jr, and W. Verbeke (2014). Consumers' valuation of sustainability labels on meat. *Food Policy 49*, 137–150.

Vecchio, R. (2013). Determinants of willingness-to-pay for sustainable wine: Evidence from experimental auctions. *Wine Economics and Policy 2*(2), 85–92.

Vecchio, R. and A. Annunziata (2015). Willingness-to-pay for sustainability-labelled chocolate: An experimental auction approach. *Journal of Cleaner Production 86*, 335–342.

World Bank (2023). State and trends of carbon pricing - 2023. Technical report.

Xu, Y., B. Xian, M. Li, Y. Wang, and L. Liangming (2023). Do carbon labels increase Chinese consumers' Willingness to Pay for carbon-labeled agricultural products? Available at SSRN.

Yang, X., Q. Chen, Z. Xu, Q. Zheng, R. Zhao, H. Yang, C. Ruan, F. Han, and Q. Chen (2021). Consumers' preferences for health-related and low-carbon attributes of rice: A choice experiment. *Journal of Cleaner Production 295*, 126443.

Zhao, R., Y. Geng, Y. Liu, X. Tao, and B. Xue (2018). Consumers' perception, purchase intention, and willingness to pay for carbon-labeled products: A case study of Chengdu in China. *Journal of Cleaner Production 171*, 1664–1671.

Zhao, R., M. Yang, J. Liu, L. Yang, Z. Bao, and X. Ren (2020). University students' purchase intention and willingness to pay for carbon-labeled food products: A purchase decision-making experiment. *International Journal of Environmental Research and Public Health 17*(19), 7026.

Zheng, Y. (2014). *Consumer preference and willingness-to-pay for locally produced, organic food: a stated choice approach*. Ph. D. thesis, University of Guelph.

Appendix

A Meta analysis

A.1 Data collection

A.1.1 Selection of studies

This section describes how we selected the studies included in the meta-analysis and presents the studies' characteristics. The dataset for the meta-analysis includes both existing stated and revealed preference studies on products with climate labels such as those indicating carbon footprint, carbon reduction, or carbon neutrality. Based on the studies with (hypothetical or real) product purchases, we derive the WTP estimates for full or partial CO_2 reductions, including through offsets. As a further qualification, we only focus on studies that value climate labels but not the other environmental or social responsibility attributes such as energy efficiency, fair trade, organic, and reduced water footprint.

In order to identify the studies of interest, we proceeded in two ways. First, by running keyword searches on Google Scholar, EconPapers (RePEc), Econlit, and Proquest, with the goal of gathering both published studies and working papers. Second, by using backward and forward citations from the studies that we had identified using the first strategy. Table A.1 outlines our search strategy, specifying both the databases visited and the keywords searched.

Our initial sample includes 83 studies. We then exclude several studies for various constraints, as detailed in Table A.2. We include only those studies that report or allow derivation of WTP for CO_2 reductions in currency units. Among the selected studies, we further narrow the scope to those that enable us to derive or make assump-

Period	Databases & Search Engines	Search Terms
Jan 2021 - Jun 2021	Google Scholar Scopus EconPapers ProQuest	Combination of words such as "carbon footprint," "carbon neutral," "climate-friendly," "low carbon," "label," "valuation," "experiment," "survey," "stated preference," "revealed preference"
Sep 2022 - Oct 2022	Google Scholar Scopus EconPapers ProQuest	(Carbon footprint label OR carbon label OR carbon neutral label OR climate-friendly OR carbon reduction OR low carbon OR carbon trust label) AND (stated preferences OR revealed preferences OR choice experiment OR contingent valuation OR field experiment OR lab experiment OR auction experiment) AND (environmental valuation OR Willingness to Pay)
July 2023	Google Scholar (2,780) Scopus (32) EconPapers (81) EconLit (6) ProQuest (549)	("carbon footprint label" OR "carbon neutral label" OR "carbon-neutral label" OR "low carbon label" OR "food miles" OR "product miles" OR "transportation distance") AND ("Willingness to Pay" OR "Willingness to Accept" OR "stated preferences" OR "revealed preferences" OR "choice experiment" OR "contingent valuation" OR "field experiment" OR "lab experiment" OR "auction experiment" OR "hedonic" OR "environmental valuation" OR "non-market valuation")

Multiple searches were conducted during the years 2021 and 2022. During the final search (July 2023), all of the search outputs, for which we specify the number of results in parentheses, were reviewed. In addition to the searches, we also checked papers cited in a review article by Rondoni and Grasso (2021). Backward citations of relevant papers' titles were checked by searching for the word "carbon," while forward citations were checked using combinations of the following words: "carbon," "label," "willingness," "kilometers," and "miles."

Table A.1: Paper Search Strategy

tions regarding the amount of CO_2 reduction. We assume that such CO_2 reduction can be achieved in various ways: by decreasing emissions in the product's production process, transportation, or overall lifecycle through technology, product varieties that result in lower emissions, carbon offsetting, or carbon capture.

First, we exclude 21 studies that lack information that would allow us to derive or make assumptions about the amount of CO_2 reductions. Second, we exclude 12 studies categorized as "carbon transparent," which value carbon footprint labels without specifying any CO_2 reduction. In addition, we exclude 6 studies that focus on reduced transportation distance. Note that under this constraint, we do not exclude studies that value carbon footprint information, which is "framed" in terms of distance traveled. Furthermore, we exclude 5 studies that discretely code cost levels (prices), and one study that reports the WTP as a percentage premium on unspecified product price, not allowing derivation of WTP in currency units. Additionally, we exclude a study that does not specify the type and amount of a product. Lastly, we exclude a study that reports WTP for a sustainability label, which refers to organic, fair trade, and carbon-neutral attributes, not allowing derivation of WTP of the carbon-neutral label alone. After accounting for these, our final dataset consists of 37 studies and 129 observations.

Exclusion Reason	Excluded Studies
Unknown carbon reduction	Michaud et al. (2013), Van Loo et al. (2015), Vecchio and Annunziata (2015), Tait et al. (2016), De Marchi et al. (2016), Feucht and Zander (2017), Lombardi et al. (2017), Menapace and Raffaelli (2017), Janßen and Langen (2017), Feucht and Zander (2018), Asioli et al. (2018), Boehm et al. (2019), Staples et al. (2020), Dudinskaya et al. (2020), Broeckhoven et al. (2021), Cubero Dudinskaya et al. (2021), Ratliff (2021), Asioli et al. (2022), Cuong et al. (2022), Asioli et al. (2023), Asioli et al. (2023), Sonntag et al. (2023)
Carbon transparent	Ozkan (2011), Caputo et al. (2013), Echeverría et al. (2014), Colantuoni et al. (2016), Moon et al. (2015), Kim et al. (2016), Erraach et al. (2017), Zhao et al. (2018), Nassivera et al. (2020), Zhao et al. (2020), Asioli et al. (2022), Chang et al. (2023)
Transportation distance reduction	Kovalsky and Lusk (2013), De-Magistris et al. (2013), Magistris et al. (2014), Zheng (2014), Adalja et al. (2015), Carroll (2018)
Discretely coded cost	Boesch and Weber (2012), Thøgersen and Nielsen (2016), Peschel et al. (2016), Steiner et al. (2017), Meyerding et al. (2019)
Percentage premium WTP on unspecified product price	Xu et al. (2023)
Unspecified product	Mostafa (2016)
Multiple sustainability labels	Sporleder et al. (2014)

Table A.2: Excluded Studies and Rationales

A.1.2 List of studies and characteristics

Table A.3 describes the literature covered in the study. It lists the valued products, the countries in which the studies were conducted, the methods used, the number of WTP observations, as well as the type of climate impact information valued in the study (based on which we derive the corresponding amount of CO_2 reduction), such as carbon footprint information, carbon neutral label, or percentage of carbon reduction.

Table A.3: Literature covered in the meta-analysis

Study	No. obs.[a]	Product	Country	Method[b]	Climate impact information[c]
Ajayi and Reiner (2020)	2	Plastic bottle	United Kingdom	DCE	Percentage of carbon capture
Akaichi et al. (2016)	6	Banana	France, Netherlands, United Kingdom	DCE	Carbon footprint from transportation
Akaichi et al. (2017)	1	Rice	United States	AFE	Carbon footprint
Akaichi et al. (2020)	4	Ground beef	Spain, United Kingdom	DCE	GHG emissions
Aoki & Akai (2020)	3	Mandarin	Japan	DCE	Carbon footprint
Bek (2022)	1	Coffee	Germany	DCE	Carbon neutrality
Birkenberg et al. (2021)	1	Coffee	Germany	DCE	Carbon neutrality
Breustedt (2014)	2	Juice, milk	Germany	DCE	Carbon footprint
Caputo et al. (2018)	6	Chicken	Belgium	DCE	Carbon footprint from transportation
Carlsson et al. (2022)	6	Lasagne	Sweden	DCE	GHG emission categories
Cerroni et al. (019b) & Ceroni et al. (2019b)	4	Lasagne	United Kingdom	DCE, AFE	Carbon footprint emission categories

[a] "No. obs." refers to the number of WTP observations included from each respective study.

[b] In our database, stated preference studies include DCE (Discrete Choice Experiments), and CV (Contingent Valuation Method). Based on Harrison and List (2004), we classified revealed preference studies as AFE (Artifactual Field Experiments) or CLE (Conventional Lab Experiments).

[c] Note that unless otherwise stated, the terms such as "carbon footprint," "carbon neutrality," and "carbon reduction" refer to emissions from either production or the entire life cycle of the product.

Table A.3: Literature covered in the meta-analysis (continued)

Study	No. obs.	Product	Country	Method	Climate impact information
Chaiyesh (2022)	2	Rice	Thailand	DCE	Percentage of carbon reduction
Chen et al. (2018)	3	Water	China	CLE	Carbon footprint
Drichoutis et al. (2016)	2	Egg, olive oil	Greece	CV	Carbon neutrality
Gassler (2015)	1	Milk	Austria	DCE	Carbon neutrality
Grebitus et al. (2013)	1	Ground Beef	Canada	DCE	Carbon footprint
Grebitus et al. (2015)	1	Potatoes	Germany	DCE	Carbon footprint
Hassen (2016)	8	Ground beef, potatoes, toilet paper, yogurt	Canada, Germany	DCE	Carbon footprint
Hassen (2016)	1	Flower	Ethiopia	DCE	Percentage of carbon reduction
Henderson (2018)	3	Chicken	United States	DCE	Carbon footprint
Kimura et al. (2010)	16	Candy, chips, chocolate, juice	Japan	CV	Carbon footprint
Lami et al. (2022)	2	Beef	Spain	DCE	Carbon footprint
Li et al. (2016)	1	Beef	United States	CV	Carbon-friendly label and annual GHG emission reduction in percentages
Li et al. (2018)	2	Beef, ground beef	United States	DCE	Carbon-friendly label
Macdiarmid et al. (2021)	2	Lasagne	United Kingdom	DCE	Carbon footprint

Table A.3: Literature covered in the meta-analysis (continued)

Study	No. obs.	Product	Country	Method	Climate impact information
Mōerbeck (2022)	10	Apples, beef, butter, cheese, chicken, eggs, flour, milk, rice, tomatoes	Germany	CV	Carbon footprint
Nesselhauf et al. (2020)	3	Wine	Germany	DCE	Percentage of carbon reduction
Nyberg (2018)	4	Lasagne	Sweden	DCE	GHG emissions, expressed in terms of carbon dioxide equivalents
Onozaka and McFadden (2011)	2	Apples, tomatoes	United States	DCE	Carbon footprint
Osawe et al. (2023)	6	Beef, chicken, vegetables	Ireland	DCE	GHG emissions, expressed in terms of carbon dioxide equivalents
Owusu-Sekyere et al. (2019)	2	Beef	South Africa	DCE	GHG emissions, expressed in terms of carbon dioxide equivalents
Rahmani et al. (2019)	12	Egg	Spain	DCE	Percentage of carbon reduction
Severens (2021)	2	Pork	Netherlands	DCE	Carbon reduction categories, expressed as equivalent kilometers driven by a car
Tu et al. (2021)	3	Rice	United Kingdom	DCE	Percentage of carbon reduction
Van Loo et al. (2014)	2	Chicken	Belgium	DCE	Carbon footprint reduction
Vecchio (2013)	1	Wine	Italy	CLE	Carbon neutrality
Yang et al. (2021)	1	Rice	China	DCE	Percentage of carbon reduction

A.1.3 Data Collection and Variable Derivation Strategies

In this section, we outline our strategies for data collection and variable derivation. First, we define the variables that we use in our analysis, discuss the general approaches that we use to derive them, and note any exceptional cases. Second, we provide a detailed information on how we derive the respective WTP estimates and amounts of carbon reduction from each study in Table A.4.

We define four measures of WTP based on all studies (37) and observations (129). The non-standardized measure ($\mathrm{WTP_{NS}}$) refers to the WTP for carbon reductions, which can vary both within and between studies. This measure is directly taken or derived from studies, and converted to 2020 USD. We use this measure in our regression analysis as the outcome variable to explore factors associated with WTP.

To facilitate comparisons of WTP estimates both within and between studies, as well as with our results from the hedonic approach, we create three alternative WTP measures. The first measure is denoted as $\mathrm{WTP_{kg}}$, which refers to the WTP for a 1 kg reduction in carbon emissions. This is obtained by dividing $\mathrm{WTP_{NS}}$ by the respective amount of carbon reduction in kilograms, and is expressed in USD. The WTP for carbon neutrality, denoted as $\mathrm{WTP_{CN}}$, is calculated by multiplying $\mathrm{WTP_{kg}}$ by the baseline carbon emissions of the respective product in kilograms, and is expressed in USD. This measure is derived for all observations and all studies in our database, not just those that value carbon-neutral labels. The proportion of a product's price that consumers would be willing to pay extra for carbon neutrality, denoted as $\mathrm{WTP_{CN\%}}$, is obtained by dividing $\mathrm{WTP_{CN}}$ by the product's price.

We follow the rules outlined below to obtain $\mathrm{WTP_{NS}}$ estimates, which are subsequently used to calculate the corresponding $\mathrm{WTP_{kg}}$, $\mathrm{WTP_{CN}}$, and $\mathrm{WTP_{CN\%}}$ measures:

1. For the purpose of this study, WTP for various forms of carbon mitigation, such as carbon offsetting, carbon reductions, and carbon capture, is treated as equivalent. Whenever the term "carbon reduction" is used throughout this study, it refers to any of these concepts.

2. If a study reports WTP for a specific amount of carbon reduction associated with a product, we use that value directly. If the amount of carbon reduction is not provided, since most of the products valued in the literature are common food products, we rely on third-party sources, such as "MyEmissions" and "Plate up for the Planet" carbon calculators, to derive it. More details are provided later in this section, where we discuss the carbon reduction variable.

3. To enable consistent comparisons across WTP estimates, we adjust all observations to represent only the WTP for carbon reduction, excluding the product's price. Such WTP measure represents the marginal WTP (MWTP) for climate impact attribute valued in the studies. However, for the purpose of our analysis, we do not distinguish between mean and median MWTP when taking or deriving CO_2 emission reduction estimates from studies, since only three studies report a median estimate, and median and mean are equivalent in the case of linear utility and symmetric mean zero error (Haab and McConnell, 2002). If a study reports WTP for a product labeled as "carbon-neutral" rather than for the "carbon-neutral label," we subtract the estimated mean WTP for the unlabeled product to obtain the MWTP for the label. In cases where this information is unavailable, we use the price of the conventional product as a proxy for the WTP for the unlabeled product and subtract it from the reported WTP for the labeled product estimate.

4. When a study provides WTP estimates for multiple carbon footprint labels with

varying baseline product emissions, we proceed with the following strategies. For two labels, the WTP estimate is derived as the difference between the reported WTP values for low and high carbon footprint levels. For three labels, three WTP estimates are derived based on the differences between the WTP estimates for the low-mid, mid-high, and low-high carbon footprint levels.

5. If WTP estimates are not reported or if additional WTP estimates can be derived from studies using DCEs, we derive them from the reported choice model outputs. Let MWTP denote the marginal WTP for the original climate impact attribute valued in the study, such as carbon footprint information or a carbon neutral label, based on which we derive the WTP for CO_2 emission reductions.

   Let β_{cost} and β_{climate} be the coefficients for price and the product's climate impact attribute, respectively. If either the cost or climate parameter specified as fixed in the study, MWTP for the climate impact attribute is derived using the following equation:

$$\text{MWTP} = -\frac{\beta_{\text{climate}}}{\beta_{\text{cost}}}$$

   Note that we do not derive a WTP estimate from that model in the following cases: if both the cost and climate parameters are specified as random; or if more than one categorical or ordinal variable interacts with the climate impact attribute.

6. For each study, we average the WTP observations that remain constant across the covariates which are used in the regressions; otherwise, we take them as they are.

7. All monetary variables, including WTP estimates, are adjusted for inflation and

exchange rate and expressed in 2020 USD values.

Next, we detail the independent variables included in the regression analysis. The first variable is the "amount of carbon reduction" in kilograms. In cases where the study does not specify, as it is sometimes the case for food and drink products, the baseline carbon emissions of products, which is necessary to calculate the corresponding amount of CO_2 emission reduction, we use online food/drink carbon calculators, specifically, MyEmissions and Plate up for the Planet. A few instances also involve non-food products, specifically flowers and plastic bottles. For flowers, we refer to Flowers from the Farm, an association supporting cut flower growers in the United Kingdom, and for plastic bottles, tappwater.co. Note that if the study does not specify the amount of CO_2 emission reduction, we have a dummy variable that takes the value of 1, which is described later in this section.

The "product price" variable is measured in 2020 USD. If a study does not specify a product's price, we use the WTP for the unlabeled product, as reported in the study. If not available and if the study confirms that these levels are aligned with observed market prices, we use the average of the price levels specified in the study as a proxy for price. We have three exceptions for which price information is unavailable: rice in Thailand, apple juice in Germany, and beef in the United States. We obtained rice price data from Globalproductprices.com for Chaiyesh (2022), apple juice prices from Selina Wamucii for Breustedt (2014), and beef prices from the United States Department of Agriculture for Li et al. (2016).

"Stated preference method" is a dummy variable that takes value 1 for observations derived from DCEs or CV method, and 0 for those obtained from revealed preference methods.

"In-person" is another dummy variable, taking value 1 for studies conducted face-to-face and 0 for online or computer-assisted surveys.

"Sample size" is a variable indicating the number of participants, which is generally available in all studies. However, there are two exceptions involving sub-samples. Van Loo et al. (2014) does not specify the sample sizes for income clusters. In this case, we assume an even distribution between high and low-income groups. In Kimura et al. (2010), the sample size varies between 18, 19, 20, and 21 for different treatment groups. A fixed sample size of 19 is assumed for all WTP observations to facilitate aggregation over fixed covariates (including sample size).

The dummy variable "Unpublished studies" takes the value of 1 for working papers, conference proceedings, or theses and 0 otherwise.

The "study year" variable refers to the year in which a study was conducted. For studies that span two consecutive years, we use the first year, while for those covering three years, the middle year is used. If a study is a conference paper and does not specify the year, as in the case of Gassler (2015), we refer to the year in which the respective conference took place.

"Carbon reduction assumptions" is a dummy variable that takes the value of 1 if a study lacks specific information on the amount of carbon reduction, requiring us to make assumptions, as described in detail for each study in Section A.4.

"WTP derivation" variable takes value 1 if we had to derive the WTP estimates ourselves, and 0 if these are directly reported in the original study. Note that in some cases, this variable can take the values of 0 and 1 for different observations originating from the same study.

"GDP per capita" refers to the per capita Gross Domestic Product of the country where the study was conducted, measured in 2020 USD.

"Europe" is a dummy variable that takes value 1 for studies conducted in Europe and 0 for those conducted in Africa, the Americas, or Asia.

Table A.4: WTP derivation strategy

Study	Details
Ajayi and Reiner (2020)	The WTP for 50% and 100% carbon capture relative to 1% capture is reported in the study (Tables 3 and 4). Assuming 1 kg of PET plastic in Europe leads to 2.15 kg carbon emissions (sourced from Tappwater.co) and that the study values a 100 ml PET-type plastic weighing 0.25 kg, its emissions are equal to 0.54 kg of carbon. Therefore, 49% carbon capture corresponds to a reduction of 0.25 kg of carbon emissions, while a 99% emission capture corresponds to a reduction of 0.50 kg carbon emissions. Following rule 6 from the Section A.1.3, we average the WTP values from different choice models as well as from preference and WTP spaces.
Akaichi et al. (2016)	The WTP estimates (from WTP space) for reducing carbon emissions by 1 kg are reported in the study (Table 4). The WTP estimates (from preference space) are derived from the study (Table 3).
Akaichi et al. (2017)	The WTP differences of four types of rice – local hybrid, non-local hybrid, local conventional, and non-local conventional – are reported in the study (Tables 5 and 6). Conventional rice has approximately 0.05 kg (1.76 oz) higher greenhouse gas (GHG) emissions from production, expressed as carbon dioxide equivalents than hybrid rice. The difference between Round 2 (WTP after GHG emissions information) and Round 1 (WTP based on appearance) is used to derive the WTP for 0.05 kg carbon reduction from Table 5, lines 2 and 3. Similarly, the difference between Round 3 (WTP after GHG information and food miles information) and Round 1 (WTP based on appearance) is used to derive the WTP for 0.05 kg carbon reduction from Table 6, lines 2 and 3. Note that our approach focuses on differences between hybrid and conventional rice while keeping the locality attribute constant (lines 2 & 3 only). Therefore, the focus is only on the derivation of the WTP for carbon reductions, not on the WTP for reduction in food miles (the distance at which food is transported from the place of production to the store).

Table A.4: WTP derivation strategy (continued)

Study	Details
Akaichi et al. (2020)	The WTP estimates for low (5.9 kg) and moderate (19.1 kg) relative to high (32.2 kg) GHG emissions are reported in the study (Table 3). As this is a common practice, we assume that GHG emissions are expressed in terms of carbon dioxide equivalents in this study. Therefore, the WTP for low relative to high carbon emissions corresponds to 26.3 kg (32.2 kg - 5.9 kg), while the WTP for moderate relative to high emissions corresponds to 13.1 kg (32.2 kg - 19.1 kg) kg of reduction in carbon emissions.
Aoki and Akai (2022)	The WTP estimates for a 0.001 kg increase in carbon emissions are reported in the study (Table 5). The WTP for decreasing carbon emissions by the same amount is derived by taking the negative of these values. Following rule 6 from Section A.1.3, the WTP estimates from hypothetical online surveys with and without cheap talk are averaged.
Bek (2022)	The WTP estimates for offsetting and reducing a product's full supply chain emissions are reported in the study (Table 7). We assume 0.5 kg of coffee leads to 2.5 kg of carbon emissions based on MyEmissions carbon calculator. Following rule 6 from Section A.1.3, the WTP estimates for offsetting and reducing product emissions are averaged.
Birkenberg et al. (2021)	The WTP estimates for carbon-neutral product are reported in the study (Table 4). WTP estimates for carbon neutrality are calculated by subtracting the WTP for the product with a carbon-neutral label from the WTP for the unlabeled product. Based on the study, carbon emissions of 1 kg of green coffee equals 4.82 kg. We use a weight conversion rate of 1.176:1 (as given in the study) between green and roasted coffee to calculate the respective emissions of 1 kg of roasted coffee, which is equivalent to 5.67 kg of carbon dioxide. Therefore, we assume 1.42 kg of carbon emissions for 0.25 kg of roasted coffee. Following rule 6 from Section A.1.3, the WTP estimates from Models 2 and 3 are averaged.
Breustedt (2014)	The WTP estimates for reducing carbon emissions by 1 kg are reported in the study (Tables 5 and 7). Following rule 6 from Section A.1.3, WTP estimates from MNL and RPL models are averaged.
Caputo et al. (2018)	The WTP estimates for 20% (1.4 kg) and 30% (2.1 kg) reduction in carbon emissions are reported in the study (Table 4).

Table A.4: WTP derivation strategy (continued)

Study	**Details**
Carlsson et al. (2022)	The WTP for large and small relative to medium GHG emissions are provided in the study (Table 2). The value for large emissions (relative to medium emissions) was multiplied by -1 to calculate the WTP for medium emissions (relative to large emissions). In the study, GHG emissions of 4 kg are classified as large, levels between 3 kg and 4 kg as medium, and levels less than 3 kg as small emissions. We assume that GHG emission levels are expressed in terms of carbon dioxide equivalents, as this is commonly the practice. A high carbon-footprint lasagna, weighing 0.4 kg, contains approximately 0.08 kg of ground beef, as given in Macdiarmid et al. (2021). Its carbon emissions are equal to 1.88 kg (according to the Plate up for the Planet calculator), which falls within the "small emissions" category defined in this study. In the meta-analysis, as we treat offsets and reductions in the same way, we assume that the carbon emissions of products can be reduced to 0 kg. Therefore, we assume an average emission of 1.5 kg for small levels (averaging 0 kg and 3 kg of carbon emissions), 3.5 kg for medium levels (averaging 3 kg and 4 kg of carbon emissions), and 4 kg for large levels. Respective carbon reduction levels for WTP estimates are calculated by determining the differences between small and medium (2 kg = 3.5 kg - 1.5 kg), and between medium and large (0.5 kg = 4 kg - 3.5 kg) carbon emissions.

Table A.4: WTP derivation strategy (continued)

Study	**Details**
Cerroni et al. (2019a,b)	The WTP estimates for low and medium carbon emissions, relative to large emissions, are provided in the studies (Tables 3, 4, D2, E2, 6, and F3 in Cerroni et al., 2019b) (and Tables 4 and 9 in Cerroni et al., 2019a). Carbon emissions are categorized as small for emissions of 0.26 kg or less, medium for emissions between 0.26 kg and 0.4 kg, and large for emissions of more than 0.4 kg per 100g of lasagna. These are multiplied by 4 for a portion (0.4 kg) of lasagna. A high carbon-footprint lasagna, weighing 0.4 kg, contains approximately 0.08 kg of ground beef, as provided in Macdiarmid et al. (2021). Its carbon emissions amount to 1.88 kg (according to the Plate Up for the Planet calculator). In the meta-analysis, as we treat offsets and reductions in the same way, we assume that the carbon emissions of products can be reduced to 0 kg. Therefore, we assume an average emission of 0.52 kg for low levels (averaging 0 kg and 1.04 kg of carbon emissions), 1.32 kg for medium levels (averaging 1.04 kg and 1.60 kg of carbon emissions), and 1.74 kg for large levels (averaging 1.60 kg and 1.88 kg of carbon emissions). Respective carbon reduction levels for WTP estimates are calculated by determining the differences between low and large (1.22 kg = 1.74 kg - 0.52 kg), and between medium and large (0.42 kg = 1.74 kg - 1.32 kg) carbon emissions. Following rule 6 from Section A.1.3, the WTP estimates obtained from colored, grey, and plain-text labels, from WTP space and preference space estimations from different models, have been averaged.
Chaiyesh (2022)	The WTP estimates for 20% (1.35 kg) and 40% (2.71 kg) carbon reductions are reported in the study (Table 4).
Chen et al. (2018)	The WTP estimates for carbon-labeled products are reported in the study (Tables 3 and 4). We subtract the WTP for a product with 0.10 kg of carbon emissions from that for a product with 0.15 kg, the WTP for a product with 0.15 kg from that for a product with 0.20 kg, and the WTP for a product with 0.10 kg from that for a product with 0.20 kg. This yields two observations for the WTP for a 0.05 kg carbon reduction and one observation for a 0.10 kg carbon reduction.
Drichoutis et al. (2016)	The WTP for carbon-neutral claims are provided by the author through direct correspondence. The carbon emissions for 1 liter of olive oil (2.53 kg of carbon) are sourced from the myEmissions carbon calculator, while the emissions for 0.38 kg of eggs (1.81 kg of carbon), assumed to be equivalent to a six pack, are sourced from the Plate up for the Planet carbon calculator. Following rule 6 from Section A.1.3, we average the WTP observations obtained from both inferred and contingent valuation methods, as well as from dichotomous choice and payment card formats.

Table A.4: WTP derivation strategy (continued)

Study	Details
Gassler (2015)	The WTP estimate for the carbon-neutral label is reported in the study (Section 4.2). The carbon emissions for 0.75 liters of wine (2.9 kg of carbon) are obtained from the Plate up for the Planet carbon calculator.
Grebitus et al. (2013)	The WTP estimates for a 1 kg increase in carbon emissions are derived from the study (Table 3). To obtain the WTP for a 1 kg reduction in carbon emissions, the negative of these estimates is taken. Following rule 6 from Section A.1.3, the WTP estimates from models 1-5 are then averaged.
Grebitus et al. (2015)	The WTP estimate for a 1 kg reduction in carbon emissions is derived from the study (Table 4).
Grebitus et al. (2016)	The WTP estimates for a 1 kg reduction in carbon emissions are reported in the study (Figure 2).
Hassen (2016)	The WTP estimates for percentage carbon reductions are derived from the study (Tables 4 and 6). The carbon reduction attribute has three levels: 25%, 50%, and high (which for simplification we assume to represent a 0% reduction). Because the carbon attribute is discretely coded, the average of 25% and 50% is taken to determine the overall percentage of carbon reduction (37.5%). The carbon emissions of 2.44 kg for the flower (assuming a Dutch rose) is obtained from the not-for-profit organization "Flowers from the Farm." Therefore, the amount of carbon reduction valued is assumed to be equal to 1.83 kg. Following rule 6 from Section A.1.3, the WTP estimates from the MNL and RPL models have been averaged.
Henderson (2018)	The WTP estimates for low (79 oz $\approx$ 2.23 kg), medium (90 oz $\approx$ 2.55 kg), and high (112 oz $\approx$ 3.18 kg) carbon footprints are derived from the study (Tables 4, 5, and 8). We subtract the WTP for low (2.23 kg) carbon emissions from that for medium (2.55 kg) carbon emissions, the WTP for low (2.23 kg) from that for high (3.18 kg), and the WTP for medium (2.55 kg) from that for high (3.18 kg). This yields observations for the WTP for carbon reductions of 0.32 kg, 0.95 kg, and 0.63 kg. Following rule 6 from Section A.1.3, the WTP estimates from MNL and LC (Latent Class) models are averaged.

Table A.4: WTP derivation strategy (continued)

Study	Details
Kimura et al. (2010)	The WTP estimates for low carbon products (0.06 kg for chocolate, 0.07 kg for chips, 0.065 kg for candy, 0.075 kg for juice), medium carbon products (0.07 kg for chocolate, 0.08 kg for chips, 0.075 kg for candy, 0.085 kg for juice), and high carbon products (0.08 kg for chocolate, 0.09 kg for chips, 0.085 kg for candy, 0.095 kg for juice) are provided by the authors through direct correspondence. We computed the WTP estimates for carbon reductions by subtracting the WTP estimates for low emission products from those of medium and high emission products, as well as the estimates for medium emission products from high emission products. This yields two observations for the WTP for a 0.01-kg carbon reduction and one observation for a 0.02-kg carbon reduction for each product.
Lami et al. (2022)	The WTP estimates for high carbon emissions (28 kg) and medium carbon emissions (18 kg) with respect to low carbon emissions (8 kg) are reported in the study (Table 7). Therefore, the WTP for medium with respect to high carbon emissions corresponds to a 10 kg (28 kg - 18 kg) carbon reduction, and the WTP for low carbon emissions with respect to high carbon emissions corresponds to a 20 kg (28 kg - 8 kg) carbon reduction.
Li et al. (2016)	The WTP estimates for annual beef consumption certified as "raised carbon friendly" are reported in the study (Section 5.2.6). To convert these values to per person and per kg of beef, we divide by 2.8 (average household size based on the study) and by 25.45 kg (annual beef consumption per person sourced from USDA). Since beef production represents 2.2% of total U.S. greenhouse gas emissions and these emissions could be reduced up to 2% if beef production was carbon (Li et al., 2016), we assume that the carbon reduction for beef is equivalent to 91% (2%/2.2%). Carbon emissions for beef are assumed to be 43.33 kg per kg (sourced from myEmissions), yielding a carbon reduction of 39.42 kg per kg of beef.
Li et al. (2018)	The WTP for a carbon-friendly label is reported in the study (Table 3). We calculate the carbon reduction as the same as Li et al. (2016) except for the fact that the amount of beef valued is 1 pound ($\approx$ 0.45 kg), which leads to 17.74 kg of carbon emissions. Note that we average the WTP estimates for sub-sample groups.

Table A.4: WTP derivation strategy (continued)

Study	Details
Macdiarmid et al. (2021)	The WTP estimates for low-level carbon (green label) and moderate-level carbon (amber label), relative to high-level carbon (red label), are reported in the study (Table 2). Carbon emissions are categorized as low for emissions of 0.26 kg or less, moderate for emissions between 0.26 kg and 0.4 kg, and high for emissions more than 0.4 kg per 100g of lasagna. These are multiplied by 4 for a 0.4 kg lasagna. A high carbon-footprint lasagna, weighing 0.4 kg, contains approximately 0.08 kg of ground beef, as described in the study. Its carbon emissions amount to 1.88 kg (according to the Plate Up for the Planet calculator). In the meta-analysis, as we treat offsets and reductions in the same way, we assume that the carbon emissions of products can be reduced to 0 kg. Therefore, we assume an average emission of 0.52 kg for low levels (averaging 0 kg and 1.04 kg of carbon emissions), 1.32 kg for moderate levels (averaging 1.04 kg and 1.60 kg of carbon emissions), and 1.74 kg for high levels (averaging 1.60 kg and 1.88 kg of carbon emissions). Respective carbon reduction levels for WTP estimates are calculated by determining the differences between low and high (1.22 kg = 1.74 kg - 0.52 kg) and between moderate and high (0.42 kg = 1.74 kg - 1.32 kg) carbon emissions.
Mōerbeck (2022)	The WTP for products labeled as carbon-neutral (group 2), both carbon-footprint and carbon-neutral (group 3), and those without any label (group 4) are reported in the study (Table 2). WTP estimates for carbon reductions are calculated by subtracting the WTP estimates for unlabeled products (group 4) from the WTP estimates for the other groups (2 and 3). Note that we average the WTP values obtained by subtracting group 4 from group 2 and group 4 from group 3 for each product.
Nesselhauf et al. (2020)	The WTP for 30% carbon reduction relative to 0% reduction, 30% carbon reduction relative to 50% carbon reduction, and 50% carbon reduction relative to 0% reduction are reported in the study (Table 7). Therefore, three WTP estimates are derived for 30%, 20%, and 50% carbon reduction, respectively. The corresponding carbon reduction amounts (7.03 kg, 4.69 kg, 11.73 kg) are calculated based on the 23.45 kg of emissions per 0.75 liters of wine, as sourced from the Plate up for the Planet calculator.

Table A.4: WTP derivation strategy (continued)

Study	**Details**
Nyberg (2018)	The WTP for low carbon emissions and medium carbon emissions, relative to large carbon emissions, are reported in the study (Tables 10, 12, A2, and A4). Carbon emissions are categorized as low for emissions of 7 kg or less, medium for emissions between 7 kg and 11 kg, and large for emissions of more than 11 kg per portion of lasagna (0.4 kg). A high carbon-footprint lasagna, weighing 0.4 kg, contains approximately 0.08 kg of ground beef, as provided in Macdiarmid et al. (2021). Its carbon emissions amount to 1.88 kg (according to the Plate Up for the Planet calculator), which falls within the "low emissions" category defined in this study. In the meta-analysis, as we treat offsets and reductions in the same way, we assume that the carbon emissions of products can be reduced to 0 kg. Therefore, we assume average emissions of 3.5 kg for low levels (averaging 0 kg and 7 kg of carbon emissions), 9 kg for medium levels (averaging 7 kg and 11 kg of carbon emissions), and 11 kg for large levels. Respective carbon reduction levels for WTP estimates are calculated by determining the differences between low and large (7.5 kg = 11 kg - 3.5 kg) and between medium and large (2 kg = 11 kg - 9 kg) carbon emissions. We average WTP estimates from the survey results from colored labels and text-only labels.

Table A.4: Data collection and WTP derivation strategy (continued)

Study	Details
Onozaka and McFadden (2011)	The WTP estimates for an increase of 10% in carbon emissions are reported in the study (Table 4). We take the negative of the reported estimates to get WTP for a decrease of 10% in carbon emissions. The carbon emission reductions for apple (0.004 kg) and tomato (0.013 kg) are calculated based on information from the myEmissions calculator.
Osawe et al. (2023)	The WTP estimates for moderate and low carbon emissions, relative to high emissions, are derived from the study (Table 5). The WTP estimates from latent classes are multiplied by their class probabilities. Carbon emissions for beef are classified as low for emissions below 20 kg, moderate for emissions between 20 kg and 30 kg, and high for emissions exceeding 30 kg. For chicken, the categories are low for emissions below 5 kg, moderate for emissions between 5 kg and 7.5 kg, and high for emissions above 7.5 kg. For vegetables, emissions below 0.22 kg are considered low, those between 0.22 kg and 0.4 kg as moderate, and those exceeding 0.4 kg as high. In the meta-analysis, as we treat offsets and reductions in the same way, we assume that the carbon emissions of products can be reduced to 0 kg. We have checked the emissions of beef, chicken, and vegetables using carbon calculators. For beef and chicken, the emissions fall below the high emissions category. For vegetables, the carbon emissions amount to 2 kg based on the MyEmissions calculator. Therefore, we assume average carbon emissions of 10 kg for low levels for beef (averaging 0 kg and 20 kg), 25 kg for moderate levels (averaging 20 kg and 30 kg), and 30 kg for high levels. For chicken, we assume average carbon emissions of 2.5 kg for low levels (averaging 0 kg and 5 kg), 6.25 kg for moderate levels (averaging 5 kg and 7.5 kg), and 7.5 kg for high levels. For vegetables, we assume average carbon emissions of 0.11 kg for low levels (averaging 0 kg and 0.22 kg), 0.31 kg for moderate levels (averaging 0.22 kg and 0.40 kg), and 1.22 kg for high levels (averaging 0.4 kg and 2.05 kg). Respective carbon reduction levels for WTP estimates are calculated by determining the differences between low and high, as well as between moderate and high carbon emissions for each product type. For beef, chicken, and vegetables, the amount of carbon reductions are 20 kg, 5 kg, and 11.11 kg for the difference between low and high categories, respectively; and 5 kg, 1.25 kg, and 9 kg for the difference between moderate and high categories.
Rahmani et al. (2019)	The WTP for 10%, 20%, and 30% GHG reduction, expressed in terms of carbon equivalents, are reported in the study (Table 6). The emissions of each type of egg are provided in the study. Therefore, the respective amount of carbon emission reduction calculated for caged eggs are 0.15 kg, 0.30 kg, and 0.44 kg; for barn eggs 0.17 kg, 0.35 kg, 0.52 kg, for free range eggs, 0.17 kg, 0.34 kg, 0.51 kg, and organic eggs 0.17 kg, 0.34 kg, and 0.51 kg. Note that we average the WTP estimates for four types of eggs.

Table A.4: Data collection and WTP derivation strategy (continued)

Study	**Details**
Severens (2021)	The WTP estimates for low, average emissions with respect to high emissions are reported in the study (Table 4). Carbon emissions levels of 4.3 kg or less are classified as low, levels between 4.4 and 6.6 kg as average, and levels more than 6.6 kg as high. Carbon emissions of 1 kg of pork equals 9.3 kg, which is sourced from the Plate up for Planet calculator. In the meta-analysis, as we treat offsets and reductions in the same way, we assume that the carbon emissions of products can be reduced to 0 kg. We assume an average emission of 2.15 kg for low levels (averaging 0 kg and 4.3 kg), 5.50 kg for average levels (averaging 4.4 kg and 6.6 kg), and 7.95 kg (averaging 9.3 kg and 6.6 kg) for high levels. We subtract high and average (2.45 kg =7.95 kg - 5.50 kg), and high and low (5.80 kg =7.95 kg - 2.15 kg) carbon emissions to calculate the respective amount of reductions.
Tu et al. (2021)	The WTP estimates for 34%, 25%, and 17% carbon reduction, relative to a 12% carbon reduction, are reported in the paper (Table 8). Carbon emissions of 1 kg of rice equal to 1.35 kg, which is sourced from the myEmissions calculator. We use this information to calculate respective carbon emission reductions (0.08 kg, 0.18 kg, and 0.30 kg).
Van Loo et al. (2014)	The WTP estimates for 20% (1.4 kg) and 30% (2.1 kg) carbon reduction are reported in the study (Table 7).
Vecchio (2013)	The WTP for the carbon-neutral product is reported in the study (Figure 2). The WTP for carbon neutrality is calculated by subtracting the WTP for conventional product from the WTP for carbon-neutral product. The carbon emissions of 0.75 liter of wine (1.03 kg) is obtained from the myEmissions calculator.
Yang et al. (2021)	WTP for a 38% carbon reduction is derived from the study (Table 4). The amount of carbon emissions of 1 kg rice (0.68 kg) is obtained from the myEmissions calculator. We use this information to calculate respective carbon emission reduction (0.26 kg).

A.2 Descriptive statistics

This section includes the main descriptive statistics for the sample used for the meta-analysis. Table A.5 shows the summary statistics of the (unweighted) sample of 129 observations, which includes one or more observations from each study. Table A.6 presents the summary statistics based on study means, including only one observation for each study (37 in total). For each product category, Table A.7 shows the mean WTP estimates, while Table A.8 displays the mean of study-specific mean WTP estimates, along with their respective number of observations.

Figure 1 in Section 3.1 shows the distribution of WTP_{NS} (non-standardized WTP for carbon reductions) as well as WTP_{kg} (WTP for 1 kg carbon reduction), while Figure A.1 shows the distribution of WTP_{CN} (WTP for carbon neutrality) and $\text{WTP}_{\text{CN\%}}$ (the proportion of a product's price that consumers would be willing to pay extra for carbon neutrality) across studies along with the magnitude of carbon reductions or baseline emissions, as well as different product categories. Figures A.2, A.3, and A.4 display the histogram of each outcome variable, WTP_{NS}, WTP_{kg}, WTP_{CN}, and $\text{WTP}_{\text{CN\%}}$, respectively, both with and without outliers.

	N	Mean	Std. Dev.	Min	Max
WTP_{NS} (USD)	129	1.213	1.736	-0.093	12.206
WTP_{kg} (USD)	129	4.295	9.166	-1.375	45.283
WTP_{CN} (USD)	129	9.307	30.650	-0.126	311.562
$WTP_{CN\%}$	129	158%	335%	-11%	1875%
CO_2 reduction (kg)	129	2.532	5.817	0.001	39.430
Product CO_2 emissions (kg)	129	5.327	9.530	0.024	43.330
Price (USD)	129	4.521	5.361	0.094	22.148
Stated pref. method	129	0.946	0.227	0.000	1.000
In-person	129	0.209	0.408	0.000	1.000
Sample size	129	538	605	19	3085
Unpublished	129	0.186	0.391	0.000	1.000
Study year	129	2015	4	2008	2021
CO_2 reduction assump.	129	0.550	0.499	0.000	1.000
WTP derivation	129	0.419	0.495	0.000	1.000
GDP per capita (100 USD)	129	425	168	6	935
Europe	129	0.674	0.470	0.000	1.000

Table A.5: Summary statistics: unweighted sample

This figure displays the number of observations (N), and the means of the outcome variables. Standard deviations are provided in parentheses. The non-standardized measure WTP_{NS} denotes non-standardized WTP for carbon reductions. WTP_{kg} is WTP per 1 kg carbon reduction, WTP_{CN} is WTP for carbon-neutrality, and $WTP_{CN\%}$ is the proportion of a product's price that consumers would be willing to pay extra for carbon neutrality. For detailed variable descriptions, see Section A.1.3.

	N	Mean	Std. Dev.	Min	Max
WTP_{NS} (USD)	37	1.242	1.237	0.005	5.575
WTP_{kg} (USD)	37	1.993	3.942	0.025	23.726
WTP_{CN} (USD)	37	11.962	30.674	0.000	176.904
$WTP_{CN\%}$	37	236%	423%	0%	1625%
CO_2 reduction (kg)	37	3.658	7.646	0.001	39.430
Product CO_2 emissions (kg)	37	7.410	11.800	0.040	43.330
Price (USD)	37	4.816	4.801	0.094	22.148
Stated pref. method	37	0.905	0.285	0.000	1.000
In-person	37	0.333	0.471	0.000	1.000
Sample size	37	572	652	19	3085
Unpublished	37	0.189	0.397	0.000	1.000
Study year	37	2015	4	2008	2021
CO_2 reduction assump.	37	0.622	0.492	0.000	1.000
WTP derivation	37	0.378	0.477	0.000	1.000
GDP per capita (100 USD)	37	408	183	6	935
Europe	37	0.635	0.481	0.000	1.000

Table A.6: Summary statistics: study means

This figure displays the number of observations (N), and the means of study specific means of the outcome variables. Standard deviations are provided in parentheses. The non-standardized measure WTP_{NS} denotes non-standardized WTP for carbon reductions. WTP_{kg} is WTP per 1 kg carbon reduction, WTP_{CN} is WTP for carbon-neutrality, and $WTP_{CN\%}$ is the proportion of a product's price that consumers would be willing to pay extra for carbon neutrality. For detailed variable descriptions, see Section A.1.3.

	Product Category	N	CO_2 (kg)	WTP_{NS} (USD)	WTP_{kg} (USD)	WTP_{CN} (USD)	$WTP_{CN\%}$
1	Dairy	21	1.43 (0.46)	0.82 (0.96)	2.19 (2.99)	1.28 (1.64)	60% (55%)
2	Fruits/vegetables	18	2.35 (2.36)	0.30 (0.42)	1.29 (1.87)	1.38 (2.66)	143% (247%)
3	Meat	49	11.75 (13.03)	2.22 (2.36)	1.39 (2.01)	22.61 (46.97)	282% (444%)
4	Non-food	5	1.12 (0.79)	0.80 (0.48)	1.54 (1.51)	0.76 (0.46)	337% (692%)
5	Oil/grain	10	2.31 (2.44)	0.58 (0.54)	1.35 (2.02)	2.37 (3.99)	65% (104%)
6	Snacks	12	0.07 (0.00)	0.33 (0.25)	21.94 (13.99)	0.02 (0.02)	2% (2%)
7	Water/drinks	14	0.65 (0.66)	0.83 (0.77)	9.46 (15.74)	0.95 (1.60)	23% (30%)

Table A.7: Means of WTP estimates by product category

This table displays the product categories, their respective number of observations (N), and the means of the outcome variables. Standard deviations are provided in parentheses. The third column presents the CO_2 emissions associated with the products, which vary according to the type and amount of product valued in studies. The non-standardized measure WTP_{NS} denotes non-standardized WTP for carbon reductions. WTP_{kg} is WTP per 1 kg carbon reduction, WTP_{CN} is WTP for carbon-neutrality, and $WTP_{CN\%}$ is the proportion of a product's price that consumers would be willing to pay extra for carbon neutrality. For detailed variable descriptions, see Section A.1.3.

	Product Category	N	CO_2 (kg)	WTP_{NS} (USD)	WTP_{kg} (USD)	WTP_{CN} (USD)	$WTP_{CN\%}$
1	Dairy	6	1.39 (0.46)	0.71 (0.63)	1.07 (1.34)	0.93 (0.75)	51.7% (31%)
2	Fruits/vegetables	7	2.77 (2.98)	0.43 (0.49)	1.33 (1.76)	2.24 (3.24)	201% (297%)
3	Meat	17	15.18 (15.04)	1.96 (1.72)	1.27 (1.63)	24.47 (42.58)	326% (476%)
4	Non-Food	3	1.34 (0.99)	0.77 (0.37)	1.34 (1.60)	0.88 (0.53)	544% (894%)
5	Oil/grain	6	2.10 (2.41)	0.57 (0.49)	1.61 (2.11)	2.14 (3.77)	61% (97%)
6	Snacks	1	0.07 (0.00)	0.33 (0.00)	21.94 (0.00)	0.02 (0.00)	2% (0%)
7	Water/drinks	7	0.91 (0.77)	1.13 (0.84)	5.33 (10.51)	1.55 (2.07)	40% (35%)

Table A.8: Means of study means: WTP estimates by product category

This figure displays the product categories, their respective number of studies (N), and the means of study specific means of the outcome variables. Standard deviations are provided in parentheses. The third column presents the CO_2 emissions associated with the products, which vary according to type and amount of product valued in studies. The non-standardized measure WTP_{NS} denotes non-standardized WTP for carbon reductions. WTP_{kg} is WTP per 1 kg carbon reduction, WTP_{CN} is WTP for carbon-neutrality, and $WTP_{CN\%}$ is the proportion of a product's price that consumers would be willing to pay extra for carbon neutrality. For detailed variable descriptions, see Section A.1.3

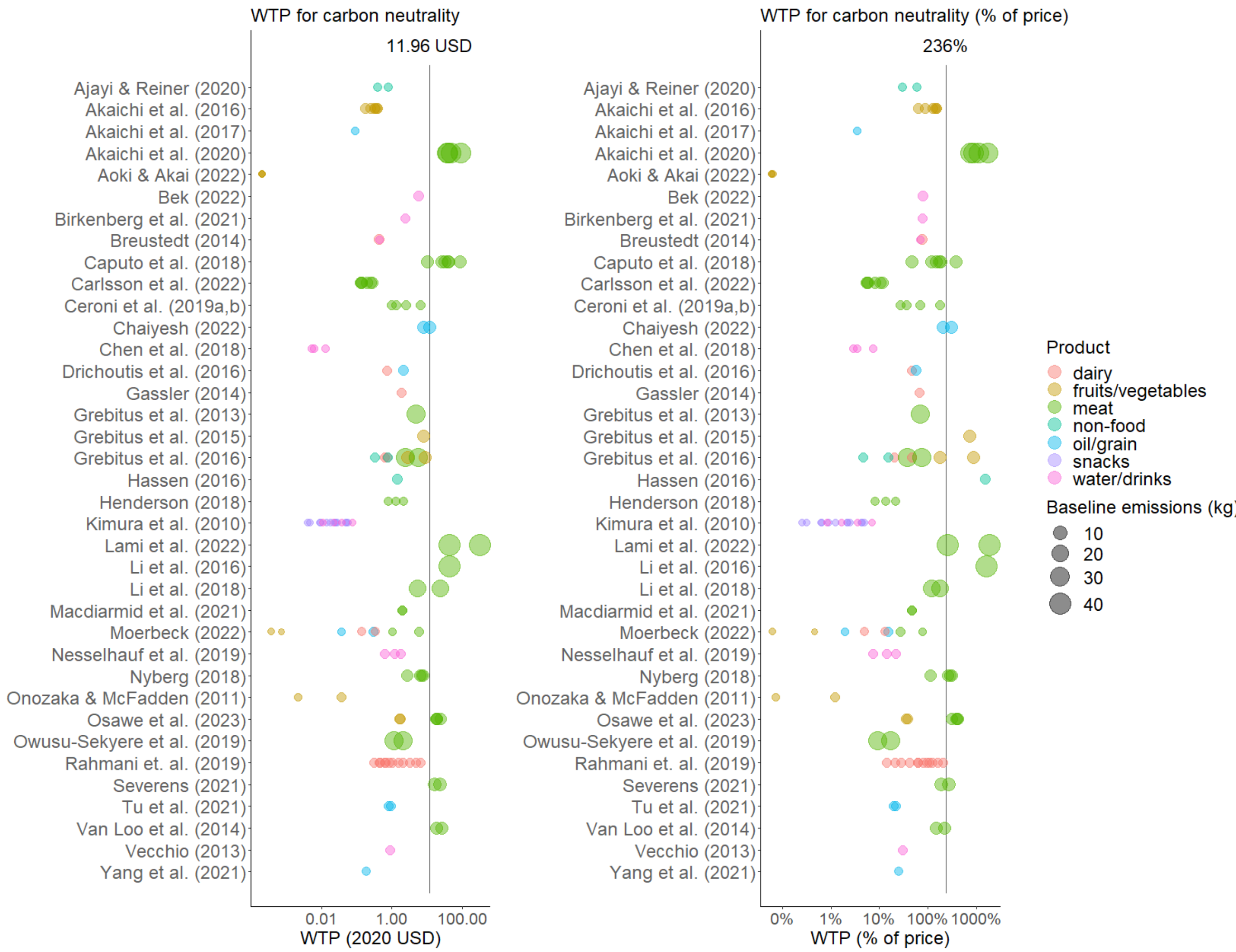


Figure A.1: WTP for carbon neutrality across studies

A logarithmic axis (base 10) is used to create this figure. The vertical lines represent the mean of study means. The left graph displays WTP_{CN} (WTP for carbon neutrality) across studies, where the size of each circle represents the baseline carbon emissions of the product in kilograms. The right graph shows $WTP_{CN\%}$, which is the proportion of a product's price that consumers would be willing to pay extra for carbon neutrality.

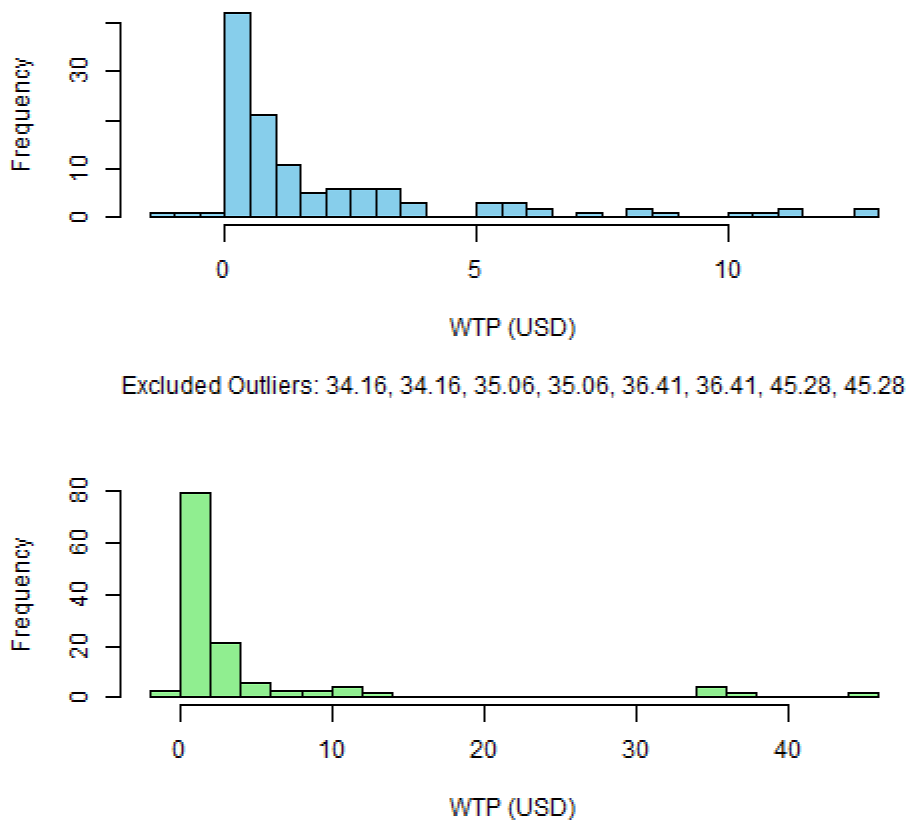


Figure A.2: WTP for 1 kg carbon reduction (WTP_{kg})

The figure at the top shows a histogram where outliers, defined as values more than 2 standard deviations from the mean, are excluded. The figure below includes the entire sample.

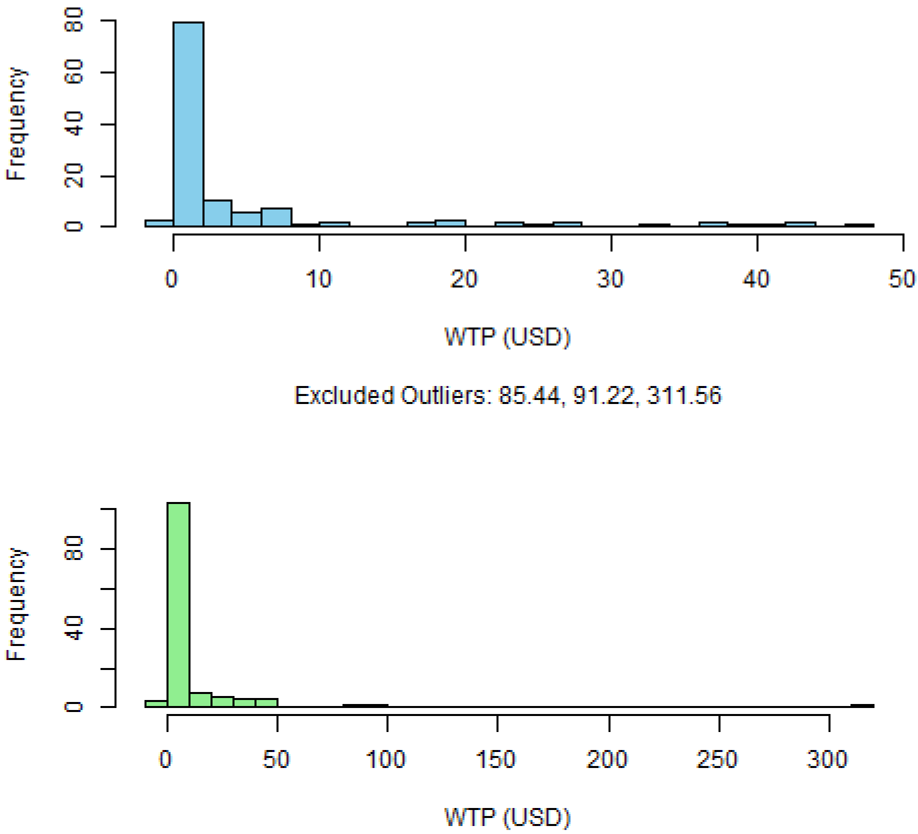
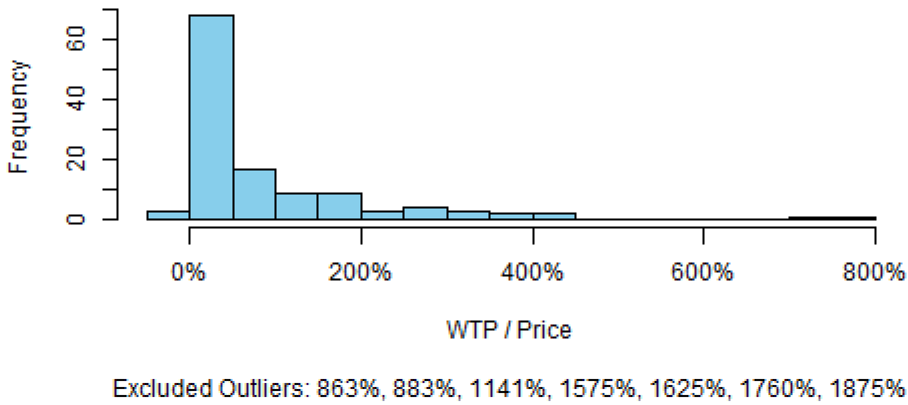


Figure A.3: WTP for carbon neutrality (WTP_{CN})

The figure at the top shows a histogram where outliers, defined as values more than 2 standard deviations from the mean, are excluded. The figure below includes the entire sample.



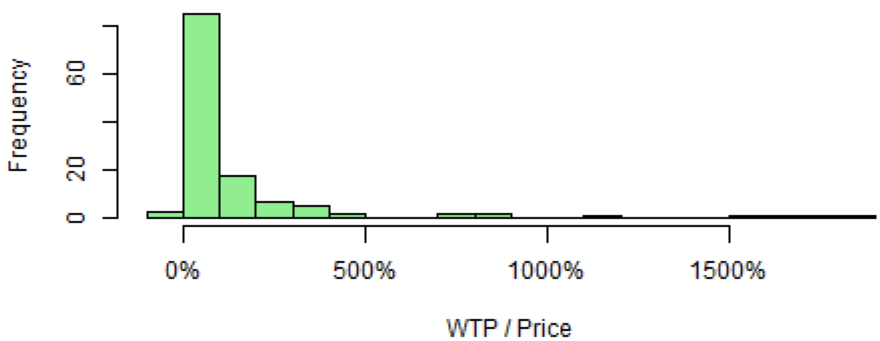


Figure A.4: The proportion of a product's price that consumers would be willing to pay extra for carbon neutrality ($\mathrm{WTP}_{\mathrm{CN\%}}$)

The figure at the top shows a histogram where outliers, defined as values more than 2 standard deviations from the mean, are excluded. The figure below includes the entire sample.

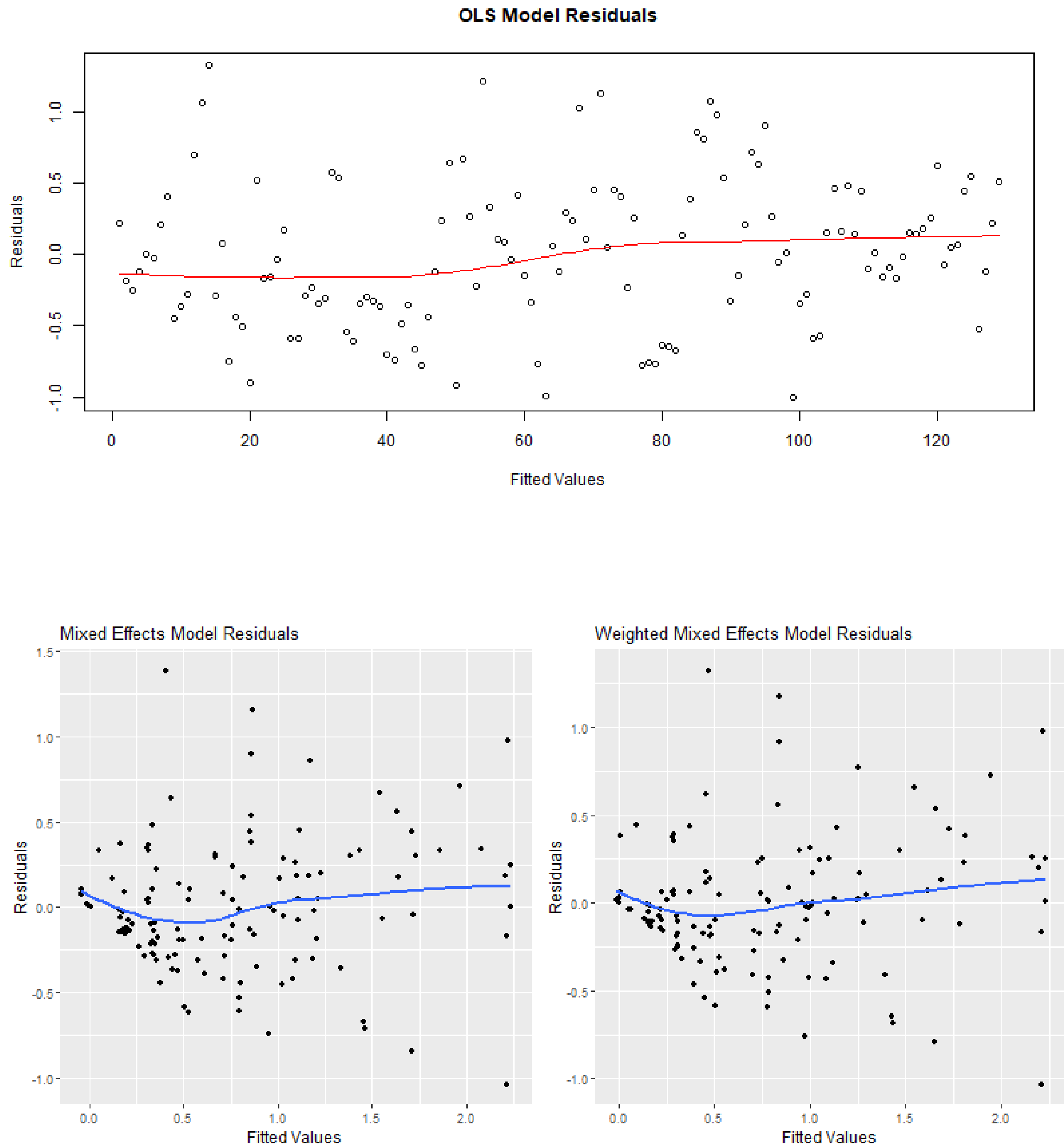


Figure A.5: Residuals versus fitted values

Table A.9: Breusch-Pagan Heteroscedasticity Test

Model	Test statistic	P-value
OLS	23.84	0.02
Mixed Effects Model	28.83	0.01
Weighted Mixed Effects Model	9.12	0.61

The table shows chi-square statistics and associated p-values.

A.3 Robustness tests

This section presents the robustness tests conducted to test the sensitivity of our main meta-analytical results. First, we run regressions with different subsets of observations. The first column of the Table A.10 provides weighted mixed effects model estimations based on the complete set of observations. The second column displays results while omitting observations that require assumptions about the amount of CO_2 reductions through CO_2 calculators and other third-party sources. The third column includes only results where WTP values are sourced directly from the studies, excluding those requiring further calculations or derivations. The final column shows the results that exclude both types of observations: those with CO_2 reduction assumptions and those with derived WTP values.

Second, we incorporate additional variables. Table A.11 includes two additional variables, carbon neutral certification and colored labels, in addition to those in our main regression results presented in Table 1 in Section 3.1.

Third, we use sample size as a weight factor instead of the inverse number of observations from each study, which is shown in the final column of A.12. For comparison purposes, the first column of Table A.12 shows estimations from the unweighted mixed effects model. The second column displays results, where the inverse number of observations from each study is used as the weight factor.

Fourth, we include country random effects. Table A.13 includes country random effects instead of product random effects for the mixed effects model estimations in the second and third columns.

Finally, we run regressions with different functional forms of the outcome variable and CO_2 reduction variable. Table A.14, column 1, displays the OLS results with the untransformed outcome variable, column 2 shows the results with inverse hyperbolic sine transformation, and column 3 shows the results with the log-transformed outcome variable. Table A.15 shows corresponding results with the weighted mixed effects model, with each column using the same transformations as in Table A.14 respectively. In Table A.15, we also include results that incorporate an additional variable for the square of CO_2 emission reduction for three types of models: OLS, mixed effects, and weighted mixed effects.

Based on the results presented in Tables A.10, A.11, A.12, A.13, A.14, and A.15, the positive significance of CO_2 emission reduction variable is confirmed across all regressions mostly at 5% or 1% levels.

Similarly, the product price is also robustly positive and significant, mainly at 1% levels. Furthermore, Europe is robustly significant at 5% or 1% levels in all regressions, except for the second and fourth columns of the estimations in Table A.10.

Unpublished studies and CO_2 reduction assumptions become positively significant only in Table A.10, columns 2 and 3, respectively. However, these results are not supported by the other regressions and are based on only a portion of the sample.

Confirming our main results in Table 1 from Section 3.1, we also observe that the coefficient for stated preferences becomes somewhat noisier in some of the specifications. Additionally, we do not find significant results for variables for in-person studies, sample size, study year, GDP per capita, and the WTP derivation in all of the tables. Similarly, the two additional variables, carbon-neutral certification, and colored labels, are not significant.

	Original	No CO_2 red.assump.	No WTP derivation	No both
Intercept	-0.18 (0.58)	0.53 (0.18)	-0.84 (0.09)	0.19 (0.62)
CO_2 reduction	0.03*** (0.00)	0.07*** (0.00)	0.05*** (0.00)	0.06** (0.01)
Price	0.30*** (0.00)	0.55*** (0.00)	0.35*** (0.00)	0.44** (0.05)
Stated pref. method	0.41* (0.24)	-0.44 (0.30)	0.72* (0.37)	
In-person	0.06 (0.76)	-0.23 (0.25)	-0.04 (0.88)	-0.03 (0.93)
Sample size	-0.06 (0.48)	0.10 (0.29)	-0.07 (0.55)	-0.01 (0.94)
Unpublished	0.23 (0.30)	0.60** (0.04)	0.43 (0.14)	0.28 (0.59)
Study year	-0.01 (0.89)	-0.18 (0.17)	-0.02 (0.86)	-0.19 (0.36)
CO_2 reduction assump.	0.17 (0.18)		0.47** (0.24)	
WTP derivation	0.06 (0.15)	0.08 (0.15)		
GDP per capita	0.01 (0.88)	0.12 (0.22)	-0.09 (0.42)	0.30 (0.15)
Europe	0.49** (0.01)	0.26 (0.11)	0.57** (0.01)	0.19 (0.53)
Number of obs.	129	58	75	30
Number of studies	37	14	24	8
AIC	253.247	122.828	160.547	82.257
BIC	296.144	151.674	192.992	99.071
Log Likelihood	-111.624	-47.414	-66.273	-29.128

***p<0.01; **p<0.05; *p<0.1

Table A.10: Factors associated with WTP for carbon reductions

This table shows coefficient estimates, and associated standard errors, which are indicated within parentheses. The standard errors for the OLS model are clustered by study. We use a weighted mixed-effects model, including product categories and studies as random effects. The weights correspond to the inverse of the number of observations from each study. The dependent variable is the unstandardized WTP for carbon emission reductions (WTP_{NS}), which is transformed using the inverse hyperbolic sine function. Price, sample size, study year, and GDP per capita variables are z-scored.

	OLS	Mixed Effects	Weighted Mixed Effects
Intercept	0.35 (0.31)	-0.07 (0.35)	-0.19 (0.33)
CO_2 reduction	0.02** (0.01)	0.03** (0.01)	0.03*** (0.01)
Price	0.35*** (0.05)	0.33*** (0.07)	0.30*** (0.07)
Stated pref. method	-0.01 (0.25)	0.31 (0.28)	0.44* (0.25)
In-person	-0.07 (0.16)	0.05 (0.22)	0.05 (0.20)
Sample size	-0.08 (0.07)	-0.05 (0.10)	-0.05 (0.10)
Unpublished	0.14 (0.15)	0.19 (0.22)	0.22 (0.22)
Study year	-0.04 (0.07)	-0.02 (0.10)	-0.02 (0.10)
CO_2 reduction assump.	0.22 (0.15)	0.19 (0.21)	0.12 (0.20)
WTP derivation	0.01 (0.13)	0.06 (0.16)	0.06 (0.16)
GDP per capita	0.05 (0.05)	0.02 (0.07)	0.02 (0.07)
Europe	0.40*** (0.15)	0.44** (0.17)	0.48*** (0.18)
Carbon-neutral label	-0.32 (0.20)	-0.06 (0.29)	0.05 (0.28)
Colored label	-0.03 (0.16)	0.04 (0.17)	0.14 (0.18)
Number of obs.	129	129	129
Var (study random effect)		0.14	0.19
Var (product random eff.)		0.00	0.02
AIC	217.81	249.17	259.01
BIC	257.85	297.79	307.63
Log Likelihood	-94.91	-107.59	-112.51

***p<0.01; **p<0.05; *p<0.1

Table A.11: Factors associated with WTP for carbon reductions

This table shows coefficient estimates, and associated standard errors, which are indicated within parentheses. The standard errors for the OLS model are clustered by study. We use a weighted mixed-effects model, including product categories and studies as random effects. The weights correspond to the inverse of the number of observations from each study. The dependent variable is the unstandardized WTP for carbon emission reductions (WTP_{NS}), which is transformed using the inverse hyperbolic sine function. Price, sample size, study year, and GDP per capita variables are z-scored.

	Mixed Effects	Weighted Mixed Effects 1 (Inverse number of obs.)	Weighted Mixed Effects 2 (Sample size)
Intercept	-0.04 (0.34)	-0.18 (0.32)	0.51 (0.57)
CO_2 reduction	0.03** (0.01)	0.03*** (0.01)	0.02*** (0.01)
Price	0.33*** (0.06)	0.31*** (0.07)	0.27*** (0.08)
Stated pref. method	0.30 (0.28)	0.41* (0.24)	-0.08 (0.52)
In-person	0.05 (0.21)	0.06 (0.19)	-0.21 (0.27)
Sample size	-0.04 (0.09)	-0.06 (0.09)	-0.07 (0.09)
Unpublished	0.18 (0.21)	0.23 (0.21)	0.32 (0.23)
Study year	-0.02 (0.10)	-0.01 (0.09)	0.07 (0.10)
CO_2 reduction assump.	0.19 (0.19)	0.17 (0.18)	-0.02 (0.20)
WTP derivation	0.05 (0.15)	0.06 (0.15)	0.01 (0.15)
GDP per capita	0.02 (0.07)	0.01 (0.07)	0.04 (0.07)
Europe	0.43** (0.17)	0.49*** (0.17)	0.44*** (0.13)
Number of obs.	129	129	129
Var (study random effect)	0.14	0.18	0.11
Var (product random eff.)	0.00	0.02	0.01
AIC	242.87	253.25	337.35
BIC	285.76	296.14	380.25
Log Likelihood	-106.43	-111.62	-153.67

***p<0.01; **p<0.05; *p<0.1

Table A.12: Factors associated with WTP for carbon reductions

This table shows coefficient estimates, and associated standard errors, which are indicated within parentheses. The standard errors for the OLS model are clustered by study. We use a weighted mixed-effects model, including product categories and studies as random effects. The weights correspond to the inverse of the number of observations from each study. The dependent variable is the unstandardized WTP for carbon emission reductions (WTP_{NS}), which is transformed using the inverse hyperbolic sine function. Price, sample size, study year, and GDP per capita variables are z-scored.

	OLS	Mixed Effects	Weighted Mixed Effects
(Intercept)	0.47 (0.30)	-0.03 (0.34)	-0.16 (0.32)
CO_2 reduction	0.02** (0.01)	0.03*** (0.01)	0.03*** (0.01)
Price	0.34*** (0.05)	0.34*** (0.06)	0.33*** (0.07)
Stated pref. method	-0.04 (0.25)	0.28 (0.28)	0.36* (0.24)
In-person	-0.08 (0.16)	0.05 (0.21)	0.07 (0.19)
Sample size	-0.05 (0.06)	-0.04 (0.09)	-0.06 (0.09)
Unpublished	0.03 (0.14)	0.19 (0.21)	0.22 (0.21)
Study year	-0.03 (0.07)	-0.01 (0.10)	-0.01 (0.09)
CO_2 reduction assump.	0.14 (0.14)	0.19 (0.19)	0.20 (0.18)
WTP derivation	-0.07 (0.12)	0.05 (0.15)	0.09 (0.15)
GDP per capita	0.07 (0.05)	0.02 (0.07)	0.00 (0.07)
Europe	0.34** (0.14)	0.43** (0.17)	0.49*** (0.17)
Number of obs.	129	129	129
Var (study random effect)		0.14	0.18
Var (country random effect)		0.00	0.00
AIC	218.72	242.93	253.77
BIC	255.90	285.82	296.67
Log Likelihood	-96.36	-106.46	-111.88

***p<0.01; **p<0.05; *p<0.1

Table A.13: Factors associated with WTP for carbon reductions

This table shows coefficient estimates, and associated standard errors, which are indicated within parentheses. The standard errors for the OLS model are clustered by study. We use a weighted mixed-effects model, including product categories and studies as random effects. The weights correspond to the inverse of the number of observations for the second column and to the sample size for the third column. The dependent variable is the unstandardized WTP for carbon emission reductions (WTP_{NS}), which is transformed using the inverse hyperbolic sine function. Price, sample size, study year, and GDP per capita variables are z-scored.

	OLS (Not transformed)	OLS (Hyperbolic sine trans.)	OLS (Log. transformation)
Intercept	0.88 (0.70)	0.47 (0.30)	-2.18*** (0.74)
CO_2 reduction	0.04* (0.02)	0.02** (0.01)	0.06*** (0.02)
Price	0.85*** (0.11)	0.34*** (0.05)	0.62*** (0.12)
Stated pref. method	-0.14 (0.58)	-0.04 (0.25)	-0.04 (0.62)
In-person	-0.28 (0.37)	-0.08 (0.16)	-0.33 (0.40)
Sample size	-0.22 (0.15)	-0.05 (0.06)	0.03 (0.16)
Unpublished	-0.22 (0.32)	0.03 (0.14)	0.34 (0.34)
Study year	0.02 (0.17)	-0.03 (0.07)	-0.34* (0.18)
CO_2 reduction assump.	-0.04 (0.32)	0.14 (0.14)	0.68* (0.34)
WTP derivation	-0.08 (0.29)	-0.07 (0.12)	0.22 (0.31)
GDP per capita	0.17 (0.12)	0.07 (0.05)	-0.02 (0.12)
Europe	0.76** (0.33)	0.34** (0.14)	1.20*** (0.35)
Number of obs.	129	129	126
AIC	440.23	218.72	444.71
BIC	477.40	255.90	481.58
Log Likelihood	-207.11	-96.36	-209.35

***$p<0.01$; **$p<0.05$; *$p<0.1$

Table A.14: Factors associated with WTP for carbon reductions

This table shows coefficient estimates, and associated standard errors, which are indicated within parentheses. The standard errors are clustered across studies. For the first column, we do not transform the outcome variable. In the second column, we transform it using the inverse hyperbolic sine function. In the third column, we use logarithmic transformation, resulting in the loss of three negative observations. The dependent variable is the unstandardized WTP for carbon emission reductions (WTP_{NS}). Price, Sample Size, Study Year, and GDP per capita variables are z-scored.

	Weighted Mixed Effects (Not transformed)	Weighted Mixed Effects (Hyperbolic sine trans.)	Weighted Mixed Effects (Log. transformation)
Intercept	0.25 (0.65)	-0.18 (0.32)	-3.08*** (0.69)
CO_2 reduction	0.04** (0.02)	0.03*** (0.01)	0.06*** (0.02)
Price	0.73*** (0.14)	0.31*** (0.07)	0.59*** (0.15)
Stated pref. method	0.19 (0.52)	0.41* (0.24)	0.88* (0.48)
In-person	-0.15 (0.39)	0.06 (0.19)	0.20 (0.39)
Sample size	-0.18 (0.16)	-0.06 (0.09)	0.02 (0.22)
Unpublished	0.14 (0.37)	0.23 (0.21)	0.61 (0.54)
Study year	0.06 (0.17)	-0.01 (0.09)	-0.13 (0.22)
CO_2 reduction assump.	0.03 (0.32)	0.17 (0.18)	0.60 (0.46)
WTP Derivation	0.06 (0.30)	0.06 (0.15)	0.24 (0.31)
GDP per capita	0.02 (0.13)	0.01 (0.07)	0.01 (0.17)
Europe	0.95*** (0.33)	0.49*** (0.17)	1.19*** (0.37)
Number of obs.	129	129	126
Var (study random effect)	0.34	0.18	1.28
Var (product random eff.)	0.00	0.02	0.24
AIC	483.62	253.25	388.20
BIC	526.52	296.14	430.74
Log Likelihood	-226.81	-111.62	-179.10

***$p<0.01$; **$p<0.05$; *$p<0.1$

Table A.15: Factors associated with WTP for carbon reductions

This table shows coefficient estimates, and associated standard errors, which are indicated within parentheses. We use weighted mixed-effects models, including product categories and studies as random effects. The weights correspond to the inverse of the number of observations from each study. The dependent variable is the unstandardized WTP for carbon emission reductions (WTP_{NS}). For the first column, we do not transform the outcome variable. In the second column, we transform it using the inverse hyperbolic sine function. In the third column, we use logarithmic transformation, resulting in the loss of three negative observations. Price, Sample Size, Study Year, and GDP per capita variables are z-scored.

	OLS	Mixed Effects	Weighted Mixed Effects
Intercept	-0.01 (0.69)	-0.32 (0.33)	-3.25*** (0.70)
CO_2 reduction	0.11* (0.06)	0.08*** (0.03)	0.14** (0.06)
CO_2 reduction^2	-0.00 (0.00)	-0.00* (0.00)	-0.00 (0.00)
Price	0.70*** (0.15)	0.29*** (0.07)	0.57*** (0.15)
Stated pref. method	0.26 (0.53)	0.43* (0.24)	0.88* (0.48)
In-person	-0.12 (0.41)	0.08 (0.19)	0.23 (0.39)
Sample size	-0.17 (0.17)	-0.05 (0.09)	0.04 (0.22)
Unpublished	0.17 (0.39)	0.24 (0.22)	0.62 (0.54)
Study year	0.01 (0.18)	-0.04 (0.10)	-0.18 (0.23)
CO_2 reduction assump.	0.11 (0.34)	0.23 (0.19)	0.71 (0.46)
WTP derivation	0.19 (0.33)	0.14 (0.16)	0.34 (0.32)
GDP per capita	0.02 (0.14)	0.01 (0.07)	0.02 (0.17)
Europe	0.91*** (0.34)	0.46*** (0.17)	1.14*** (0.37)
Number of obs.	129	129	126
Var (study random effect)	0.41	0.19	1.28
Var (product random eff.)	0.00	0.01	0.21
AIC	495.21	264.82	399.12
BIC	540.97	310.58	444.50
Log Likelihood	-231.60	-116.41	-183.56

***p<0.01; **p<0.05; *p<0.1

Table A.16: Factors associated with WTP for carbon reductions

This table shows coefficient estimates, and associated standard errors, which are indicated within parentheses. The standard errors for the OLS model are clustered by studies. We use a weighted mixed-effects model, including product categories and studies as random effects. The weights correspond to the inverse of the number of observations from each study. The dependent variable is the unstandardized WTP for carbon emission reductions (WTP_{NS}), which is transformed using the inverse hyperbolic sine function. Price, Sample Size, Study Year, and GDP per capita variables are z-scored.

B Hedonic analysis

B.1 Carbon neutrality on Amazon's marketplace

Amazon, in collaboration with Global Optimism, an organization focused on environmental and social change, initiated the Climate Pledge in 2019. As a co-founder and participant, Amazon started an initiative to promote the sale of more sustainable products among its vendors.

Products meeting required standards can earn one of the program's sustainability labels, known as Climate Pledge Friendly labels, if demanded by its vendor. Independent organizations, namely Climate Impact Partners (previously named Natural Capital Partners), SCS Global Services, Climate Partner, and Carbon Fund, offer carbon-neutral certifications.

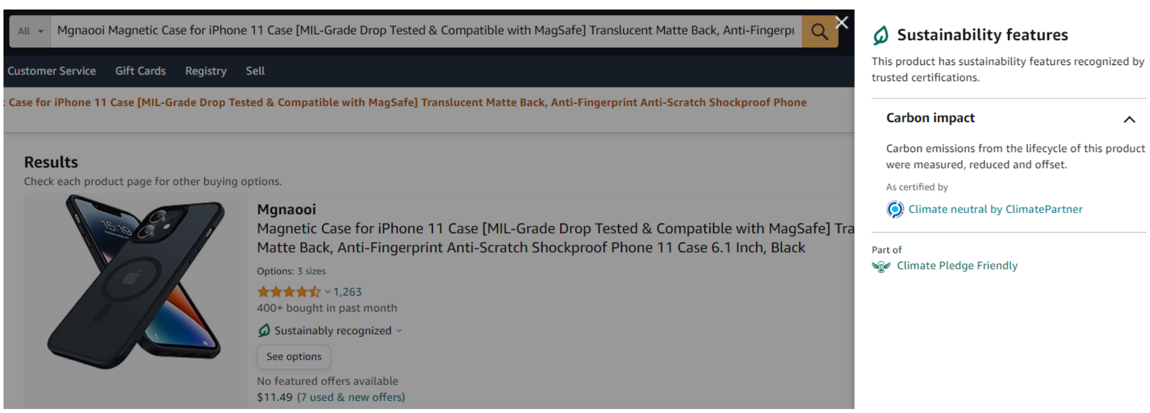


Figure B.1: A product certified carbon neutral by Climate Partner on Amazon.com

B.2 List of experiments

This section contains the list of products that are part of our experiments from March 2023 to December 2023. It also includes their ASINs, product categories, the first date on which they were identified as carbon-neutral labeled, and their prices in March 2023 and December 2023.

Table B.1: Natural experiments March 2023 - December 2023

Product ASIN	Category	First Treated	Price March 23	Price Dec 23
B0BFGYBBC	Cell Phones & Accessories	03.04.2023	14.99	10.68
B0BQ6PYVLM	Cell Phones & Accessories	03.04.2023	34.99	35.88
B0771VVJRW	Beauty & Personal Care	10.04.2023	19.99	19.99
B0B5192DMN	Cell Phones & Accessories	10.04.2023	14.99	12.93
B0B6BBC1FL	Cell Phones & Accessories	10.04.2023	10.99	15.99
B0B6RWP6FC	Cell Phones & Accessories	10.04.2023	15.99	15.99
B0B6V9D89F	Cell Phones & Accessories	10.04.2023	13.06	12.44
B0B6VBSKKT	Cell Phones & Accessories	10.04.2023	13.06	12.52
B0B7D5QD1Z	Cell Phones & Accessories	10.04.2023	23.68	21.49
B0BLRXFDBL	Cell Phones & Accessories	10.04.2023	35.32	29.66
B0BRB4G2N7	Cell Phones & Accessories	10.04.2023	18.99	10.99
B0BRB642GZ	Cell Phones & Accessories	10.04.2023	21.32	12.99
B08CXZHG4C	Cell Phones & Accessories	17.04.2023	13.95	14.2
B08QF83ZCH	Cell Phones & Accessories	17.04.2023	12.11	11.48
B08QF8FWTZ	Cell Phones & Accessories	17.04.2023	14.23	13.98
B091T7G6DT	Cell Phones & Accessories	17.04.2023	13.23	13.14
B09BP1CXT9	Cell Phones & Accessories	17.04.2023	15.18	15.18
B09BP234TP	Cell Phones & Accessories	17.04.2023	13.65	12.48
B0BGJ8PDDS	Cell Phones & Accessories	17.04.2023	16.98	15.16
B0BGJ9WJNW	Cell Phones & Accessories	17.04.2023	15.98	13.96
B0BGJGTCB1	Cell Phones & Accessories	17.04.2023	17.65	15.98
B0BJKLF4WV	Cell Phones & Accessories	17.04.2023	16.98	16.98
B0BTPZHGM4	Cell Phones & Accessories	17.04.2023	16.98	14.98
B09RKDGYJD	Health & Household	24.04.2023	19.89	24.87
B09YLNY2DD	Tools & Home Improvement	24.04.2023	39.99	38.19
B09YLQV98H	Tools & Home Improvement	24.04.2023	39.99	38.19
B0BF9N2RP2	Cell Phones & Accessories	24.04.2023	14.66	14.99
B09FTCCNZY	Beauty & Personal Care	01.05.2023	13.69	25.99
B07M91R8PN	Electronics	08.05.2023	17.99	16.99

Table B.1: Natural experiments March 2023 - December 2023

Product ASIN	Category	First Treated	Price March 23	Price Dec 23
B07VFT4D6B	Electronics	08.05.2023	14.99	14.99
B08M5L57KT	Electronics	08.05.2023	23.99	22.99
B08SGM6F79	Electronics	08.05.2023	27.99	27.99
B095BZT4SD	Electronics	08.05.2023	11.99	11.99
B097GLJ758	Clothing, Shoes & Jewelry	08.05.2023	23.68	28.62
B09H2QKVDM	Electronics	08.05.2023	23.99	22.49
B09NKJ5MCV	Electronics	08.05.2023	15.32	18.99
B09NNJYGB4	Video Games	08.05.2023	229.62	175.66
B09VBWWVBP	Electronics	08.05.2023	23.99	18.99
B0BS362YV7	Cell Phones & Accessories	08.05.2023	14.24	12.99
B08LXQQ638	Baby Products	15.05.2023	22.16	16.98
B09V9S5JDM	Cell Phones & Accessories	15.05.2023	13.99	7.99
B09W36RMCX	Health & Household	15.05.2023	44.50	44.50
B09W36YKY7	Health & Household	15.05.2023	42.99	42.99
B0B4W7ZR3D	Cell Phones & Accessories	15.05.2023	11.66	8.99
B0B5KDNTWS	Health & Household	15.05.2023	58.00	54.74
B0BF9DTJ7G	Cell Phones & Accessories	15.05.2023	10.66	6.99
B0BFQT9Y3D	Cell Phones & Accessories	15.05.2023	9.99	9.99
B0BGMY687R	Cell Phones & Accessories	15.05.2023	8.99	6.99
B0BGN3C8QG	Cell Phones & Accessories	15.05.2023	10.32	9.99
B0BNPHKFC7	Cell Phones & Accessories	15.05.2023	10.99	9.99
B0BNPJZR8D	Cell Phones & Accessories	15.05.2023	8.95	7.95
B07M8HLGBF	Electronics	22.05.2023	49.99	43.74
B07VHL9VPB	Clothing, Shoes & Jewelry	22.05.2023	30.00	34.00
B086BGH11N	Cell Phones & Accessories	22.05.2023	9.32	9.24
B0948ZFQFR	Electronics	22.05.2023	25.99	25.99
B09W363MVD	Health & Household	22.05.2023	42.99	36.47
B0BPHLRYY8	Cell Phones & Accessories	22.05.2023	18.99	15.86
B0BQVQTPHN	Automotive	22.05.2023	16.14	12.99
B0BC2SF59D	Tools & Home Improvement	29.05.2023	60.66	62.99

Table B.1: Natural experiments March 2023 - December 2023

Product ASIN	Category	First Treated	Price March 23	Price Dec 23
B085733KQW	Health & Household	05.06.2023	27.08	44.50
B0B1ZG7FKS	Electronics	05.06.2023	10.99	9.97
B0B6ZJJSXM	Clothing, Shoes & Jewelry	05.06.2023	16.95	19.99
B0BKW7CK5H	Cell Phones & Accessories	05.06.2023	15.99	12.99
B0BM5XSKDR	Electronics	05.06.2023	10.66	9.57
B0BPGX9RR6	Cell Phones & Accessories	05.06.2023	12.99	12.99
B0BRPWLB39	Cell Phones & Accessories	05.06.2023	22.99	22.99
B0764K79GM	Health & Household	12.06.2023	25.80	18.18
B09CTLNCFG	Electronics	12.06.2023	19.99	20.99
B09FFGMK9J	Beauty & Personal Care	12.06.2023	27.91	28.00
B09HBLMK6N	Electronics	12.06.2023	17.76	18.99
B0B14KKLZJ	Cell Phones & Accessories	12.06.2023	17.89	15.95
B0B6VXF379	Cell Phones & Accessories	12.06.2023	19.44	14.12
B0BG4WH995	Cell Phones & Accessories	12.06.2023	13.32	9.99
B0BG875KCH	Cell Phones & Accessories	12.06.2023	14.92	14.87
B0BL44JK2F	Cell Phones & Accessories	12.06.2023	20.31	16.99
B0BNQPPCM4	Cell Phones & Accessories	12.06.2023	20.88	14.98
B0073UBRP2	Electronics	19.06.2023	23.99	25.64
B014G1G10Q	Beauty & Personal Care	19.06.2023	34.98	26.97
B08J3K4N15	Electronics	19.06.2023	23.99	25.99
B08K383X9Q	Electronics	19.06.2023	10.32	9.49
B08P37VLHY	Video Games	19.06.2023	16.47	18.99
B09QLWKZL8	Cell Phones & Accessories	19.06.2023	21.67	26.99
B0B1BSLRGT	Cell Phones & Accessories	19.06.2023	34.19	28.99
B0B31Q1FNJ	Cell Phones & Accessories	19.06.2023	6.99	7.99
B06XG93V8K	Beauty & Personal Care	26.06.2023	14.98	10.48
B09LLPSVBY	Electronics	26.06.2023	39.98	34.97
B0BHMMH9KM	Video Games	26.06.2023	34.99	14.99
B0BL66ZW9H	Video Games	26.06.2023	59.89	56.10
B0BL67RHS6	Video Games	26.06.2023	183.76	148.98

Table B.1: Natural experiments March 2023 - December 2023

Product ASIN	Category	First Treated	Price March 23	Price Dec 23
B07GSLHXXQ	Electronics	03.07.2023	9.98	10.97
B08C8TVWYT	Electronics	03.07.2023	32.99	31.74
B097G8KX16	Electronics	03.07.2023	28.99	27.99
B09KC6PSR9	Electronics	03.07.2023	22.64	20.98
B0B1TQTNMC	Electronics	03.07.2023	20.99	20.99
B0BLRGQF3M	Cell Phones & Accessories	03.07.2023	9.98	15.98
B093PT44N1	Electronics	10.07.2023	30.99	28.99
B0B1TVD3HK	Electronics	10.07.2023	20.99	20.99
B0BJFFGLHM	Electronics	10.07.2023	27.66	28.24
B0BN63HZVK	Cell Phones & Accessories	10.07.2023	9.98	15.98
B072K1LNNY	Beauty & Personal Care	24.07.2023	20.00	18.67
B07GZFJ4G5	Cell Phones & Accessories	24.07.2023	36.37	38.99
B07RQRMGKB	Electronics	24.07.2023	11.32	11.99
B07ZV6FHWF	Electronics	24.07.2023	8.99	8.99
B085ZXC2HS	Cell Phones & Accessories	24.07.2023	15.99	13.44
B08GJ3F11N	Beauty & Personal Care	24.07.2023	11.99	9.99
B08L3WX26S	Electronics	24.07.2023	24.99	19.99
B09FDJFJ6Z	Electronics	24.07.2023	7.99	6.99
B09LGSTYHH	Cell Phones & Accessories	24.07.2023	6.99	5.99
B09P53JX4R	Tools & Home Improvement	24.07.2023	37.59	39.99
B09P54CLDQ	Tools & Home Improvement	24.07.2023	37.59	37.59
B09P56Z4JC	Tools & Home Improvement	24.07.2023	37.59	38.19
B09QPMVMMR	Tools & Home Improvement	24.07.2023	69.99	58.9
B09T6929J6	Tools & Home Improvement	24.07.2023	69.99	58.9
B09YFH1C8X	Beauty & Personal Care	24.07.2023	15.09	15.24
B0B1YVZGC4	Beauty & Personal Care	24.07.2023	11.99	13.74
B0BBKVM6RS	Cell Phones & Accessories	24.07.2023	9.99	5.99
B0BBPY5MLY	Cell Phones & Accessories	24.07.2023	8.99	5.99
B0BGRFNVYN	Cell Phones & Accessories	24.07.2023	12.99	9.24
B07CVX3516	Electronics	31.07.2023	9.49	8.99

Table B.1: Natural experiments March 2023 - December 2023

Product ASIN	Category	First Treated	Price March 23	Price Dec 23
B07FMGCK32	Cell Phones & Accessories	31.07.2023	18.99	21.59
B086JBZW48	Health & Household	31.07.2023	12.97	12.30
B089LDX88M	Cell Phones & Accessories	31.07.2023	15.03	14.44
B08P27Y27M	Health & Household	31.07.2023	12.99	11.99
B08PHY1PJF	Health & Household	31.07.2023	12.99	11.99
B09JC5BZCJ	Electronics	31.07.2023	36.66	36.66
B09JZG79QN	Cell Phones & Accessories	31.07.2023	9.99	9.99
B09L9RKN7W	Health & Household	31.07.2023	10.99	10.99
B0BG6MLRPQ	Cell Phones & Accessories	31.07.2023	25.12	25.99
B0BG6NB4F4	Cell Phones & Accessories	31.07.2023	30.39	31.99
B0BQBYDX8N	Cell Phones & Accessories	07.08.2023	10.65	7.98
B0BR6JRG3S	Cell Phones & Accessories	07.08.2023	14.99	13.99
B0BRHW3F81	Cell Phones & Accessories	07.08.2023	14.32	11.99
B0BRK812Q7	Cell Phones & Accessories	07.08.2023	14.24	9.60
B0BVLHR8N4	Cell Phones & Accessories	07.08.2023	14.99	13.99
B08773X9FV	Electronics	14.08.2023	18.99	18.99
B087PCLLGC	Electronics	14.08.2023	16.79	17.99
B0B6H3K8WP	Cell Phones & Accessories	14.08.2023	8.54	8.49
B0B6MNZYPQ	Cell Phones & Accessories	14.08.2023	7.59	6.99
B0B6ZL99L5	Cell Phones & Accessories	14.08.2023	7.99	7.24
B0B7JYYRFD	Cell Phones & Accessories	14.08.2023	7.36	4.74
B0BG6NW2SV	Cell Phones & Accessories	14.08.2023	25.12	25.99
B0BQF1F7HC	Cell Phones & Accessories	14.08.2023	10.43	9.12
B0BQF1Y2WY	Cell Phones & Accessories	14.08.2023	11.39	4.98
B0BRCL6F63	Cell Phones & Accessories	14.08.2023	12.99	12.99
B0BRKQXMTM	Cell Phones & Accessories	14.08.2023	14.99	14.99
B0BWMPBZML	Cell Phones & Accessories	14.08.2023	19.99	27.69
B0B81RWR6G	Cell Phones & Accessories	21.08.2023	14.91	14.91
B0BGHM8SY4	Electronics	21.08.2023	11.90	9.99
B0BLK79BZ2	Electronics	21.08.2023	28.95	25.95

Table B.1: Natural experiments March 2023 - December 2023

Product ASIN	Category	First Treated	Price March 23	Price Dec 23
B086QW23YD	Electronics	28.08.2023	12.99	14.12
B08BR4V18G	Electronics	28.08.2023	14.99	14.38
B09HKX6HRB	Electronics	28.08.2023	10.99	9.99
B0BG2K7GHW	Cell Phones & Accessories	28.08.2023	49.99	49.99
B0BMZV9L78	Cell Phones & Accessories	28.08.2023	30.32	29.24
B0BQTKZ19H	Cell Phones & Accessories	28.08.2023	39.99	39.99
B08LZWD1FT	Beauty & Personal Care	04.09.2023	32.00	32.00
B093T7GQWB	Electronics	04.09.2023	18.79	14.72
B09J1DFTTV	Electronics	04.09.2023	19.91	17.99
B0B9YH9PZK	Beauty & Personal Care	04.09.2023	22.00	22.00
B0BGHRM5DV	Electronics	04.09.2023	18.99	16.99
B0BGP4NLB7	Cell Phones & Accessories	04.09.2023	36.98	33.24
B0BHHD13CW	Cell Phones & Accessories	04.09.2023	25.99	19.99
B074KV9TT4	Electronics	11.09.2023	37.32	36.24
B08233Z4V8	Sports & Outdoors	11.09.2023	23.99	23.99
B088RHCSG3	Electronics	11.09.2023	14.99	14.99
B09FL54WR6	Beauty & Personal Care	11.09.2023	12.49	9.99
B09J1F9S2D	Electronics	11.09.2023	21.99	23.24
B09J1FYF9V	Electronics	11.09.2023	20.95	19.99
B09P8C7K1K	Beauty & Personal Care	11.09.2023	8.99	8.99
B09Z68HZFK	Beauty & Personal Care	11.09.2023	16.82	18.24
B078MGXLVS	Musical Instruments	18.09.2023	34.95	46.12
B07Y9G18V7	Electronics	18.09.2023	36.32	32.99
B0831BF1FH	Cell Phones & Accessories	18.09.2023	28.49	28.49
B08883JK8Y	Electronics	18.09.2023	33.99	36.24
B08GG42WXY	Tools & Home Improvement	18.09.2023	11.19	14.24
B08K8S4ZDW	Electronics	18.09.2023	45.99	43.99
B08RDF9B3F	Cell Phones & Accessories	18.09.2023	12.38	13.5
B08XQQ5XTZ	Cell Phones & Accessories	18.09.2023	27.66	25.49
B095GJDXNG	Electronics	18.09.2023	31.99	32.32

Table B.1: Natural experiments March 2023 - December 2023

Product ASIN	Category	First Treated	Price March 23	Price Dec 23
B095VM6J1R	Electronics	18.09.2023	23.32	25.99
B09PR1BTM7	Tools & Home Improvement	18.09.2023	15.99	15.02
B09PV827TS	Electronics	18.09.2023	31.99	35.24
B09TZWLFLY	Video Games	18.09.2023	28.99	27.95
B09XHQDP18	Electronics	18.09.2023	18.46	18.99
B0B84TC271	Tools & Home Improvement	18.09.2023	15.57	13.32
B0BGN9R72N	Tools & Home Improvement	18.09.2023	10.99	13.19
B0BHH7M4YJ	Cell Phones & Accessories	18.09.2023	9.99	9.99
B0BHHVN541	Cell Phones & Accessories	18.09.2023	9.99	9.37
B0BLTDYG2B	Cell Phones & Accessories	18.09.2023	14.99	14.99
B0BM4QL882	Cell Phones & Accessories	18.09.2023	9.99	9.99
B0893XB5KN	Electronics	25.09.2023	24.99	24.98
B08S3X391Q	Cell Phones & Accessories	25.09.2023	10.75	13.74
B09FSGT2V7	Cell Phones & Accessories	25.09.2023	9.98	11.98
B0BM4LPT4Y	Cell Phones & Accessories	25.09.2023	9.99	9.99
B0BTCPGJMT	Electronics	25.09.2023	19.99	24.99
B084CVZH4W	Beauty & Personal Care	02.10.2023	12.99	11.86
B088QLW78X	Video Games	02.10.2023	99.99	89.99
B09JC2VJYT	Electronics	02.10.2023	39.99	37.49
B0BHHCWRQ3	Cell Phones & Accessories	02.10.2023	10.99	9.99
B08K8DNVB4	Cell Phones & Accessories	09.10.2023	43.88	36.93
B09NFNWQ18	Cell Phones & Accessories	09.10.2023	33.24	33.99
B0BV2WC579	Cell Phones & Accessories	09.10.2023	20.32	19.99
B083W1SDK1	Tools & Home Improvement	16.10.2023	20.66	19.99
B0B66RHD7B	Video Games	16.10.2023	28.49	36.12
B0B96PKNVL	Video Games	16.10.2023	20.32	19.99
B0BJCQ8LSM	Cell Phones & Accessories	16.10.2023	36.99	36.99
B0BV2TBKZK	Cell Phones & Accessories	16.10.2023	19.99	19.99
B016XTADG2	Electronics	06.11.2023	25.99	25.99
B07Z4RF1D3	Electronics	06.11.2023	16.78	17.58

Table B.1: Natural experiments March 2023 - December 2023

Product ASIN	Category	First Treated	Price March 23	Price Dec 23
B09Y5366WN	Cell Phones & Accessories	06.11.2023	6.99	7.99
B07KC2TTGV	Electronics	13.11.2023	53.99	52.99
B07QN9NPKN	Electronics	13.11.2023	31.99	31.99
B087LRK3H4	Electronics	13.11.2023	17.99	17.99
B096BCMK8N	Electronics	13.11.2023	27.32	24.49
B01BT02Q88	Beauty & Personal Care	20.11.2023	14.99	14.99
B082Y6YDZZ	Electronics	20.11.2023	64.98	61.72
B093C2B4K3	Electronics	20.11.2023	19.32	18.27
B097H42RK9	Electronics	20.11.2023	78.98	79.98
B09XXN2VXX	Electronics	20.11.2023	69.98	72.23
B0B2BSQQL7	Electronics	20.11.2023	89.89	79.99
B0B9S3XWH9	Cell Phones & Accessories	20.11.2023	15.99	18.99
B0BLBQ9G2C	Cell Phones & Accessories	20.11.2023	26.99	26.99
B0BQB8JNFB	Cell Phones & Accessories	20.11.2023	23.99	25.99
B0BRC415HH	Cell Phones & Accessories	20.11.2023	21.99	20.99
B0BTRTFK4S	Cell Phones & Accessories	20.11.2023	26.99	26.99
B07J4TNYV8	Electronics	27.11.2023	139.99	122.49
B07JR1XZ78	Electronics	27.11.2023	67.99	74.99
B0874M3KW4	Electronics	27.11.2023	66.49	69.99
B0BJZ5VMD6	Cell Phones & Accessories	27.11.2023	26.99	26.99
B07QXV6N1B	Cell Phones & Accessories	04.12.2023	21.99	20.06