Demand for carbon-neutral products[*]

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Abstract

Corporate social responsibility and the private provision of (global) public goods are of key interest to economists and policymakers. Over the last few years, many more private companies made their operations carbon neutral. It is an empirical question how consumers value carbon-neutral and low-carbon products, which we address as follows. First, we provide a meta-analysis of the literature. We analyze consumers' demand for carbon-neutral and low-carbon products, based on an overall sample of 29,666 participants. The focus is on average willingness to pay for carbon reductions as well as on the characteristics of the underlying literature, which is mainly based on stated preferences and controlled environments. Second, we leverage information on prices and product characteristics from one of the largest online marketplaces, Amazon's. Using a hedonic approach, we infer from revealed preferences on consumers' valuation of carbon-neutral products. 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 suggests a positive willingness to pay for carbon reductions that exceeds most estimates of the social cost of carbon. However, this finding is not supported by the hedonic analyses, where we do not find evidence that consumers value carbon neutrality.

Keywords corporate social responsibility; pro-social behavior; stated and revealed preferences; meta-analysis; hedonic analysis; carbon-neutral labels

JEL codes D12; D22; H41; Q51; Q54

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 expands, 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 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 was 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 a premium for carbon-neutral products.

This paper aims to address this question. It does so as follows. First, it collects evidence from the literature on consumers' willingness to pay (WTP) for products that are presented as either carbon neutral or low carbon, as certified by labels. The literature that we cover includes 37 studies, providing 126 observations, and an overall sample of 29,666 participants. From this body of evidence, it is possible to estimate average WTP for carbon reductions, including carbon neutrality, across studies, geographies, and samples, and compare it with the range of estimates that economists have provided for the social cost of carbon, with the goal of understanding whether and to what extent consumers privately internalize the climate externality. Further, with the tools of meta-analysis, it is possible to determine the product and study features that are associated with higher or lower WTP for carbon reductions.

Second, this paper uses hedonic difference in differences to complement with real-world data the meta-analysis, which, as described, is based on surveys and experiments, with samples of different nature. In particular, we use publicly available information on prices, product characteristics, and reviews from the Amazon marketplace, covering a wide range of products, tracked over several months in different countries – the United States, the United Kingdom, and Germany – to assess in a hedonic framework whether there is any demand for the carbon neutrality of products. Amazon is by far the most important online marketplace in many countries around the world.[1]

In line with other marketplaces, many products on Amazon have recently been certified carbon neutral. Consumers buying these products would in principle access a climate-friendly product, without the need for any action on their part, unlike in the case of offsetting. Carbon-neutral products remain niche products, but their recent expansion allows the application of a hedonic approach to investigate whether consumers value their climate-friendly nature. From an empirical standpoint, the emergence of these certifications creates a multitude of quasi-natural experiments, which we leverage to causally identify consumers' interest in the carbon neutrality of products. We do so with event-study analysis, which also allows us to test pre-trends and ensure the suitability of control groups.

We collected data on over 120,000 products across the three Amazon's marketplaces over many months on a weekly basis. In the United States, we identify 207 treated products that received carbon-neutral certifications on Amazon during the observation period and 7,526 category-matched control products without such certification. In the United Kingdom, we identify 50 treated products and 5,876 control

[1] Of the 129 million households in the United States (US Census Bureau, 2025), more than half had an Amazon Prime subscription already in 2019 (Statista, 2022b). Amazon plays a dominant role in European markets as well. 86% of shoppers in the United Kingdom use Amazon. More than 25% of British adults had an Amazon Prime membership in 2018 (Mintel, 2019). More than 75% of online German consumers made at least one purchase per month on Amazon in 2022 (Statista, 2022a).

products. In Germany, we identify 84 treated products and 5,451 controls. Given the staggered nature of these certifications, we rely on recent advances in the difference-in-difference literature, and in particular on Callaway and Sant'Anna (2021). This estimator allows us to examine causally the effect of treatment in the presence of dynamic effects and heterogeneity across cohorts. This estimator also allows leveraging propensity scores to maximize comparability between treatment and control groups, which we also inspect visually based on pre-trends (or absence thereof).

The results from the meta-analysis point to a positive WTP for carbon-neutral and low-carbon products, where at USD 1993 per ton of carbon dioxide (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 CO_2 reduction. Higher product prices are associated with a higher WTP, suggesting that the relative cost of CO_2 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.

With the hedonic difference-in-difference approach, we find no evidence of a relationship between carbon-neutral labeling and product prices. Treatment effects derived from the hedonic approach are statistically indistinguishable from zero across all three markets, implying that consumers do not value carbon neutrality. Crucially, keyword searches applied to customer reviews of treated products reveal that mentions of carbon neutrality and related terms are negligible in all three markets ($<$0.14%). This observation is consistent with the absence of a positive relationship between carbon-neutral labeling and product prices. Hence, the substantial WTP for the carbon neutrality of products reported in the literature is not reflected in how consumers value carbon neutrality on the main online marketplace, Amazon, across three countries. We also do not find consistent evidence for an effect of carbon-neutral labeling on the quantities sold – proxied by customer ratings.

This paper contributes, with its unique angle, to multiple strands of literature. First, we add to 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 CO_2 emissions (e.g. Kim and Lyon, 2011; Doda et al., 2016). We examine the extent to which consumers may value producers' efforts to abate emissions. Companies may engage in voluntary abatement for a variety of reasons, but if consumers were tangibly willing to pay more for carbon-neutral and low-carbon products, firms would have an incentive to abate more. Although the evidence from the meta analysis points to a considerable WTP, sufficiently high to support the widespread adoption of carbon-neutral labels, findings from the hedonic model provide a different picture. According to the hedonic model, consumers do not really value carbon neutrality as a product feature, which may explain their niche nature.

Second, we speak to 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, 2008; 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; Mortensen et al., 2019; Spencer et al., 2019; Andreoni et al., 2021; Bicchieri and Dimant, 2022; Carattini and Blasch, 2024). Our focus is on carbon-neutral products, whose purchase represents a relatively recent form of climate-friendly behavior. The combination of meta-analysis and observational study provides new knowledge to this area of research. Our findings from the hedonic model indicate that carbon-neutral products would remain niche in the absence of a change in consumer preferences, unless corporate social responsibility motives continue to support their expansion. Future research may investigate whether increasing the visibility of carbon-neutral products may generate social rewards and potentially increase consumers' attention to them, as shown for instance in the case of peer-to-peer solar (Carattini et al., 2024).

Third, we contribute to 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; Rodemeier, 2023). An important distinction exists between carbon-neutral products and carbon offsets. Many companies give consumers the option to offset their emissions when purchasing a good or service. Consumers may opt in, though generally most do not. In the case of carbon-neutral products, producers always incur the cost of reducing emissions. Consumers can either buy the carbon-neutral product, rewarding the producer for its efforts, or buy another product.

Fourth, we relate to a varied scholarship estimating WTP for labeled products, including carbon-neutral labels (e.g. Akaichi et al., 2017; Birkenberg et al., 2021; Muller et al., 2019), as well as theoretical literature on environmental labels (e.g. Fischer and Lyon, 2014; Brécard, 2017; Heyes and Martin, 2018; Poret, 2019; Fischer and Lyon, 2019). We provide the first meta-analysis of the literature on carbon-neutral products, as well as original evidence from a hedonic exercise. Fifth, we connect to a strand of literature comparing various methods, in particular in light of 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). We do so within the meta-analysis as well as by comparing estimates from the meta-analysis and the hedonic model. Sixth, we contribute to 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 this new application, we use a hedonic approach to examine demand for carbon-neutral products, also leveraging recent advances in econometrics allowing for the staggered timing of treatment.

In terms of policy implications, assessing the demand for carbon-neutral products contributes 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. Although large publicly-traded firms pledged to become carbon neutral due to pressure from investors, including at the time in expectation of future policy tightening, this paper examines whether there is a rationale for many other firms to pursue carbon neutrality. Unlike our meta-analysis of the underlying literature, which relies heavily on stated preferences and controlled environments, our hedonic approach finds no evidence that consumers value carbon neutrality, based on actual purchasing decisions across three large markets. Overall, people's private motivations to contribute to (global) public goods do not seem a sufficiently strong force to spur the adoption of carbon-neutral products, though there is some suggestive evidence of a potential effect on quantities in one of the markets, as proxied by the number of customer ratings.

The remainder of the paper proceeds as follows. Section 2 introduces our data and empirical approach for meta-analysis and hedonics. In turn, Section 3 provides empirical evidence for meta-analysis and hedonics. Section 4 concludes.

2 Data and empirical approach

2.1 Meta-analysis

This section concisely describes the data and empirical approach used for the meta-analysis, while pointing the reader to a set of sections in the Appendix that provide more detailed information. The underlying literature and derivation procedure of WTP for reductions in CO_2 emissions is described in Appendix A.1.[2] In our main analyses, we have a total of 126 observations from 37 studies,[3] which use a variety of methodologies, including four contingent valuation (CV) surveys and 29 discrete choice experiments (DCEs) based on stated preferences, two lab experiments and one field experiment inferring from revealed preferences, as well as one study that leverages both a DCE and a field experiment. The underlying sample includes 29,666 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 on the marginal value of CO_2 reductions via carbon-neutral or carbon-reduced labels, excluding the cost of the product. The studies in our database focus on a variety of products, which we categorize into dairy and eggs, fruits and vegetables, meat, non-food items, oil and grain, snacks, and water and drinks. Our database includes not only observations of reductions in CO_2 emissions, but also reductions in greenhouse gas emissions expressed as CO_2 equivalents,

[2]All WTP estimates extracted from the original studies are either already expressed as or converted to marginal WTP for reductions in CO_2 emissions, excluding product prices. Therefore, WTP throughout the paper refers to the marginal WTP for carbon reductions.

[3]Cerroni et al. (2019a) and Cerroni et al. (2019b) are counted as a single study because they analyze the same underlying sample.

and we treat these equally. Additionally, we consider the term "CO_2 reduction" in a broad sense, encompassing actual CO_2 reductions via abatement, offsets, and CO_2 capture. We elaborate more on these concepts in Appendix A.1.3.

To standardize WTP estimates, we use four different WTP measures. First, the measure WTP_R refers to the 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. WTP_{kg} represents the WTP per 1 kg of CO_2 reduction, calculated by dividing WTP_R by the amount of CO_2 reduction in kilograms, and is expressed in USD. This WTP measure is useful for comparing with estimates of the social cost of carbon, and hedonic estimates, which we convert to the same units. WTP_{CN} denotes the WTP for achieving carbon neutrality of a product. It is calculated by multiplying WTP_{kg} by the baseline CO_2 emissions of the product, and is also expressed in USD. This measure provides an alternative benchmark for comparing our results with those from the hedonic approach. 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 is calculated by dividing WTP_{CN} by the price of the product. From each study, we extract one of the four WTP measures and, for comparability, derive additional measures by converting this estimate into alternative metrics, depending on the information reported in each study.

To summarize the findings from the literature, we first report the mean of study-level mean WTP_R, WTP_{kg}, WTP_{CN}, and $WTP_{CN\%}$. Second, we present the distribution of the WTP measures across studies in the literature and compare the WTP_{kg} with the social cost of carbon. Next, we assess publication bias using the funnel plot asymmetry - precision-effect test with weighted least squares (FAT-PET-WLS) method (Stanley and Doucouliagos, 2014). Because less than half of the studies report sufficient information to recover standard errors (see Figures A.9 and A.10 in Appendix A.4), we follow a common alternative approach used in prior meta-analyses and use the square root of the study sample size as a proxy for precision (Florax et al., 2005; Tunçel and Hammitt, 2014; Mattmann et al., 2016; Penn and Hu, 2019).

Furthermore, we conduct regression analysis to understand which factors are associated with WTP_R, including the amount of CO_2 reduction, product price, stated versus revealed preference methods, in-person studies, study sample size, published versus unpublished studies, study year, GDP per capita, and studies conducted in Europe versus elsewhere. We control for observations that required assumptions regarding the amount of CO_2 reduction or where we made additional calculations based on the information provided in the studies to derive WTP estimates. We leverage the ordinary least squares (OLS) model with standard errors clustered at the study level.

Our analyses of factors associated with WTP_R include a series of robustness tests using alternative models, including a mixed-effects model that incorporates random effects for studies and product categories, as well as a weighted mixed-effects model, where equal weights are given to each study in the meta-analysis. Moreover, we introduce additional independent variables, such as carbon-neutral and colored labels, and explore the possibility of using sample size as an alternative weighting factor. Furthermore, we apply two-way clustering based on product categories or countries, integrate country-specific random effects, and investigate different functional forms for the dependent variable and the CO_2 reduction variable. Finally, we run regressions excluding observations that require assumptions regarding the amount of CO_2 reductions or own derivations of WTP from studies. The goal of these exercises is to ensure the robustness of our results.

2.2 Hedonic approach

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 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 and several geographies (United States, United Kingdom, Germany) 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 as a feature that consumers value. Further, over the last few years, Amazon gave high importance to carbon neutrality, among other environmental aspects, by collaborating with several organizations to provide labels for carbon-neutral products. More than 50 different sustainability certifications are currently displayed on Amazon's marketplace, which Amazon refers to as "Climate Pledge Friendly" certifications. Among them are five carbon-neutral labels, certified by various entities, as described in Appendix B.1. Figure B.1 in Appendix B.1 provides an example of a carbon-neutral product on Amazon.com.

Our hedonic analysis is based on a weekly panel of products sold on Amazon's marketplace. We employ the following strategy to construct the panel. First, we identify a list of several thousand products with carbon-neutral labels using built-in filters 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 that we identify, we scrape many untreated products without carbon-neutral labels. This process ensures that for each already-treated product, we obtain many control units from the same product category. We proceed similarly with Amazon.co.uk and Amazon.de.

The benefits of this product selection strategy are threefold. First, selecting products to be monitored from categories that already contain treated products ensures that, in principle, it is possible to make such products carbon neutral and label them accordingly. Second, it also implies that there are some motivations among producers to make these products carbon-neutral in the near future, 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 38,974 products from 35 categories on Amazon's American marketplace, 41,384 products from 134 categories on Amazon's marketplace in the United Kingdom, and 40,031 products from 48 categories on Amazon's German marketplace. We scrape the same set of product information each week for all these products, as displayed on Amazon's website, for IP addresses from the United States, the United Kingdom, and Germany. The data collection started in March 2023 and ended in November 2024. Data from Amazon.com, the American marketplace, was scraped for this entire period. For the United Kingdom and Germany, we have data from May 2024 through November 2024. In all markets, we have many quasi-natural experiments to leverage for empirical purposes.

From this broad set of products, we identify treated products that obtain new carbon-neutral labels, and, in turn, control products. 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-difference analysis. The staggered adoption of carbon-neutral labels by products sold on Amazon provides the ideal features of a quasi-natural experiment. Here, a product changes its treatment status when it receives one of the abovementioned carbon-neutral labels. Control units are represented by products that are arguably comparable within the same product category assigned by Amazon and pre-trends are examined accordingly. We exclude Amazon's own products as well as books from the analysis, since these categories might have different market dynamics than the other products on Amazon.

The 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 tend to automatically adjust to changes in demand, in principle quickly approaching equilibrium prices. Still, we also examine effects on quantities, which are proxied by the number of ratings a product receives, to provide a fuller picture.

For the difference-in-difference analysis, we focus on products whose information – including labels and prices – could be scraped consistently and which were most often available for purchase, while also excluding product links redirecting to a different item on Amazon.[4] We further exclude always-treated products from the hedonic analysis (2,759 for the United States, 1,881 for the United Kingdom, and 1,943 for Germany).

We identify 207 treated and 7,526 control products in the United States, 50 treated and 5,876 control products in the United Kingdom, and 84 treated and 5,451 control products in Germany. When selecting suitable control products among untreated candidate products, i.e. products without a carbon-neutral label at the beginning of the timeframe of reference (23,935 products in the United States, 32,486 in the United Kingdom, and 33,224 in Germany), we first consider products that, at the beginning of the panel, do not have another "Climate Pledge Friendly" label (e.g. organic, fair

[4]Note that it is not plausible to expect prices to be successfully scraped 100% of the time. We interpolate (and extrapolate) the missing data points linearly.

trade) and then match each treated product's category node to find control products that share at least one of these nodes. Each product on Amazon is assigned up to 10 category nodes, ranging from broader to more specific classifications. If fewer than 10 suitable controls are available within the most precise node, we move to a higher-level node. Only control products matched to the category of at least one treated product are retained in the final dataset. Tables B.2, B.3, and B.4 in Appendix B.3 present the number of treated and control products by category across the three markets. Tables B.6, B.7, and B.8 in Appendix B.3 provide Amazon Standard Identification Numbers (ASINs) of treated products, their categories, as well as their prices at the start and at the end of the panel for each country.

We estimate the treatment effect of carbon neutrality in non-canonical difference in differences. We assume that the timing at which products get treated is plausibly random and assess pre-trends accordingly. We also take treatment as irreversible (at least within our time frame), leading to a difference-in-difference setup with staggered treatment assignment and treatment being absorbed. Accordingly, we proceed with Callaway and Sant'Anna (2021), as now standard in these circumstances. Our setting is also such that only a small share of products receives the treatment, making economically meaningful general equilibrium effects unlikely. In our main estimations, we also control for 57 different product categories from Amazon United States, 15 from Amazon United Kingdom, and 21 from Amazon Germany, as well as initial product prices.

Event analyses are used to verify that the (conditional) parallel trend assumption holds (when conditioning on the finest-level product category available and initial price) and to examine dynamic treatment effects. We focus on products that receive the treatment (label) during the period of interest and, as control group, use not-yet-treated products and never-treated products. Event-time effects are obtained by aggregating cohort-time effects, as in Callaway and Sant'Anna (2021):

$$ATT^{\text{Event Study}}(e) = \sum_{c \in \mathcal{C}_e} ATT(c, c+e)\ \Pr(C = c \mid C \in \mathcal{C}_e)$$

where $e = t - c$ is the event time for cohort c, $\mathcal{C}_e = \{\, c \in \mathcal{C} : c + e \leq T \,\}$ is the set of cohorts that we observe to be treated for at least e periods up to period T, $\Pr(C = c \mid C \in \mathcal{C}_e)$ is the share of cohort c among other cohorts observed at event time e. Each Average Treatment Effect on the Treated ($ATT_{c,t}$) compares cohort c at time t with not-yet-treated and never-treated units at time t.

We express the outcome variable in terms of the percentage change in a product's price, relative to its initial price, in our main specifications, but also provide estimates based on absolute prices. We also translate the effect into USD per kilogram (ton) of CO_2 by accounting for the average carbon footprint of the treated products. Appendix B.4 provides more details on the carbon footprint calculations. As mentioned, we also consider the number of ratings a product receives as a proxy for quantities (sales).

We conduct a variety of robustness tests: alternative sample restrictions; using the unbalanced-data option instead of filling missing data by interpolation or extrapolation; excluding control variables; including additional controls (e.g., the number of initial product ratings as a proxy for sales); and using the absolute price level as the outcome. We also estimate treatment effects on products' price change relative to baseline price, accounting for product heterogeneity across four dimensions: price ranges (within and above the range of prices observed in the meta-analysis), product categories, carbon intensity, and certifiers.

To explore mechanisms, we analyze the content of customer reviews, paying particular attention to references to carbon neutrality or climate friendliness more generally. We scrape the first page of product reviews weekly from Amazon's marketplace in the United States (May 2024-November 2024), the United Kingdom (March 2024-November 2024), and Germany (March 2024-November 2024). We then selected keywords pointing to carbon neutrality or climate friendliness in general and count their occurrence. A minimal occurrence would indicate that customers do not value carbon neutrality. Many mentions would indicate that many customers value carbon neutrality. We assess the occurrence of keywords to complement the results from the hedonic analysis.

We analyze keyword occurrences in the always-treated group, which includes products with a carbon-neutral label at the start of the panel, in comparison with the never-treated group, which includes products that never receive such a label. We restrict the always-treated sample to reviews posted after the panel start date, to ensure we only analyze reviews of products at a time when they are treated. In total, we have 127,268 reviews for always-treated products and 450,448 reviews for never-treated products, written by individuals making purchases on Amazon.

3 Empirical evidence

3.1 Meta-analysis

In this section, we describe average WTP measures, descriptive in nature, from the literature that the meta-analysis covers, with each study in our sample yielding one or several WTP estimates, which are then averaged out at the study level. We then discuss study characteristics that correlate with WTP, based on meta-regressions.

We start with the WTP_{kg} measure, the WTP for a reduction of 1 kg of product CO_2 emissions, based on the mean of the study means. We compare the average WTP_{kg} with recent estimates of the social cost of carbon, taking the average WTP_{kg}

at face value and assessing the extent to which consumers internalize the climate externality in their provision of a global public good. 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). We also consider WTP_R, the WTP for CO_2 reductions, as introduced in Section 2.1.

Figure 1 shows the distribution of WTP_R and WTP_{kg} across studies, where a logarithmic x-axis is used for a better representation of the distribution of observations. Table A.9 in Appendix A.2 provides a full summary of WTP estimates for all four WTP measures and their respective 95% confidence intervals. As illustrated in Figure 1, the average WTP_R of the study averages is USD 1.30 [0.89, 1.79]. The average WTP_{kg} is USD 1.99 [1.06, 3.45] per kg of CO_2 reduction, or USD 1993 per ton of CO_2. To put these estimates into perspective, the social cost of carbon during the Obama administration was around USD 40 per ton of CO_2 (IWG on Social Cost of Carbon, 2010, 2013), while under the Biden administration it was 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) towards its end and before the start of a new administration. 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 a few Nordic countries, Switzerland, and Uruguay have carbon prices above USD 130 per ton of CO_2 (World Bank, 2025), about a fifteenth of the average WTP_{kg} derived from the literature that the meta-analysis covers. The economic literature points, however, to potentially higher 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, hence much lower than the average WTP_{kg} that the meta-analysis provides.

A few interesting observations emerge from Figure 1. First, there is a substantial variation in WTP_R 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_R and the amount of CO_2 reductions, indicated by the more numerous larger circles on the right-hand side of the average (vertical line). Third, there is heterogeneity in WTP estimates across products, a point to which we return below.

Next, we discuss two alternative WTP measures: WTP_{CN} and $WTP_{CN\%}$ based on the mean of study means. WTP_{CN} of USD 14.99 [4.35, 32.86] represents the WTP to make a product carbon neutral. Because this estimate aggregates a variety of products with different prices from the meta-analysis, we also report $WTP_{CN\%}$, the percentage premium over product price that consumers are willing to pay for carbon neutrality, which equals 252% [119, 412]. Similar to other WTP measures discussed above, Figure A.1 in Appendix A.2 shows the distribution of WTP_{CN} and $WTP_{CN\%}$ measures across studies and provides several insights. First, substantial variation across studies in WTP estimates remains. Second, there appears to be a positive relationship between WTP for carbon neutrality and product carbon footprint. Third, we still observe heterogeneity in WTP across product categories. Additional results are provided in the Appendix, including Figures A.2–A.5 in Appendix A.2, which present WTP estimates by product category for all four measures. Figures A.11 and Figure A.12 show the relationship of WTP_R and WTP_{kg} with emission reductions; as well as the relationship of WTP_{CN} and $WTP_{CN\%}$ with products' carbon footprints, respectively.

Next, we assess publication bias using the FAT-PET-WLS specification. We do so in Appendix A.4 and report here the main conclusion. We find no evidence of publication bias, since the intercepts for all WTP measures are statistically insignificant.

We then turn to meta-regressions to try to determine the main factors, including methodological, that may drive WTP for CO_2 reductions. This analysis is correlational in spirit, yet informative in contributing to addressing our overarching question about the real-world demand for climate certifications, including carbon neutrality. As described, for this analysis we use WTP_R. The main meta-analytical results providing associations between study characteristics and WTP_R are shown in Table 1. We use OLS with standard errors clustered by study.

Our independent variables in the first model (OLS I) include key product characteristics that may explain variation in WTP_R, namely the amount of CO_2 reduction, which is z-scored, to understand whether study participants value greater contributions to climate mitigation; and product price, which is also z-scored, to assess the proportionality of WTP_R to product price. In the second model (OLS II) we add study characteristics, including a dummy variable for stated preference methods, to account for potential biases such as hypothetical bias that may arise in hypothetical survey settings, a dummy variable for in-person studies to account for potential differences relative to computer-based or online studies, a variable indicating the sample size of the study, which is z-scored, a dummy variable for published studies, to account for potential biases in comparison to unpublished studies, and study year, which is z-scored, to account for potential secular trends in public awareness regarding climate change. Contextual controls include 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 environmental friendliness. In the third model (OLS III) we add control variables for observations requiring assumptions about the amount of CO_2 reductions, and for observations we derived from studies ourselves (as opposed to those directly reported in the original study), to account for the need to make additional calculations and interpret the results from the original findings. Appendix A.1.3 provides more details on carbon reduction assumptions and WTP derivations.

Table 1 shows that coefficients remain largely unchanged across different model specifications, in particular for estimates that are statistically significant, which we discuss first. The estimates confirm the positive and significant association between CO_2 reductions and WTP_R, indicating that study participants may tend to be sensitive to the amount of CO_2 reductions. Other interesting associations also emerge. For instance, a higher product price is associated with a higher WTP. That is, a price increase for achieving comparable reductions in CO_2 emissions may be more easily accepted by study participants when it 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 Africa, America, and Asia) also seem to be associated with a higher WTP, even when controlling for the GDP per capita.

We do not find a robust significant association of WTP_R with the following variables, neither in OLS II nor in OLS III models: stated preference studies; in-person studies; sample size of the study; published studies; study year; and GDP per capita. Similarly, in OLS III we do not find a robust significant association of WTP_R with the control variables for CO_2 assumptions and WTP derivations.

Appendix A.3 includes our battery of robustness tests and a detailed discussion thereof. The main takeaway is that also in robustness tests the significance of the abovementioned coefficients shows little sensitivity to specification changes, which we summarize shortly here. First, we present the estimates of alternative models, including the mixed-effects and weighted mixed-effects models, in Table A.11. Second, we incorporate two additional variables: a dummy variable for colored labels, which are used in the literature to distinguish between higher and lower carbon footprint options, and a dummy variable for carbon-neutral certifications, as opposed to carbon reductions and carbon footprint certifications in Tables A.12 and A.13. Third, we show WLS (weighted least squares) and weighted mixed-effects models in Tables A.14 and A.15. Fourth, we compare alternative transformations of the dependent variable in Tables A.16 and A.17. Fifth, we run the OLS model with two-way clustered errors: studies and product categories or countries in Table A.18. Sixth, we conduct mixed effects regressions with random effects for studies and either product categories or countries in Table A.19. Seventh, we include the square of the z-scored CO_2 emission reduction variable in Tables A.20 and A.21. Finally, we show regressions with different subsets of the sample that exclude observations requiring CO_2 reduction assumptions, WTP derivations, or both, in Tables A.22 and A.23.

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

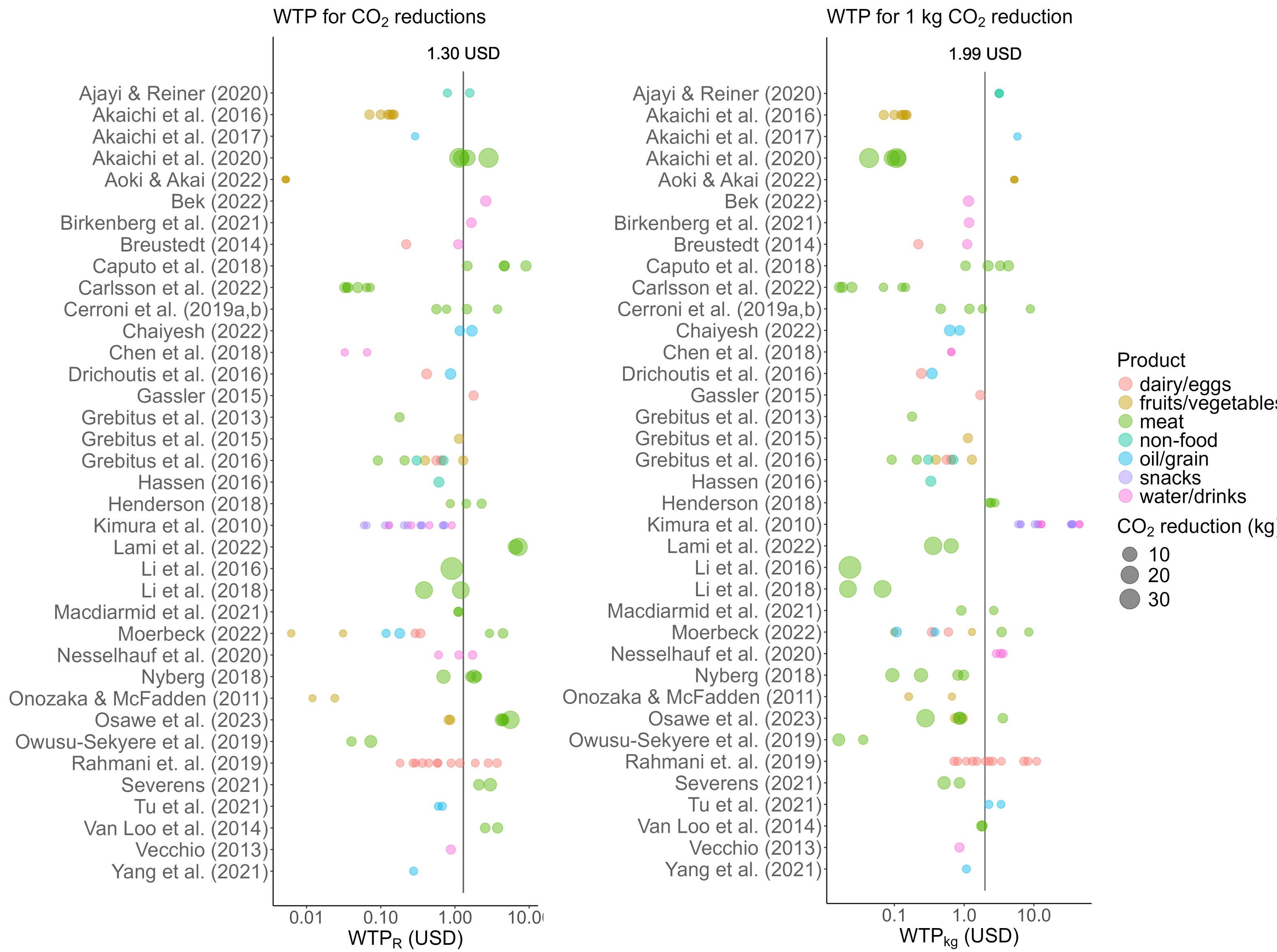

Figure 1: WTP estimates for CO_2 reductions across studies

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_R (non-standardized WTP for CO_2 reductions) across studies, where the size of each circle represents the amount of CO_2 reduction in kilograms. The right-hand graph shows WTP_{kg} (WTP for 1 kg CO_2 reduction), which is calculated by dividing WTP_R by the amount of CO_2 reduction. Both WTP_R and WTP_{kg} are measured in 2020 USD.

	OLS I	OLS II	OLS III
Intercept	0.75*** (0.08)	0.51 (0.33)	0.58* (0.32)
CO_2 reduction	0.12** (0.05)	0.11*** (0.04)	0.11*** (0.04)
Price	0.38*** (0.05)	0.35*** (0.05)	0.35*** (0.05)
Stated pref. method		0.00 (0.24)	-0.02 (0.25)
In-person		-0.08 (0.24)	-0.10 (0.23)
Sample size		-0.05 (0.08)	-0.06 (0.08)
Publication		0.01 (0.23)	0.00 (0.22)
Study year		0.04 (0.09)	0.02 (0.10)
GDP per capita		0.06 (0.08)	0.07 (0.08)
Europe		0.37** (0.17)	0.33* (0.18)
CO_2 reduction assump.			-0.09 (0.12)
WTP derivation			0.07 (0.15)
R^2	0.40	0.50	0.50
Adj. R^2	0.39	0.46	0.45
Num. obs.	126	126	126
Number of obs.	126	126	126
Adjusted-R^2	0.39	0.46	0.45
AIC	217.05	209.92	212.91
BIC	228.40	241.12	249.78
Log Likelihood	-104.53	-93.96	-93.45

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

Table 1: Factors associated with WTP_R for CO_2 reductions

This table shows coefficient estimates and associated standard errors, which are indicated within parentheses. We use an OLS model with clustered standard errors by study. The dependent variable is the (unstandardized) WTP for CO_2 emission reductions (WTP_R), which is transformed using the inverse hyperbolic sine function. CO_2 reduction, price, sample size, study year, and GDP per capita variables are z-scored.

3.2 Hedonic approach

In this section, we describe the main findings from the hedonic analyses using Amazon's data from the United States, the United Kingdom, and Germany. We start by showing the standard event analysis, in Figure 2, for the United States, based on Callaway and Sant'Anna (2021). Figure 2 serves two purposes. First, it allows to test how comparable the control group is to the group that receives the treatment, by inspecting pre-trends. Second, Figure 2 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 percentages to the product average price in March 2023. Table B.9 in Appendix B.5 contains the coefficients describing the dynamic effects.

The pre-treatment coefficients generally fluctuate around zero and are not statistically significant, with standard errors that are quite tight. In terms of the causal effects of carbon-neutral labels, Figure 2 shows that carbon neutrality does not have a positive effect on the price of a product after treatment. The dynamic effects of a carbon-neutral label are never statistically significant. 95% confidence intervals are a bit wider than in the pre-period, as may be expected, but are tight enough long enough to rule out any substantial positive effects following the treatment. Standard errors widen over time, mechanically, due to 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. Overall, the average effect of a carbon-neutral label over the 19-month observation period is -1.91% (95% CI: -3.88, 0.06) of the initial product price, and not significantly different from zero. In short, consumers do not seem to value carbon neutrality, given the absence of a relationship between prices and labels.

While the effect that we document is clearly indistinguishable from zero, there may be readers who still wonder about how to interpret the point estimate. The average effect of a carbon-neutral label on product price translates to USD -0.60 in absolute terms, given the average initial price of treated products of USD 31.2. This corresponds to USD -0.13 per kilogram of reduced CO_2 emissions, based on the average CO_2 emissions (4.6 kg) of treated products (from 191 out of 207 products with available carbon footprint information). Once again, -0.13 per kilogram of reduced CO_2 emissions is statistically indistinguishable from zero.

Evidence from the hedonic approach suggests that consumers do not value carbon neutrality. To provide additional evidence on the relationship – or absence thereof – between carbon neutrality and prices, we report the occurrence of carbon neutrality and related keywords in customer reviews of both always-treated and never-treated products. Our headline finding is that the share of reviews mentioning carbon neutrality and related, less technical, terms is negligible for treated products. This statement is true both at the level of each keyword and when summing occurrences over multiple relevant keywords (0.1% of reviews). In short, consumers do not seem to care about carbon neutrality. Appendix B.9 provides more details about our approach and Table B.11 provides the corresponding summary statistics for the United States.

Our estimates from the hedonic model are robust to a variety of tests, summarized in Figure 3 and described in detail in Appendix B.6. Overall, we do not find evidence that consumers value carbon neutrality. On occasion, the negative point estimate turns significant. Magnitudes, however, remain moderate and are generally consistent across robustness tests. That is, even as we deviate from our preferred specification, the main conclusions are unchanged. We describe our robustness tests in what follows.

First, we relax the restriction that the scraped product information needs to contain the carbon-neutral label in more than 90% of the observations after treatment.

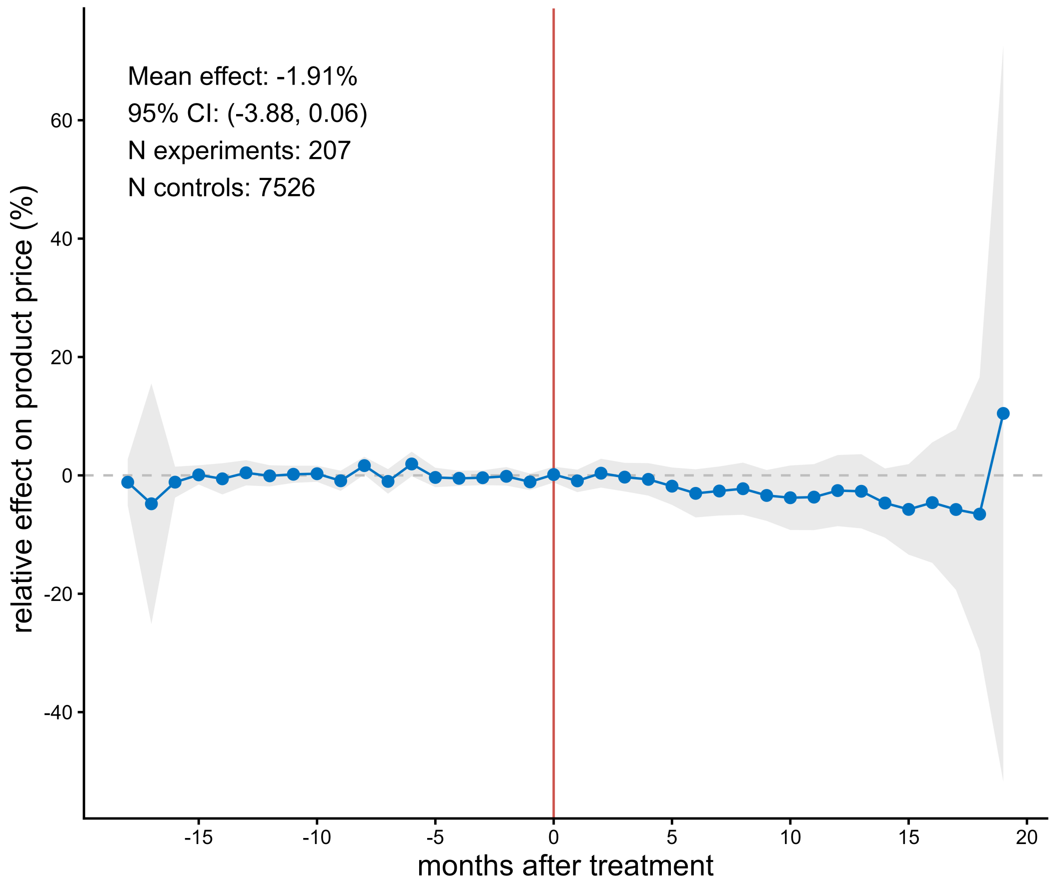

Figure 2: Effect of carbon-neutral label on products' price change (United States)

This plot shows the dynamic treatment effect in percentages relative to the product's price at baseline. Vertical red line marks treatment onset. The shaded area indicates a 95% confidence interval of the treatment effect based on 1,000 bootstrap samples that control for multiple hypothesis testing. The control variables include product categories and the product's initial price at the beginning of the panel.

Relaxing this condition does not affect our conclusions, as seen in Figure B.2 in Appendix B.6. The average treatment remains statistically insignificant.

Second, we estimate treatment effects using an unbalanced version of the panel without filling gaps in the scraping process by interpolating (or extrapolating). The corresponding robustness test is presented in Figure B.3, Appendix B.6. While this

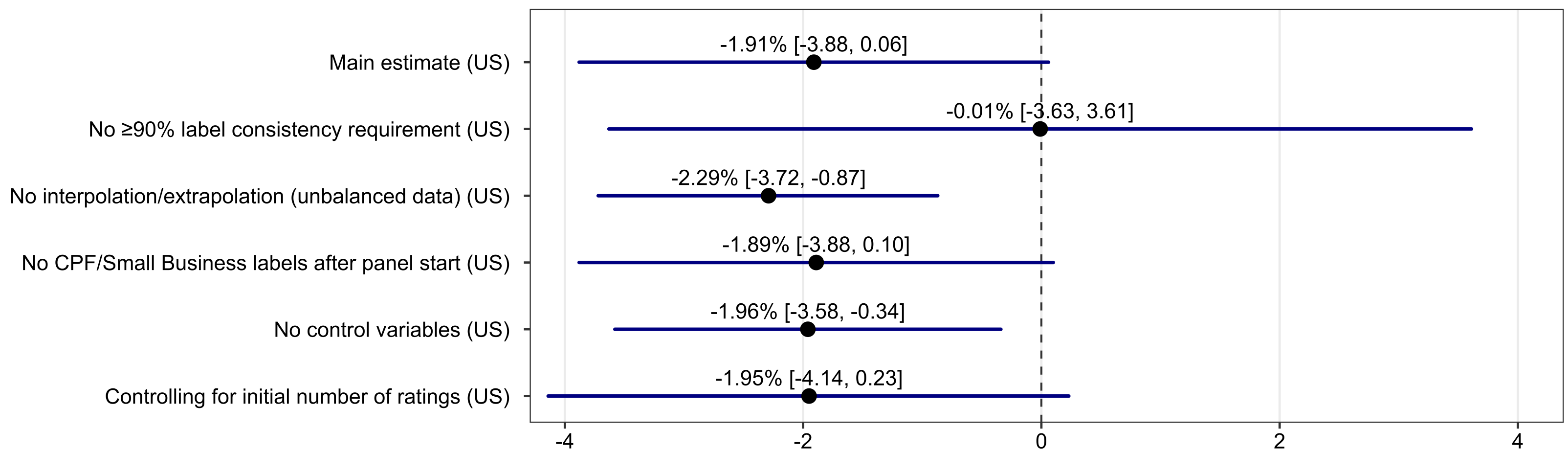

Figure 3: Summary of results for the average effect of the carbon-neutral label on product price changes (United States)

This figure summarizes (a) the main estimate and (b) robustness checks, detailed in Appendix B.6: (i) removing the 90% post-treatment consistency requirement for treated products; (ii) not filling missing points by interpolation and extrapolation and allowing an unbalanced panel; (iii) excluding the Climate Pledge Friendly labels (introduced after the panel started) and Small Business labels; and (iv) excluding control variables.

approach restricts the inclusion of control variables in the estimation, our conclusions remain again unchanged. The average treatment effects are, if anything, negative, also using unbalanced data and in the absence of control variables.

Third, since for our main analysis we only exclude the products with other Climate Pledge Friendly labels (e.g, organic, fair trade), which we detected at the beginning of our panels, we further detect and exclude from the analysis any products that received another label after March 2023, as well as those with a Small Business badge.[5] This approach results in 207 (the same number as the main analysis) treated products and 7,476 control products. Appendix B.6, Figure B.4 shows that once more, the effect of a carbon-neutral label is overall statistically non-significant.

Fourth, we examine the impact of removing control variables over the balanced panel. While the upper bound of the confidence interval is still close to zero, the effect of the carbon neutral label in this case is -1.96% of the baseline price (95% CI: [-3.58, -0.34]) and significant. The overall effect is close to that of the main estimation, as shown in Figure B.5 in Appendix B.6.

Fifth, we assess the effect of controlling for the initial number of product ratings, as a proxy for products' initial popularity (sales), alongside product categories and products' initial prices. Here too the treatment effect is undistinguishable from zero. The estimate is at -1.95% of products' baseline price [-4.14, 0.23], as shown in Figure B.6 in Appendix B.6.

Lastly, using the absolute price levels as the dependent variable in the hedonic analysis instead of the relative price change confirms that consumers tend not to value carbon neutrality. The average effect of a carbon-neutral label on the absolute product price over the 19-month observation period is -0.81 USD (95% CI: -1.81, 0.19),

[5] Amazon provides products with a Small Business badge if the producer has fewer than 100 employees and less than 50 million USD in annual revenue.

as shown in Figure B.7, Appendix B.6. This effect is also indistinguishable from zero. Overall, these robustness tests confirm that our main findings for the United States are not sensitive to the use of different specifications or sample restrictions.

We then continue our analyses by assessing whether consumers may value carbon neutrality in some specific subsamples of the data. We thus examine treatment effects, using the same outcome variable as in the main analysis, while taking the heterogeneity of products into account. We distinguish products along four dimensions: price ranges (within and above the range of prices in the meta-analysis), product categories, carbon-intensity groups, and certifiers. Our analyses confirm that consumers tend not to value carbon neutrality, not even for specific subsamples. We discuss the heterogeneity analysis in more detail and present the corresponding event-study plots in Appendix B.8.

Relatedly, we also examine heterogeneity in treatment timing. Given the staggered nature of treatment assignment, calendar effects (effects in specific calendar months) differ from dynamic effects (effects observed after certain months of treatment) and are estimated separately. As shown in Table B.10 in Appendix B.5, no specific pattern emerges from the calendar effects.

To provide a fuller picture, we also consider treatment effects on product sales, which we proxy by the number of ratings. When doing so, we also find a non-significant effect, although the point estimate is positive, at 1560 ratings (95% CI: -5, 3126), as shown in Figure B.8 in Appendix B.6. That is, there is a hint of increased popularity of carbon-neutral products on Amazon, at the same time that we provide consistent evidence that consumers do not care about their climate-friendly properties and do not seem to value them. The fact that based on our proxy there is some indication of movement around sales in this market may suggest that relying on prices only, as is usually done in the non-market valuation literature, could potentially mask some effects that may contribute to explain the adoption of labels.

To provide additional evidence concerning whether consumers value carbon neutrality, we move beyond American consumers shopping on Amazon in the United States. In particular, we examine evidence from two more countries, the United Kingdom and Germany, where we perform the same analyses using as outcome variables products' price change relative to their baseline price as well as the number of ratings. We provide a concise summary here and present the event-study plots in Appendix B.7.

Figure B.9 in Appendix B.7 presents the main results for the United Kingdom. It shows the dynamic effects of receiving a carbon-neutral label on the price change of the product relative to its initial price. Here too, pre-treatment estimates are not statistically significant, although with fewer observations from which to derive inference, the time series tends to be a bit more volatile than as observed with data for the United States. In terms of treatment effects, the average effect of a carbon-neutral label over the five-month observation period is again indistinguishable from zero. The point estimate is slightly positive, but small at 2.98% (95% CI: -5.89, 11.84). Here too, we observe that consumers do not tend to value carbon neutrality. Accordingly, we return to the analysis of customer reviews, this time analyzing reviews by customers shopping on Amazon in the United Kingdom. Once more, we find that mentions of carbon neutrality and similar keywords are negligible, in isolation as well as when summing over keywords, as shown in Table B.12 in Appendix B.9. Hence, it seems that also in the United Kingdom, consumers do not really value carbon neutrality.

As just described, the effect of carbon-neutral labels on prices is indistinguishable from zero also in the United Kingdom. However, there may be readers still interested in how to interpret this point estimate as well. The effect of a carbon-neutral label on product price translates to GBP 0.69, given that the average initial price of treated products is GBP 23.3. This corresponds to 0.33 GBP per kg of reduced CO_2 emissions, given that the average CO_2 emissions of treated products is 2.1 kg (based on 49 out of 50 products with available carbon footprint information). If taken at face value, this effect would be substantial, albeit still considerably lower than observed in the meta-analysis. However, the effect is statistically indistinguishable from zero, and so is 0.33 GBP per 1 kg of reduced CO_2 emissions. Recall also that reviews do not provide any indication that consumers in the United Kingdom would value carbon neutrality.

We now turn to product sales for the United Kingdom. In this case, the average treatment effect on our proxy of product sales, the number of ratings a product receives, is negative and statistically insignificant. We find an average effect of -612 ratings (95% CI: -1346, 122), as shown in Figure B.10 in Appendix B.7.

Next, we turn to Amazon's German marketplace. We start again with product prices and use an event analysis to test pre-trends and estimate treatment effects. We do so in Figure B.11 in Appendix B.7. Similarly to the case of the United States, pre-trends are flat and confidence intervals tight, confirming the validity of our approach. In terms of treatment effects, the average effect of a carbon-neutral label over the five-month observation period is undistinguishable from zero here too. The point estimate is -11.42% (95% CI: -32.25, 9.4), but standard errors are wide. Also for Germany, we examine customer reviews. Here too, we find that mentions of carbon neutrality and similar keywords are negligible, in isolation as well as when summing over keywords, as shown in Table B.13 in Appendix B.9. Hence, it seems that also in Germany, consumers do not really value carbon neutrality.

As just described, the effect of carbon-neutral labels on prices is indistinguishable from zero also in Germany. In terms of point estimate, though, the effect of a carbon-neutral label on product price translates to EUR -2.49 in absolute terms, given the average initial price of treated products of EUR 21.8. This corresponds to EUR -0.45 per kg of reduced CO_2 emissions, based on the average CO_2 emissions of 5.48 kg of treated products (based on 76 out of 84 products with available carbon footprint information).

Also for Germany, we estimate treatment effects on the number of ratings as a proxy for product sales. Once again, we find a non-statistically significant effect. The point estimate is 145 ratings (95% CI: -680, 970), as shown in Figure B.12 in Appendix B.7.

Based on the hedonic approach, we conclude that there is little evidence to support the notion that consumers value carbon neutrality. This statement follows from the analysis of product prices, product sales, and customer reviews across three major markets, the United States, the United Kingdom, and Germany. The substantial WTP found in the meta-analysis, even exceeding many estimates of the social cost of carbon, do not find support when looking at a popular marketplace such as Amazon's.

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 have increasingly become available, they still remain a niche market. Companies that made carbon-neutral products available often did so in response to broader efforts to decarbonize their operations, generally in response to expectations of future policy tightening as reflected in investors' pressure.

In this paper, we analyze the demand for carbon-neutral products empirically. Our approach is twofold. First, we implement a meta-analysis of existing studies in the literature assessing the demand for carbon-neutral and low-carbon products. Second, we focus on online marketplaces in three different countries (United States, United Kingdom, and Germany) and their staggered introduction of carbon-neutral certified products to causally estimate the effect of carbon-neutral labels on product prices. To shed more light on whether consumers value carbon neutrality, we also examine the content of thousands of customer reviews.

The results of the meta-analysis indicate a large, positive WTP for carbon-neutral labeled products and products with lower emissions (1.99 USD per kilogram of CO_2 reduction), implying that the WTP for climate-friendly 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, which are mainly based on stated preference studies and controlled environments, point to a strong demand for carbon-neutral products among potential consumers, the hedonic analysis of actual market data does not support this finding. Across the three markets, covering two continents, we find no evidence of demand for carbon neutrality. That is, our analyses of data from actual marketplaces do not lend support to the notion that consumers value carbon neutrality. Consistently, in customer reviews the fraction of customers that refers to the climate-friendly nature of carbon-neutral products is minuscule.

Hence, the hedonic analysis of consumer demand for carbon-neutral products suggests that, based on actual market data, the potential of carbon-neutral labeling for climate change mitigation is to be considered with caution, in contrast with the current state of the literature valuing carbon-neutral and low-carbon products and their labels, as summarized in our meta-analysis. Future research may investigate under which circumstances shoppers may start to pay attention to carbon-neutral products, depending on the salience of their climate-friendly nature or the social observability of the pro-social behavior of purchasing them. Future research may also provide more evidence from observational studies in different contexts, thus contributing to more variety in the literature that examines the question of whether consumers value carbon-neutral products.

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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, specifically 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 do not focus on studies that value environmental or social responsibility attributes, such as energy efficiency, fair trade, organic, and reduced water footprint, unless they also value climate labels.

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, CO_2 offsetting, or CO_2 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 providing information that would allow us to derive the amount of CO_2 reduction associated with the label. In addition, we exclude 6 studies that focus on reduced transportation distance unless the study values the carbon footprint of the product (from its production, distribution, or overall lifecycle) and just "frames" it in terms of distance traveled by car, for example, to make it easier for consumers to gauge the amount of CO_2 emissions. 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 a 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 these exclusions, our final dataset consists of 37 studies and 126 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. (2024)
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 meta-analysis. 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 emission-related 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 CO_2 reduction.

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

Study	**No. obs.**[a]	**Product**	**Country**	**Method**[b]	**Information provided to participants**[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 and Akai (2022)	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)	4	Chicken	Belgium	DCE	Carbon footprint from transportation
Carlsson et al. (2022)	6	Lasagne	Sweden	DCE	GHG emission categories
Cerroni et al. (2019a) & Cerroni 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**	**Information provided to participants**
Chaiyesh (2022)	2	Rice	Thailand	DCE	Percentage of carbon reduction
Chen et al. (2018)	2	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
Grebitus et al. (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	Climate-friendly label and annual GHG emission reduction in percentages
Li et al. (2018)	2	Beef, ground beef	United States	DCE	Climate-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	Information provided to participants
Mōerbeck (2022)	10	Apples, beef, butter, cheese, chicken, eggs, flour, milk, rice, tomatoes	Germany	CV	Carbon neutrality
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 CO_2 reduction from each study in Table A.4.

We define four WTP measures, derived for all 37 studies and 126 observations: WTP_R, WTP_{kg}, WTP_{CN}, and $WTP_{CN\%}$. The definition and derivation procedure for each WTP measure are provided in Section 2.1.

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

1. For the purpose of this study, WTP for various forms of CO_2 mitigation, such as CO_2 offsetting, CO_2 reductions, and CO_2 capture, is treated as equivalent. Whenever the term "CO_2 reduction" is used throughout this study, it refers to any of these concepts.

2. If a study reports WTP for a specific amount of CO_2 reduction associated with a product, we use that value directly. If the amount of CO_2 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 CO_2 reduction variable.

3. To enable consistent comparisons across WTP estimates, we adjust all observations to represent only the WTP for CO_2 reduction, excluding the product's

price. Such WTP measure represents the marginal WTP for climate impact attribute valued in the studies. However, for the purpose of our analysis, we do not distinguish between mean and median marginal WTP 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” only, we subtract the estimated mean WTP for the unlabeled product to obtain the marginal WTP 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. We include carbon footprint labels in our database only if they enable us to calculate the associated CO_2 reduction. If a study provides a WTP estimate for a carbon footprint label with constant baseline product CO_2 emissions (i.e., without variation such as low and high levels), we classify it as “carbon transparent” and exclude it from our database. Conversely, when a study allows us to derive WTP estimates for carbon footprint labels with varying baseline product CO_2 emissions (i.e., including low and high levels), we apply the following approaches. For two levels, the WTP estimate is derived from the difference between the WTP values reported for the low and high carbon footprint levels. For three levels, we derive three separate WTP estimates based on the differences between the WTP values for the low-mid, mid-high, and low-high carbon footprint levels.

5. We first compute marginal WTP for the climate-impact attribute valued in the

original study (e.g., carbon-footprint information or a carbon-neutral label); this serves as the basis for deriving WTP for CO_2 emission reductions. 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 β_{cost} and β_{climate} be the coefficients for price and the product's climate impact attribute, respectively. Marginal WTP for the climate impact attribute is derived using the following equation:

$$\text{Marginal WTP} = -\frac{\beta_{\text{climate}}}{\beta_{\text{cost}}}$$

Note that we do not derive a WTP estimate from the choice model in the following cases: if both the cost and climate parameters are specified as random terms; 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 that are used in the regressions; otherwise, we take them as they are.

7. All monetary variables, including WTP estimates, price of product and GDP per capita, 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 CO_2 reduction" in kilograms. In cases where the study does not specify the baseline CO_2 emissions of products, which is necessary to calculate the corresponding amount of CO_2 emission reduction, as it is sometimes the case for food and drink products, we, as mentioned, use online food/drink carbon calculators, specifically, My Emissions 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, a company that makes water-filtration products. Note that if the study does not specify the amount of CO_2 emission reduction, we have a control (dummy) variable for such observations, 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 this information is also unavailable 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 cases 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, an agricultural produce marketplace, 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 on a value of 1 for observations derived from CV and DCE methods, 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 "publication" takes the value of 1 for published studies, and 0 for working papers, conference proceedings, or theses.

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.

"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 the value of 1 for studies conducted in Europe and 0 for those conducted in Africa, the Americas, or Asia.

"CO_2 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 Table A.4.

"WTP derivation" variable takes the value of 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.

We also include two additional variables in the robustness tests: "colored labels" and "carbon-neutral labels." "Colored label" variable takes the value of 1 if colors are used to differentiate the CO_2 intensity of the valued product. "Carbon-neutral label" variable takes the value of 1 for carbon-neutral certifications and 0 for carbon reduction and carbon footprint certifications.

Finally, the "product CO_2 emissions" variable, which is measured in kilograms, indicates the CO_2 emissions produced during the production or life-cycle of the product. This variable is not included in the meta-regressions but used for calculating $\mathrm{WTP}_{\mathrm{CN}}$ and $\mathrm{WTP}_{\mathrm{CN\%}}$ and plotting their distributions.

We initially collected 37 studies and 224 observations. We then aggregate observations that remained constant across studies, product categories, and the aforementioned independent variables that are used in the last column of Table 1 in Section 3.1. Detailed explanations of WTP derivation and aggregations per study are provided in Table A.4. Consequently, our final dataset comprises 37 studies and 126 observations.

There are two instances, as described below, where we use a different aggregation rule. Firstly, before we test publication bias, we aggregate observations at the sample level (identified by equal n and the same country within each study), yielding 52 observations from 37 studies, as multiple estimates can originate from the same underlying sample.

Secondly, while we use the full sample for our main analyses, we also construct a subset of observations with available standard errors for plotting WTP estimates and their standard errors, as in Figures A.9 and A.10. This subset is restricted to observations with reported or derivable standard errors. When p-values or confidence intervals are available, we derive standard errors accordingly; if a reported p-value equals zero, the standard error cannot be recovered. For the standard-error subset, we do not aggregate observations because doing so would require covariances between estimates; instead, we randomly select one observation per covariate-constant group. A study may still report multiple samples; thus, this subset contains 49 observations from 15 studies. All standard errors are scaled by the same factor used to standardize the WTP measures: $\mathrm{WTP}_{\mathrm{R}}$, $\mathrm{WTP}_{\mathrm{kg}}$, $\mathrm{WTP}_{\mathrm{CN}}$, and $\mathrm{WTP}_{\mathrm{CN\%}}$.

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 100 g 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 climate friendly (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 climate 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 (≈ 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.
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.

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

Study	Details
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.
Owusu-Sekyere et al. (2019)	The WTP estimates for high GHG emissions (27.50 kg) and medium GHG emissions (26.37 kg) with respect to low GHG emissions (22.90 kg), measured in carbon equivalents, are reported in the study (Table 8). Hence, the WTP for medium relative to high GHG emissions corresponds to a 1.13 kg GHG reduction (27.50 - 26.37) in carbon equivalents, and the WTP for low relative to high GHG emissions corresponds to a 4.6 kg GHG reduction (27.50 - 22.90) in carbon equivalents.

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

Study	Details
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 for organic eggs 0.17 kg, 0.34 kg, and 0.51 kg. Note that we average the WTP estimates for four types of eggs.
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 liters 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 of rice (0.68 kg) is obtained from the myEmissions calculator. We use this information to calculate the respective carbon emission reduction (0.26 kg).

A.2 Descriptive statistics and supplementary material

This section includes the main descriptive statistics for the sample used for the meta-analysis and supplementary material. Table A.5 shows the summary statistics of the (unweighted) sample of 126 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). Table A.7 shows the mean WTP estimates for each product category, while Table A.8 displays the mean of study-specific mean WTP estimates, along with their respective number of observations.

Figures A.6, A.7, and A.8 display the histograms of various WTP measures: WTP_{R}, WTP_{kg}, WTP_{CN}, and $WTP_{CN\%}$, respectively, both with and without outliers. Table A.9 reports the mean and 95% confidence intervals for these WTP measures, based on percentile bootstrap with 10,000,000 samples.

Figures A.2–A.5 show WTP estimates by product category. Figures A.9 and A.10 illustrate WTP estimates and their respective standard errors. Because a logarithmic axis is used, negative observations are excluded and documented in the tables' notes.

Figures A.11 and A.12 show the relationship of WTP measures with CO_2 emission reduction levels and baseline product CO_2 emissions, while Figure A.13 shows residuals versus fitted values from the main model (OLS III) shown in Table 1 in Section 3.1. The results of the Breusch-Pagan test for heteroskedasticity are reported in Table A.10.

	N	Mean	Std. Dev.	Min	Max
WTP_R (USD)	126	1.18	1.59	-0.09	9.06
WTP_{kg} (USD)	126	4.34	9.26	-1.38	45.28
WTP_{CN} (USD)	126	10.66	38.84	-0.13	311.56
$WTP_{CN\%}$ (%)	126	168.72	360.28	-10.94	1874.74
CO_2 reduction (kg)	126	2.56	5.88	0.00	39.43
Product CO_2 emissions (kg)	126	5.34	9.63	0.02	43.33
Carbon neutral label	126	0.13	0.33	0.00	1.00
Colored label	126	0.14	0.34	0.00	1.00
Price (USD)	126	4.28	4.92	0.09	22.15
Stated pref. method	126	0.95	0.21	0.00	1.00
In-person	126	0.21	0.41	0.00	1.00
Sample size	126	549	609	19	3085
Publication	126	0.81	0.39	0.00	1.00
Study year	126	2015	4.22	2008	2021
GDP per capita (100 USD)	126	427.37	166.69	5.84	935.47
Europe	126	0.68	0.47	0.00	1.00
CO_2 reduction assump.	126	0.56	0.50	0.00	1.00
WTP derivation	126	0.42	0.50	0.00	1.00

Table A.5: Summary statistics: unweighted sample

This table displays the number of observations (N), and the summary statistics of the variables. Standard deviations are provided in parentheses. The WTP_R denotes (unstandardized) WTP for CO_2 reductions. WTP_{kg} is the WTP for 1 kg CO_2 reduction, WTP_{CN} is the 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_R (USD)	37	1.30	1.43	0.00	6.85
WTP_{kg} (USD)	37	1.99	3.94	0.02	23.73
WTP_{CN} (USD)	37	15.01	49.18	0.00	296.92
$WTP_{CN\%}$ (%)	37	251.71	464.05	0.06	1786.64
CO_2 reduction (kg)	37	3.66	7.65	0.00	39.43
Product CO_2 emissions (kg)	37	7.41	11.80	0.04	43.33
Carbon neutral label	37	0.16	0.37	0.00	1.00
Colored label	37	0.12	0.29	0.00	1.00
Price (USD)	37	4.82	4.80	0.09	22.15
Stated pref. method	37	0.90	0.28	0.00	1.00
In-person	37	0.33	0.47	0.00	1.00
Sample size	37	574	652	19	3085
Publication	37	0.81	0.40	0.00	1.00
Study year	37	2015	3.77	2008	2021
GDP per capita (100 USD)	37	407.84	182.90	5.84	935.47
Europe	37	0.64	0.48	0.00	1.00
CO_2 reduction assump.	37	0.62	0.49	0.00	1.00
WTP derivation	37	0.38	0.48	0.00	1.00

Table A.6: Summary statistics: study means

This table displays the number of observations (N), and the summary statistics of the study means. Standard deviations are provided in parentheses. The WTP_R denotes (un-standardized) WTP for CO_2 reductions. WTP_{kg} is the WTP for 1 kg CO_2 reduction, WTP_{CN} is the 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_R (USD)	WTP_{kg} (USD)	WTP_{CN} (USD)	$WTP_{CN\%}$ (%)
Dairy & eggs	21	1.43 (0.46)	0.82 (0.96)	2.19 (2.99)	1.28 (1.64)	60.24 (55.00)
Fruits & vegetables	18	2.35 (2.36)	0.30 (0.42)	1.29 (1.87)	1.38 (2.66)	142.89 (246.63)
Meat	47	11.96 (13.27)	2.14 (2.14)	1.31 (1.95)	26.60 (60.64)	313.50 (489.23)
Non-food	5	1.12 (0.79)	0.80 (0.48)	1.54 (1.51)	0.76 (0.46)	337.13 (692.36)
Oil & grain	10	2.31 (2.44)	0.58 (0.54)	1.35 (2.02)	2.37 (3.99)	65.29 (103.91)
Snacks	12	0.07 (0.00)	0.33 (0.25)	21.94 (13.99)	0.02 (0.02)	2.03 (1.67)
Water & drinks	13	0.69 (0.68)	0.89 (0.77)	10.14 (16.16)	1.03 (1.64)	24.96 (30.28)

Table A.7: Mean 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 the studies. WTP_R denotes (non-standardized) WTP for CO_2 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_R (USD)	WTP_{kg} (USD)	WTP_{CN} (USD)	$WTP_{CN\%}$ (%)
Dairy & eggs	6	1.39 (0.46)	0.71 (0.63)	1.07 (1.34)	0.93 (0.75)	51.73 (30.86)
Fruits & vegetables	7	2.77 (2.98)	0.43 (0.49)	1.33 (1.76)	2.24 (3.24)	200.75 (297.28)
Meat	17	15.18 (15.04)	2.09 (1.97)	1.27 (1.60)	31.10 (70.26)	359.79 (549.37)
Non-food	3	1.34 (0.99)	0.77 (0.37)	1.34 (1.60)	0.88 (0.53)	543.45 (893.59)
Oil & grain	6	2.10 (2.41)	0.57 (0.49)	1.61 (2.11)	2.14 (3.77)	60.62 (97.33)
Snacks	1	0.07 (0.00)	0.33 (0.00)	21.94 (0.00)	0.02 (0.00)	2.03 (0.00)
Water & drinks	7	0.92 (0.77)	1.13 (0.84)	5.33 (10.51)	1.55 (2.07)	40.11 (34.74)

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

This table 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_R 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

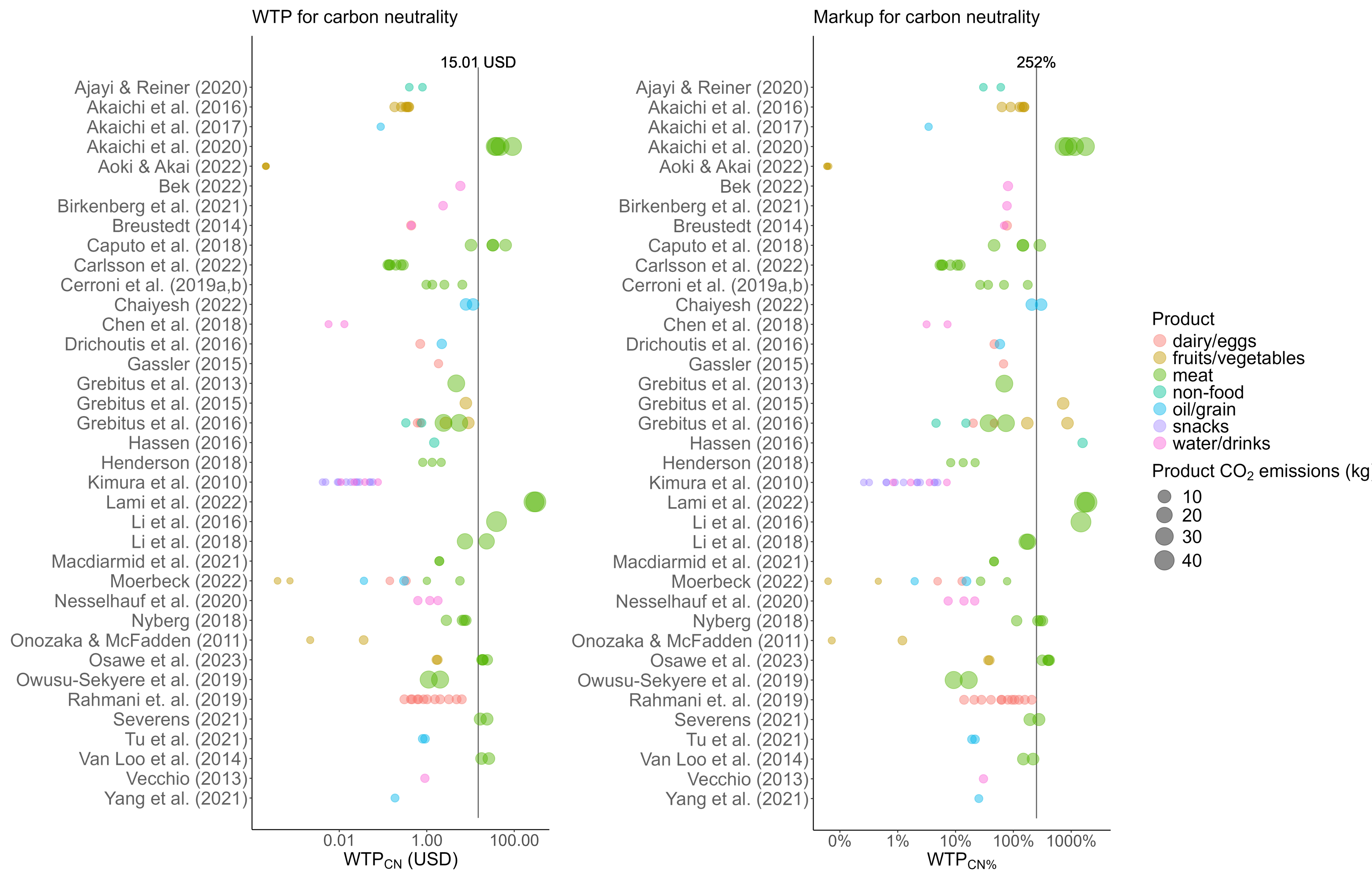


Figure A.1: WTP for carbon neutrality across studies

A logarithmic x-axis (base 10) is used to create this figure. The left graph displays WTP_{CN} (WTP for carbon neutrality), The right graph displays $WTP_{CN\%}$, which is the proportion of the product's price that consumers would be willing to pay extra for carbon neutrality.

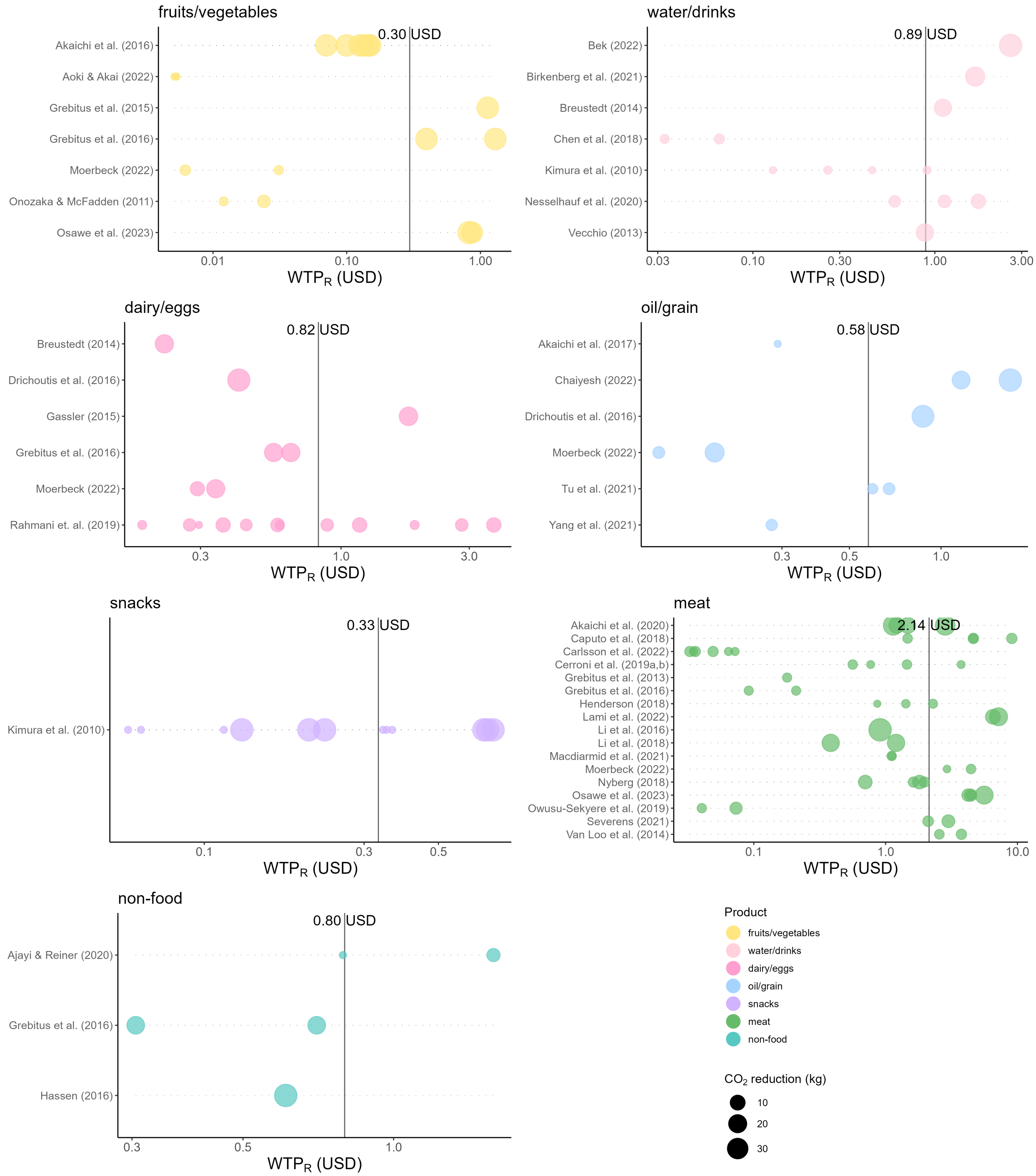


Figure A.2: WTP for carbon reductions (WTP_R) by product category

A logarithmic axis (base 10) is used. Vertical lines show the mean of the study means. Panels by product category display the non-standardized measure; WTP_R denotes the non-standardized willingness to pay for carbon reductions. Circle size represents the amount of CO_2 emission reduction (kg).

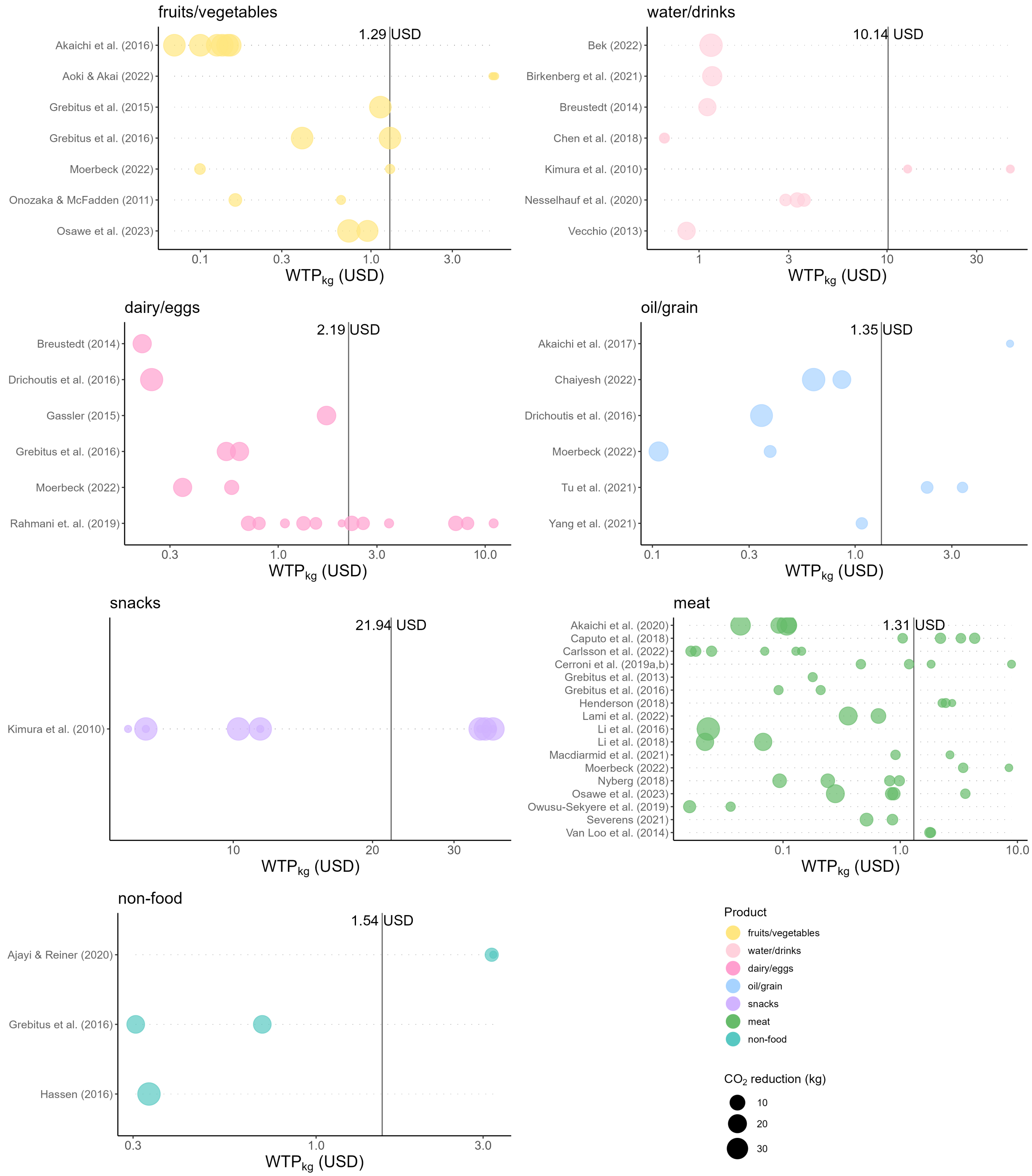


Figure A.3: WTP for reducing emissions by 1 kg (WTP_{kg}) by product category

A logarithmic axis (base 10) is used. Vertical lines show the mean of the study means. Panels by product category display WTP_{kg}, which denotes WTP per 1 kg carbon reduction. Circle size represents the amount of CO_2 emission reduction (kg).

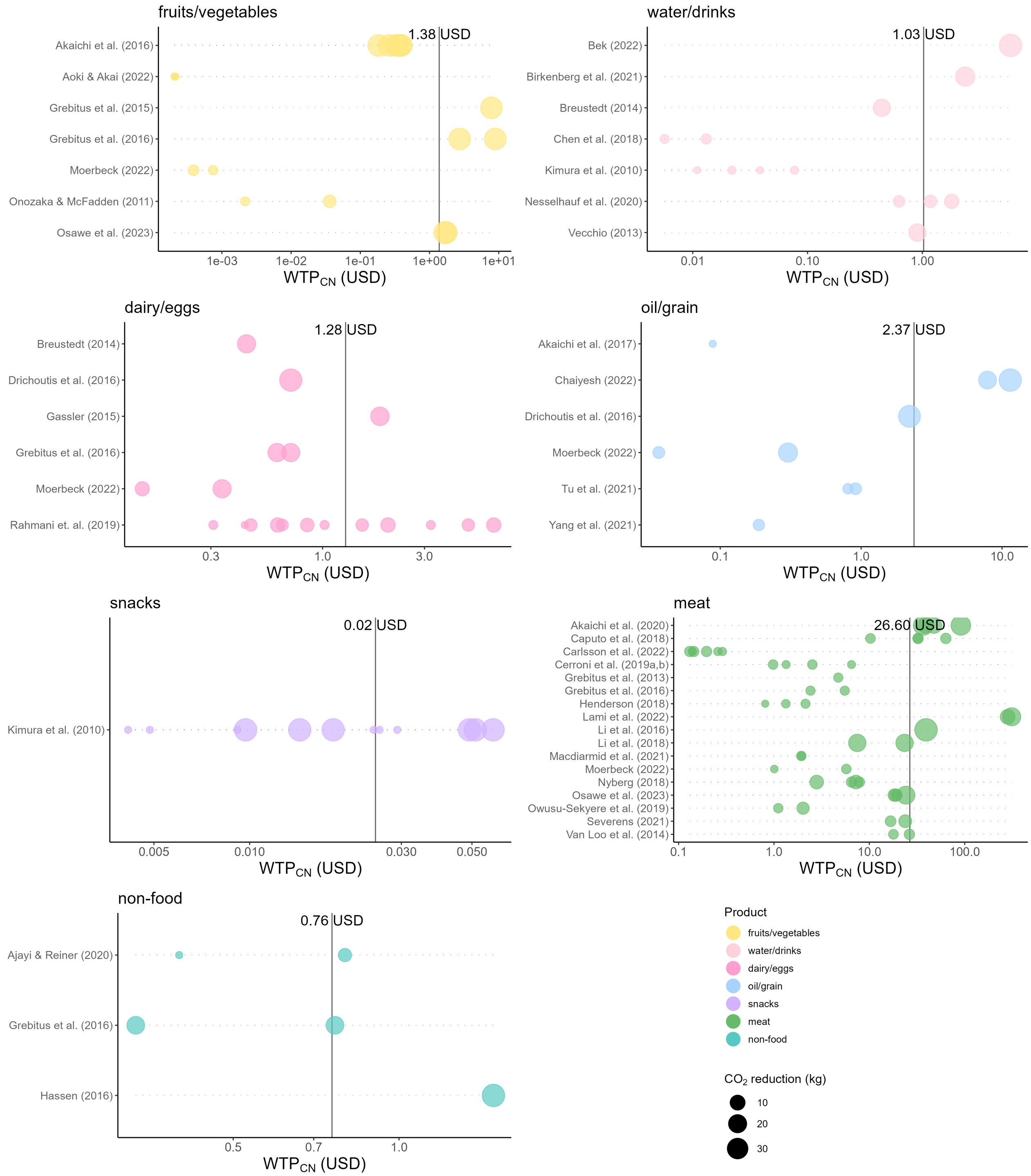


Figure A.4: WTP for carbon neutrality (WTP_{CN}) by product category

A logarithmic axis (base 10) is used. Vertical lines show the mean of the study means. Panels by product category display WTP_{CN}, which denotes WTP for carbon neutrality. Circle size represents the amount of CO_2 emission reduction (kg).

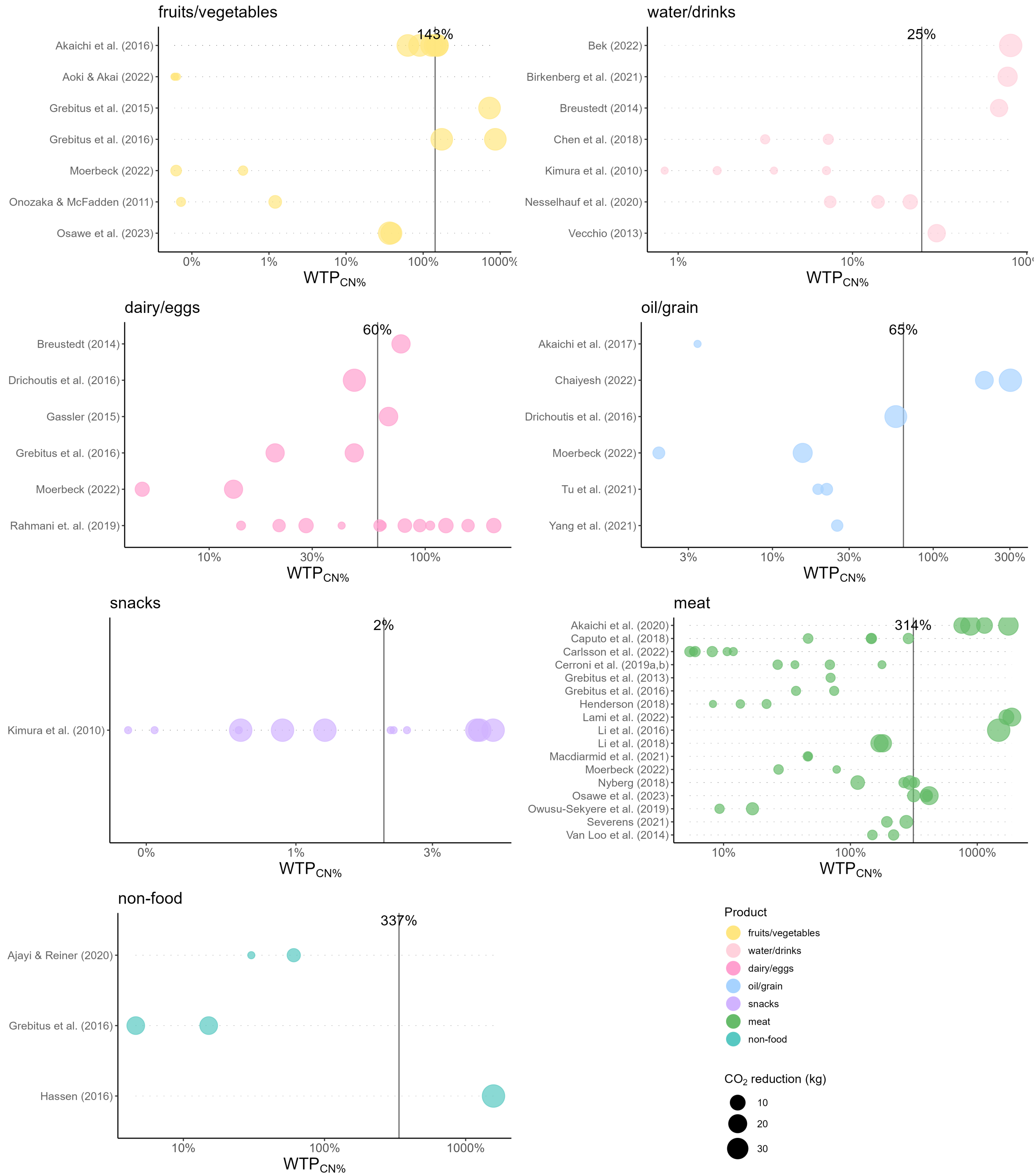


Figure A.5: Markup for carbon neutrality ($WTP_{CN\%}$) by product category

A logarithmic axis (base 10) is used. Vertical lines show the mean of the study means. Panels by product category display $WTP_{CN\%}$, which denotes the proportion of a product's price that consumers would be willing to pay extra for carbon neutrality. Circle size represents the amount of CO_2 emission reduction (kg).

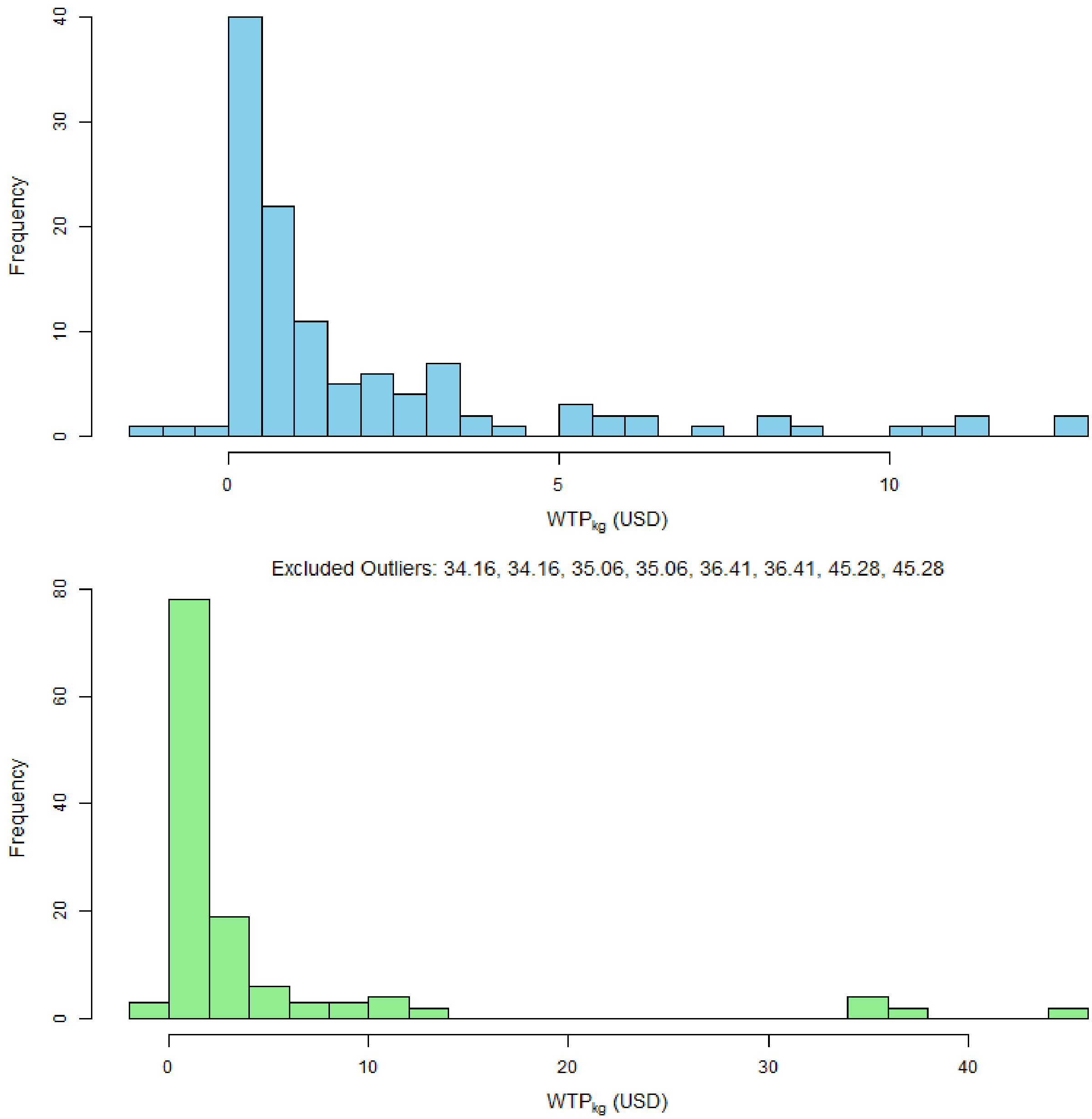
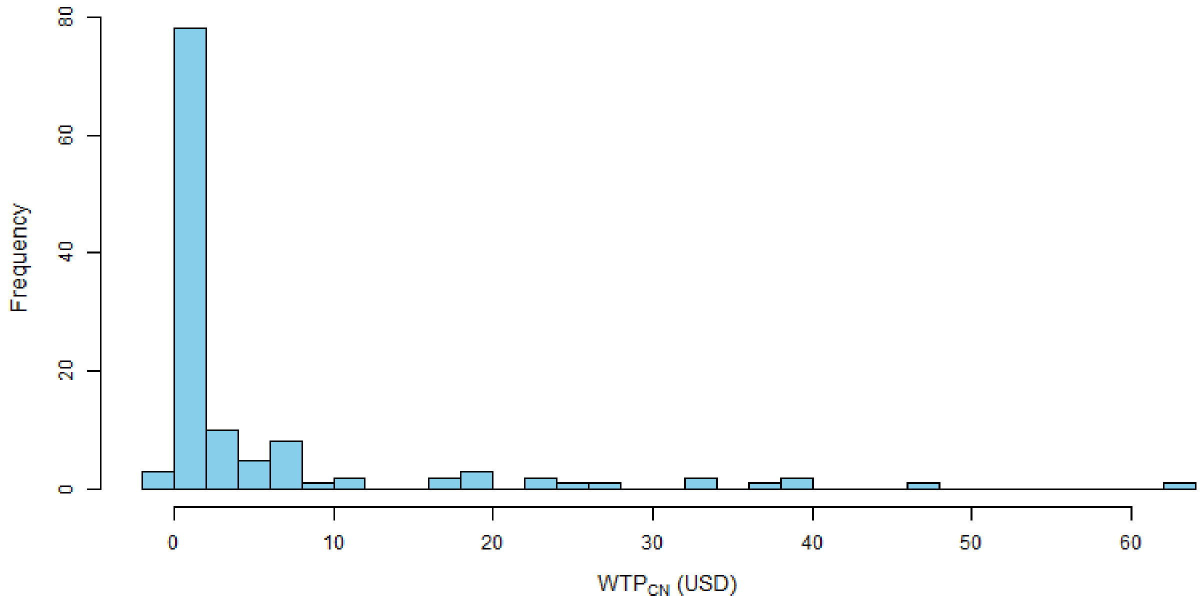


Figure A.6: WTP for 1 kg carbon reduction (WTP$_{\text{kg}}$)

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.



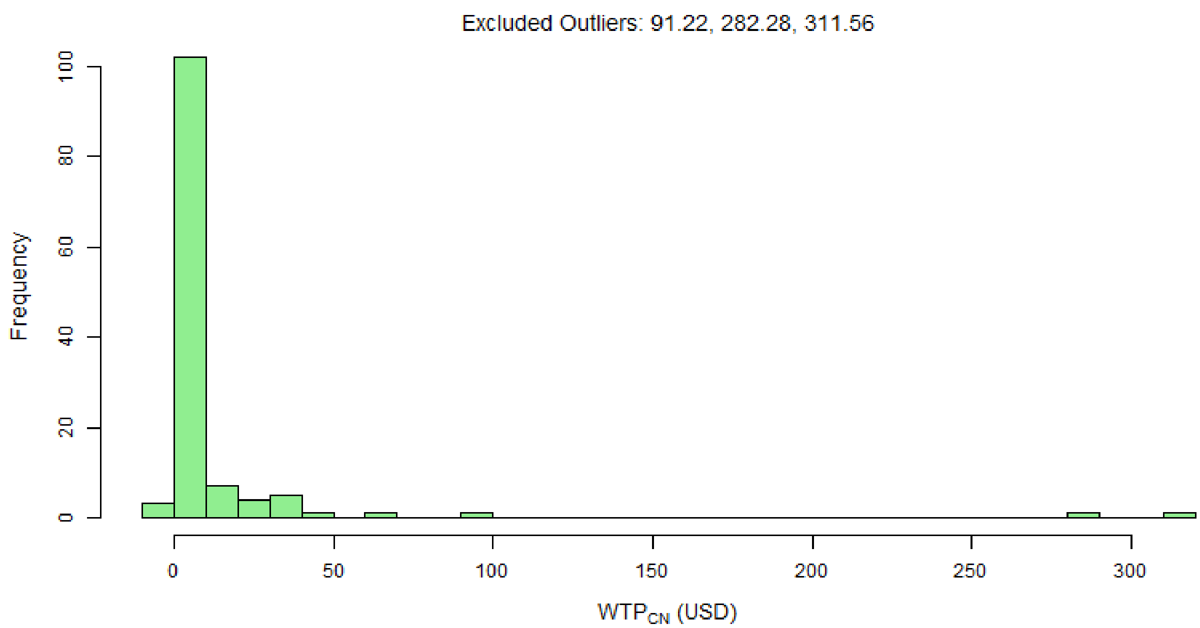
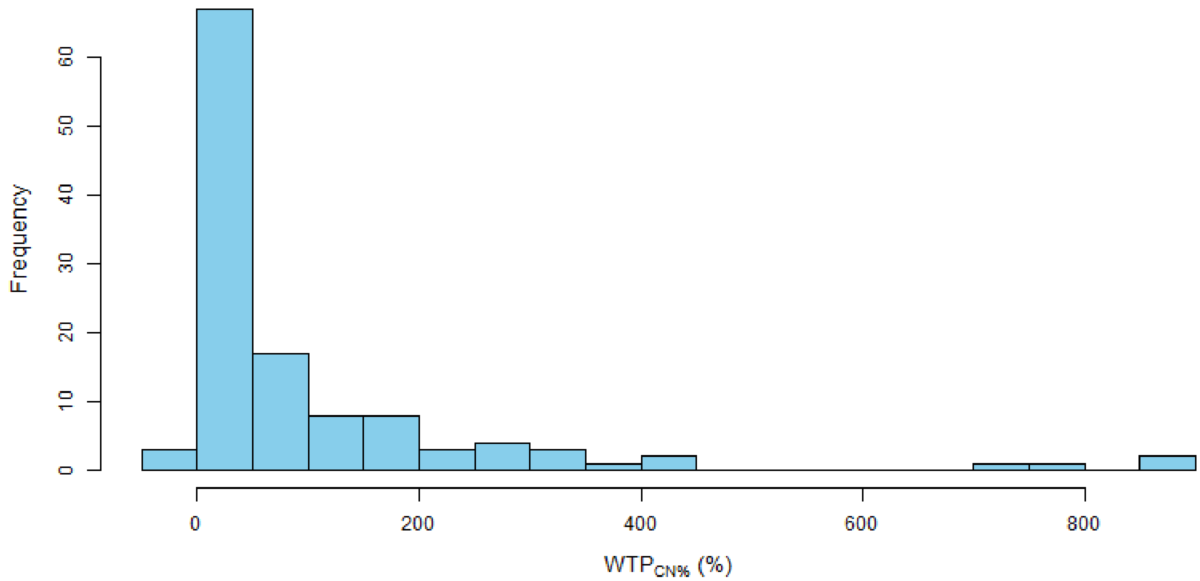


Figure A.7: WTP for carbon neutrality (WTP_{CN})

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.



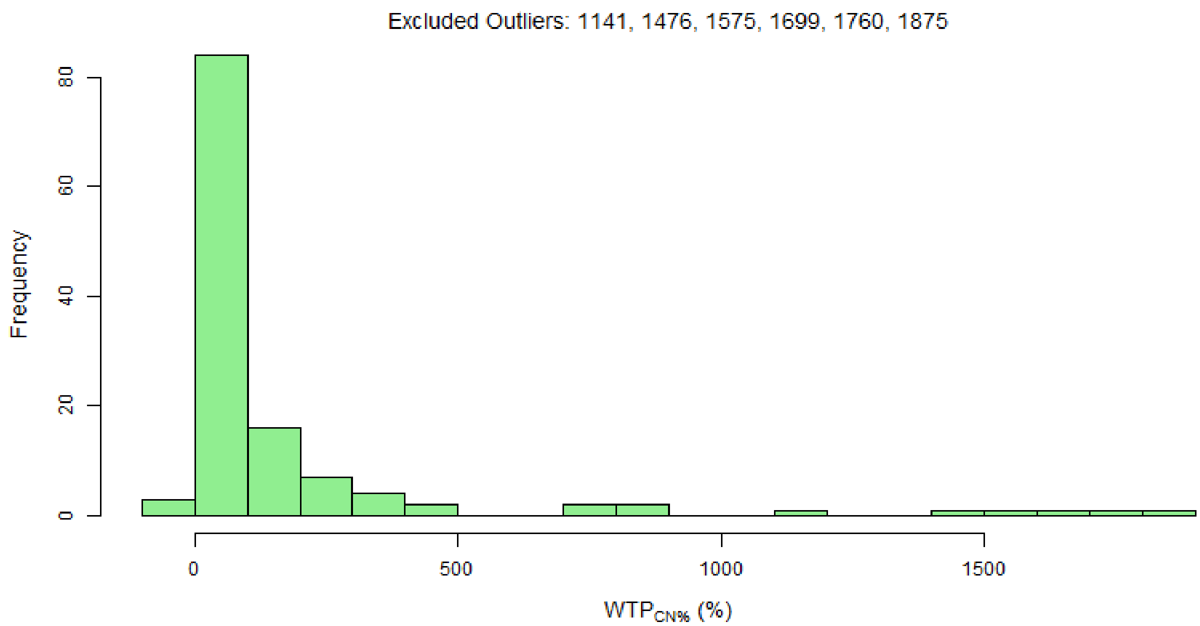


Figure A.8: The proportion of a product's price that consumers would be willing to pay extra for carbon neutrality (WTP$_{CN\%}$)

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.

Measure	Mean	95% Confidence Interval
WTP_R (USD)	1.30	[0.89, 1.79]
WTP_{kg} (USD)	1.99	[1.06, 3.45]
WTP_{CN} (USD)	15.01	[4.35, 32.91]
$WTP_{CN\%}$ (%)	251.71	[119.02, 412.26]

Table A.9: WTP estimates and 95% confidence intervals

95% confidence intervals are computed using the percentile bootstrap with $10,000,000$ resamples. The mean of WTP estimates for the full sample of 37 studies is obtained by averaging the study-specific WTP estimates and bootstrapping. The non-standardized measure WTP_R 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.

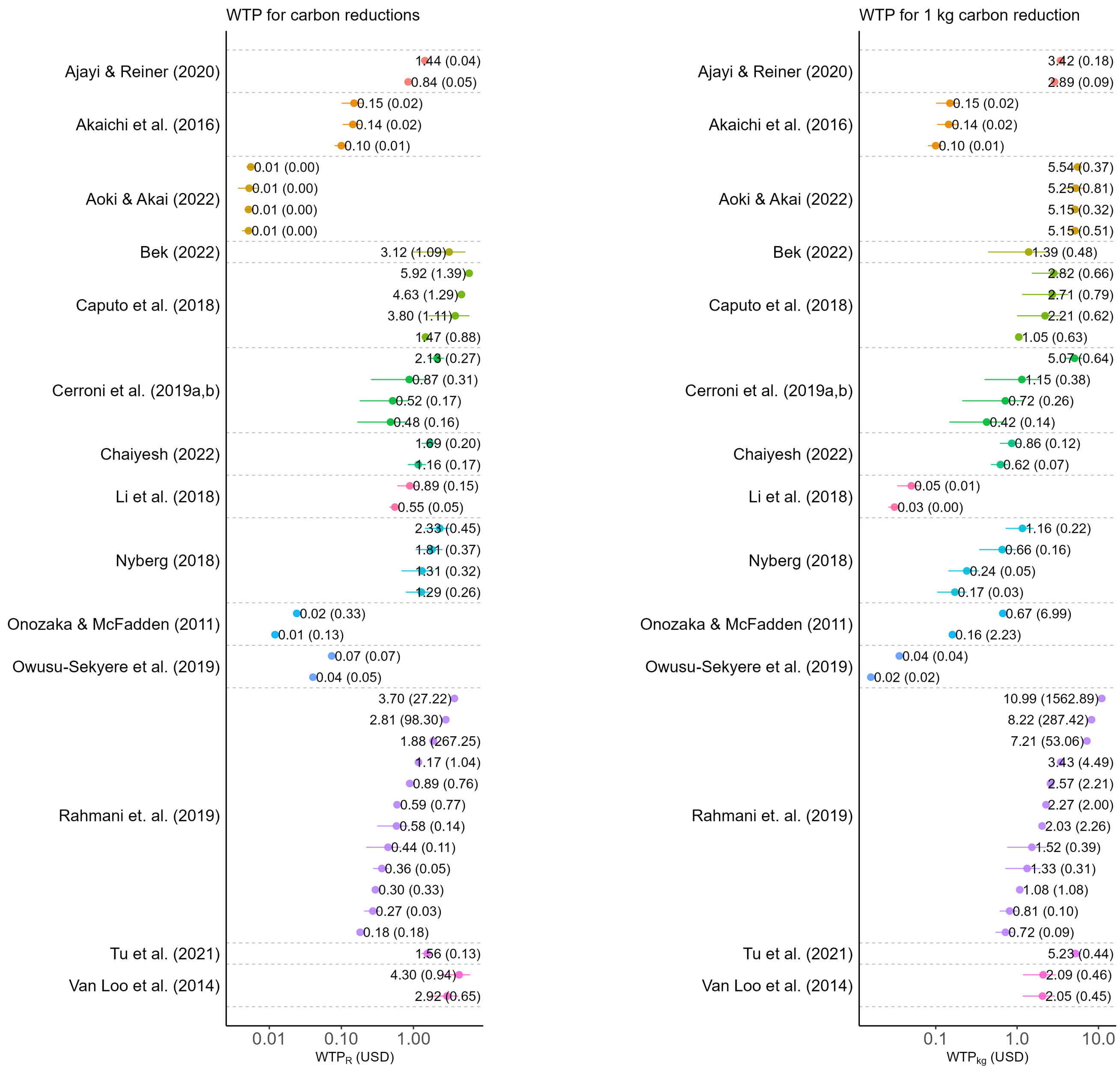


Figure A.9: WTP$_\mathrm{R}$ and WTP$_\mathrm{kg}$ with corresponding standard errors by studies

Observations with negative WTP were excluded from this figure due to the logarithmic (base 10) x-axis. Excluded observations are based on the following studies: Macdiarmid et al. (2021): $WTP_R = -0.28$ (SE = 0.28), -0.01 (SE = 0.22); $WTP_{kg} = -0.66$ (SE = 0.67), -0.01 (SE = 0.18). Tu et al. (2021): $WTP_R = -0.45$ (SE = 0.11), -0.27 (SE = 0.11); $WTP_{kg} = -3.95$ (SE = 1.67), -2.54 (SE = 0.64). The left graph displays WTP$_\mathrm{R}$ (non-standardized WTP for CO_2 reductions) across studies. The right-hand graph shows WTP$_\mathrm{kg}$ (WTP for 1 kg CO_2 reduction), which is calculated by dividing WTP$_\mathrm{R}$ by the amount of CO_2 reduction. Both WTP$_\mathrm{R}$ and WTP$_\mathrm{kg}$ are measured in 2020 USD.

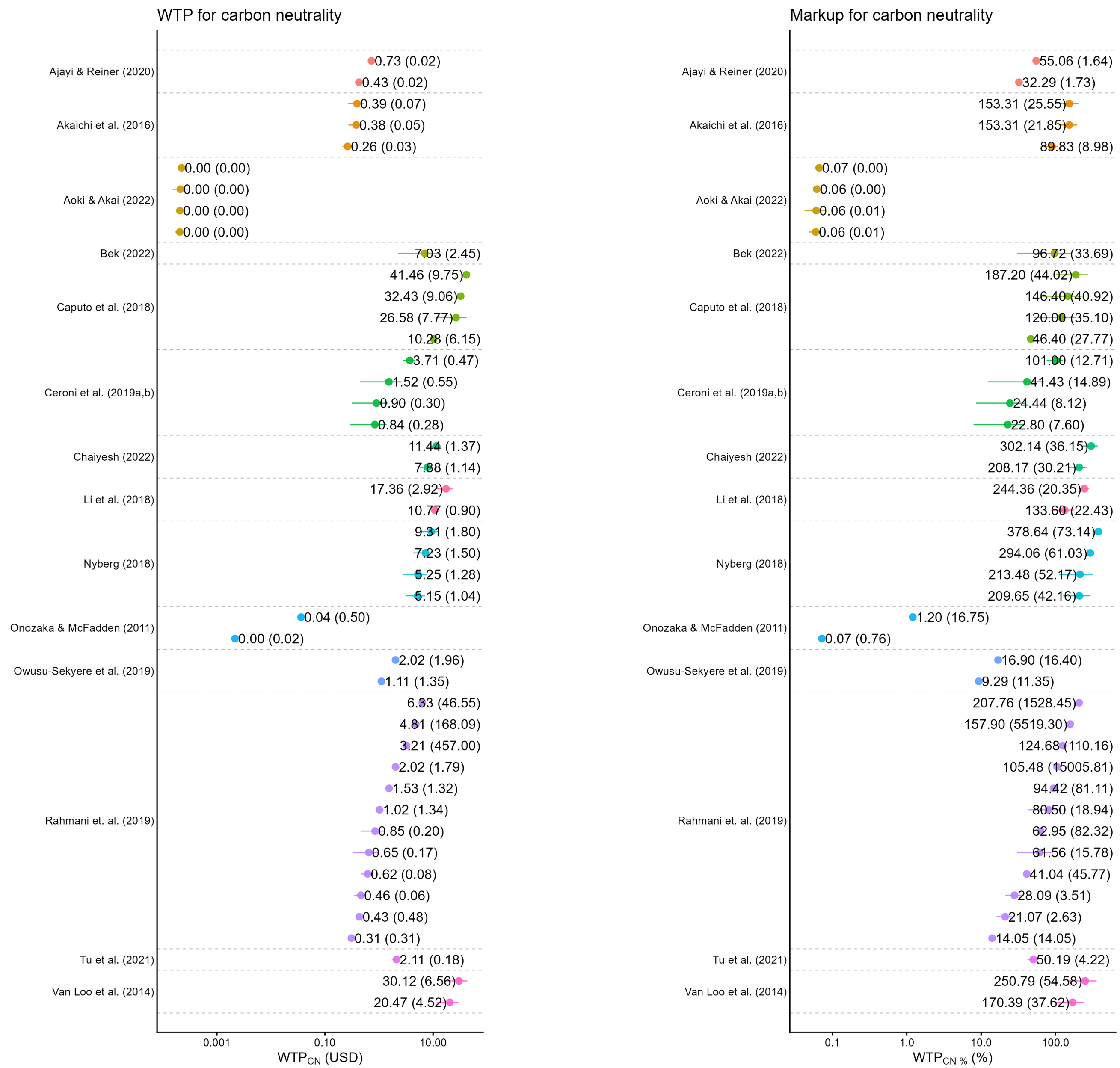
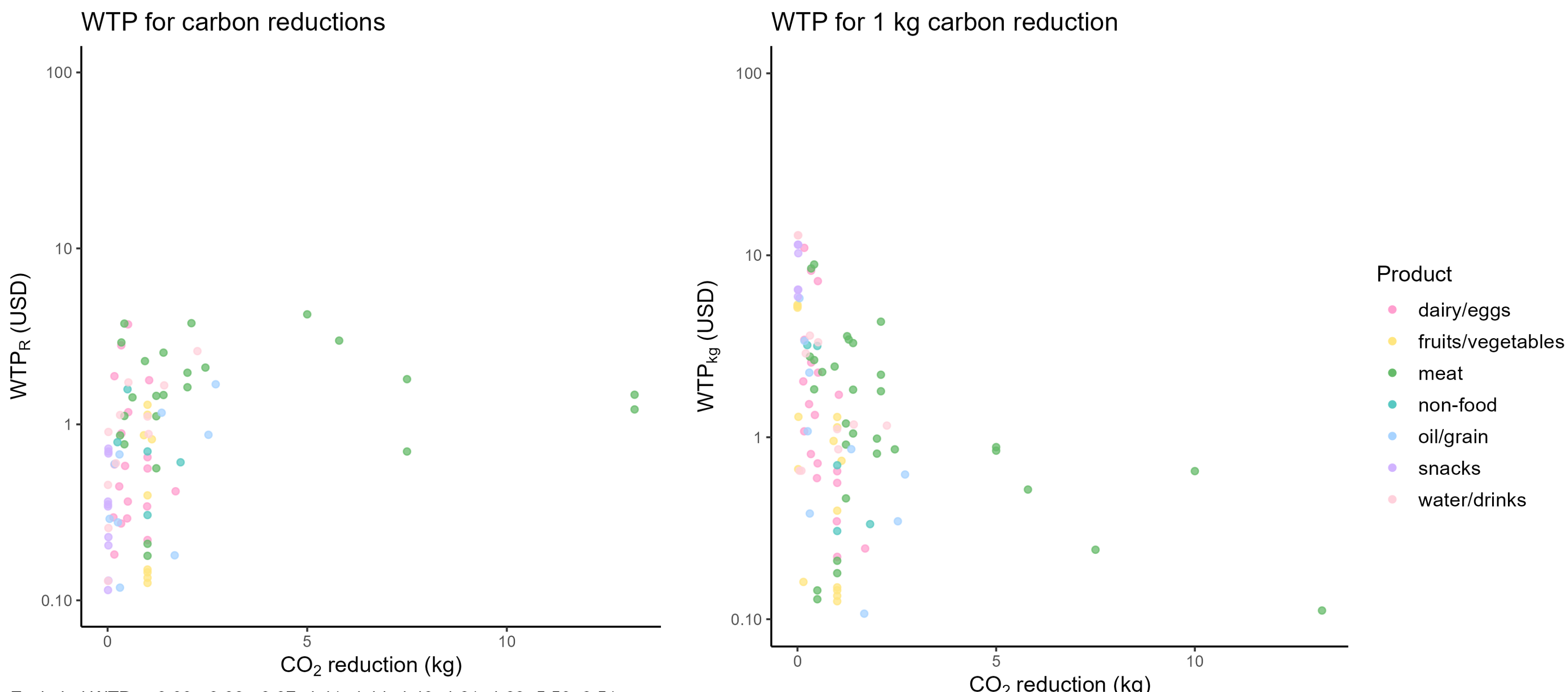


Figure A.10: $\mathrm{WTP}_{\mathrm{CN}}$ and $\mathrm{WTP}_{\mathrm{CN\%}}$ with corresponding standard errors by studies

Observations with negative WTP were excluded from this figure due to the logarithmic (base 10) x-axis. Excluded observations are based on the following studies: Macdiarmid et al. (2021): $WTP_{CN} = -0.48$ (SE $= 0.49$), -0.01 (SE $= 0.39$); $WTP_{CN\%} = -11.50$ (SE $= 11.70$), -0.35 (SE $= 9.22$). Tu et al. (2021): $WTP_{CN} = -0.61$ (SE $= 0.15$), -0.36 (SE $= 0.15$); $WTP_{CN\%} = -14.40$ (SE $= 3.64$), -8.61 (SE $= 3.64$). The left graph displays $\mathrm{WTP}_{\mathrm{CN}}$ (WTP for carbon neutrality) across studies, where the size of each circle represents the baseline CO_2 emissions of the product in kilograms. The right graph displays $\mathrm{WTP}_{\mathrm{CN\%}}$, which is the proportion of the product's price that consumers would be willing to pay extra for carbon neutrality.

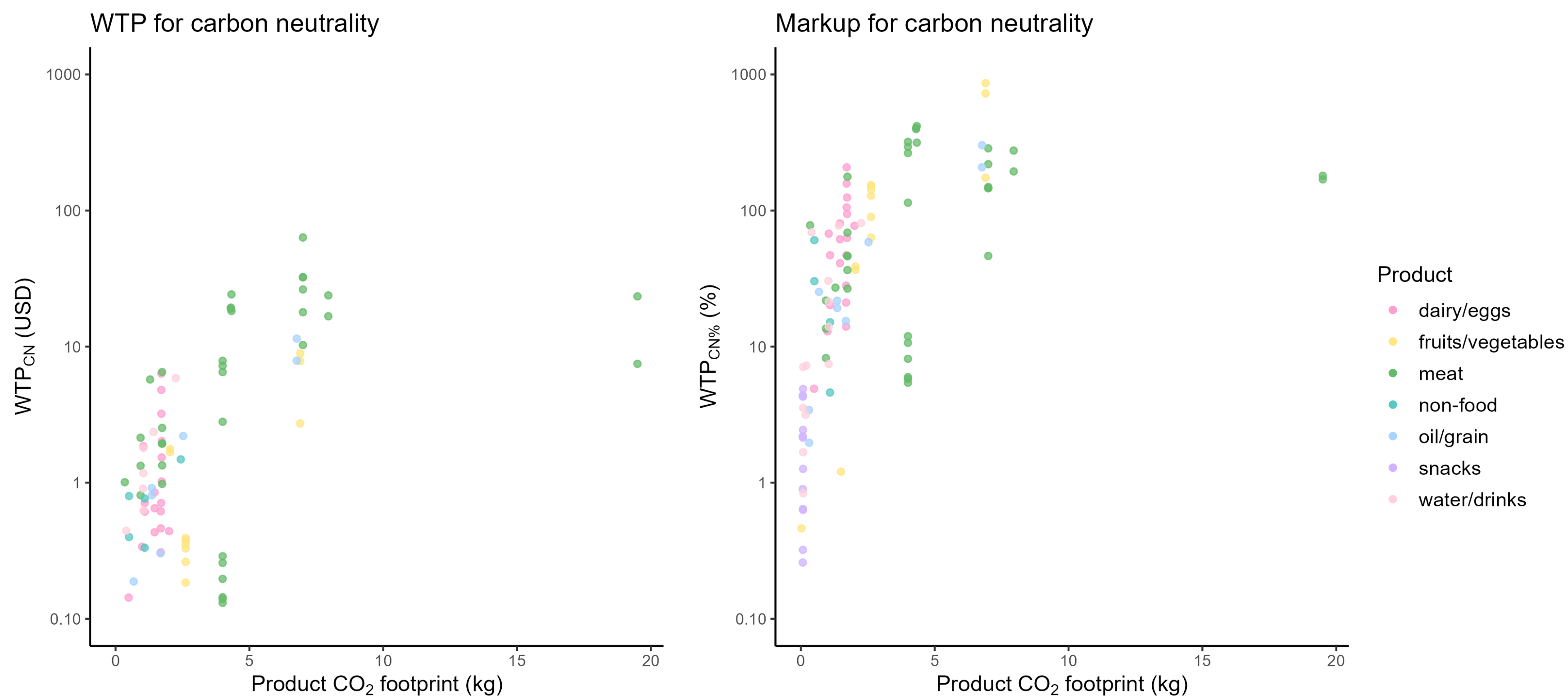


Excluded WTPs: -0.09, -0.08, -0.07, 4.41, 4.44, 4.49, 4.61, 4.63, 5.59, 6.51 7.19, 9.06
Excluded CO_2 reduction values: 17.74, 20, 26.3, 39.43

Excluded WTPs: -1.38, -0.51, -0.04, 34.16, 34.16, 35.06, 36.41, 36.41, 45.28
Excluded CO_2 reduction values: 17.74, 20, 26.3, 39.43

Figure A.11: WTP_R and WTP_{kg} by the amount of CO_2 emission reduction

A logarithmic y-axis (base 10) is used to create this figure. The left graph displays WTP_R (non-standardized WTP for CO_2 reductions). The right-hand graph shows WTP_{kg} (WTP for 1 kg CO_2 reduction), which is calculated by dividing WTP_R by the amount of CO_2 reduction. Both WTP_R and WTP_{kg} are measured in 2020 USD. Outliers, defined as values exceeding two standard deviations from the mean, and negative values are excluded from the figure.



Excluded WTPs: -0.13, -0.12, -0.01, 91.22, 282.28, 311.56
Excluded CO_2 footprint values: 26.37, 27.5, 32.2, 43.33

Excluded WTPs: -10.94, -3, -0.37, 1140.8, 1475.55, 1575.08, 1698.54, 1760.27, 1874.74
Excluded CO_2 footprint values: 26.37, 27.5, 32.2, 43.33

Figure A.12: WTP_{CN} and $WTP_{CN\%}$ by product CO_2 emissions

A logarithmic y-axis (base 10) is used to create this figure. The left graph displays WTP_{CN} (WTP for carbon neutrality) across studies. The right graph displays $WTP_{CN\%}$, which is the proportion of the product's price that consumers would be willing to pay extra for carbon neutrality. Outliers, defined as values exceeding two standard deviations from the mean, and negative values are excluded from the figure.

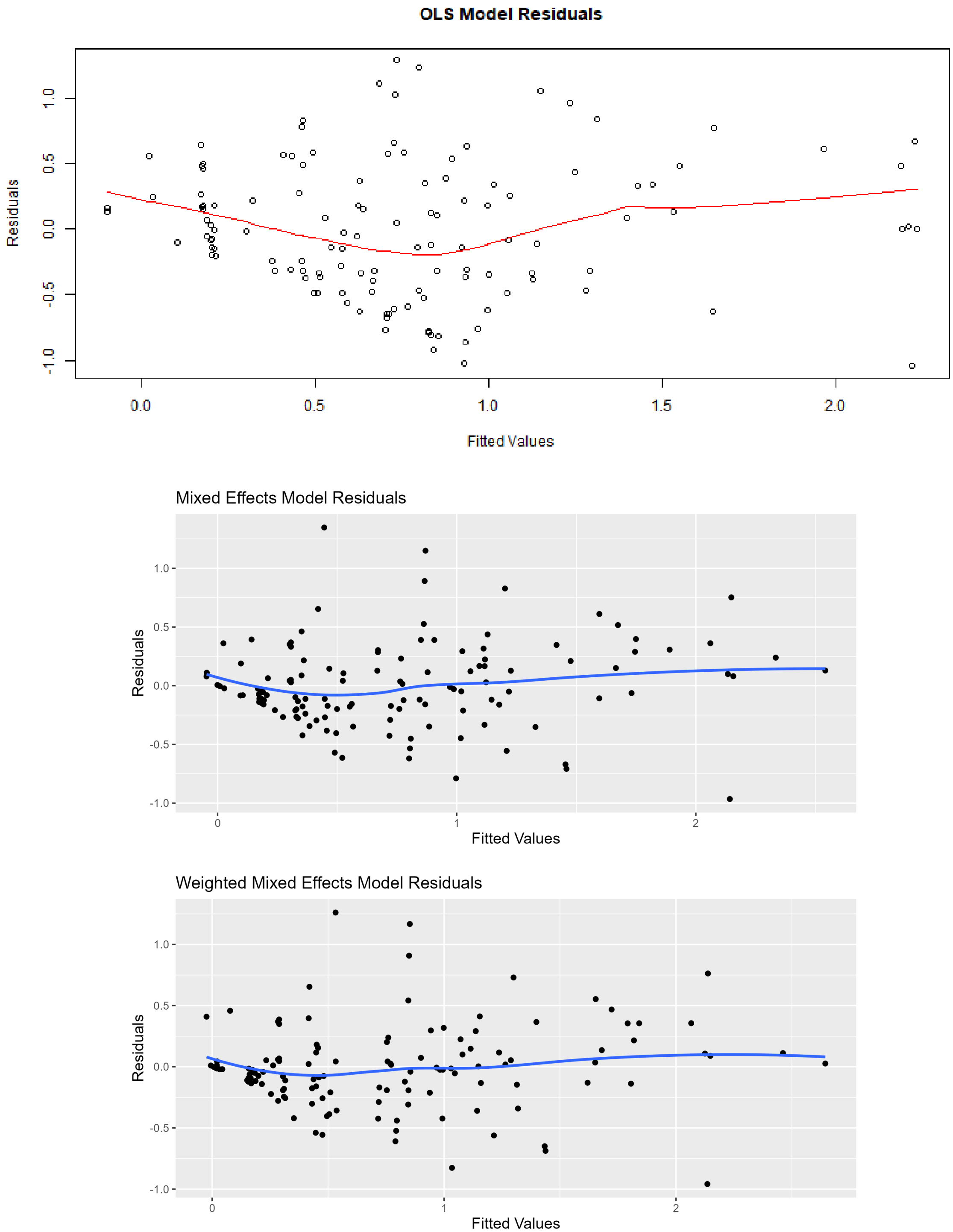


Figure A.13: Residuals versus fitted values

The top, middle, and bottom panels display residuals versus fitted values from the OLS model (Table 1, Section 3.1, column 3), the mixed-effects model (Table A.11, Section A.3, column 2), and the weighted mixed-effects model (Table A.11, column 3), respectively.

Model	Breusch-Pagan Stat.	p-value
OLS I	5.02	0.08
OLS II	22.69	0.01***
OLS III	21.91	0.03**

*p<0.05 **p<0.01 ***p<0.001

Table A.10: Breusch-Pagan test for OLS models presented in Table 1

The table displays the Breusch Pagan heteroskedasticity test from the OLS models in Table 1, Section 3.1.

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 models. The first column of Table A.11 provides baseline OLS III model estimations with standard errors clustered by study. The second column shows mixed-effects model estimations with random effects for studies and product categories. The third column includes the weighted mixed-effects model where weights are based on the inverse number of estimates obtained from each study to equally weigh studies in the meta-analysis.

Second, Tables A.12 and A.13 include two additional variables, carbon-neutral certification and colored labels, analyzed using OLS and mixed-effects models, compared to the baseline regression results presented in Table 1 in Section 3.1. In the first column, we include only the CO_2 reduction, price, colored label, and carbon-neutral label variables. In the second column, we add variables for stated preference studies, in-person studies, sample size, published studies, study year, GDP per capita, and studies conducted in Europe. In the last column, we further add controls for studies requiring making assumptions about the amount of CO_2 reduction, and for which WTP estimates had to be derived.

Third, we report WLS and weighted mixed-effects model estimations in Tables A.14 and A.15, respectively. For comparison purposes, we use the baseline unweighted models in the first column. In the second column, we apply weights based on the inverse number of estimates from each study to equalize each study's contribution. In the third column, we use the sample size of the study as weights.

Fourth, we report OLS and mixed-effects regression results using different transformations of the dependent variable in Tables A.16 and A.17, respectively. For comparison purposes, the first column shows baseline estimations with the untransformed dependent variable. The second column displays the results based on the inverse hyperbolic sine transformation, and the last column uses the logarithmic transformation.

Fifth, we show the OLS model results with two-way clustered errors in Table A.18. For comparison, the first column includes the baseline OLS model with clustered standard errors for studies. The second column presents the OLS model with two-way clustered standard errors for studies and product categories. The third column includes two-way clustered errors for studies and countries.

Sixth, we run the mixed-effects regressions with alternative random effects as shown in Table A.19. For comparison, the first column includes the baseline mixed-effects model with random effects for studies only. The second column incorporates random effects for both studies and product categories. The third column includes random effects for both studies and study countries.

Seventh, we include the square of the z-scored CO_2 emission reduction variable in OLS and mixed-effects regressions. The results are shown in Tables A.20 and A.21, respectively. The first column includes the CO_2 reduction, CO_2 reduction squared, and product price variables. The second column includes additional variables capturing study characteristics and contextual factors. In the last column, we add control variables for CO_2 reduction assumptions and WTP derivations.

Eighth, we present the results from OLS and mixed-effects regressions with different subsets of observations in Tables A.22 and A.23 respectively. The first column is based on the complete set of observations. The second column displays results without observations that require assumptions about the amount of CO_2 reductions. The third column includes only observations where WTP values are sourced directly from the studies, omitting those requiring further calculations or derivations. The final column shows model results that excludes both types of observations: those requiring CO_2 reduction assumptions and those with derived WTP estimates.

Across the robustness checks in Tables A.11-A.23, the coefficient on CO_2 reduction is positive and statistically significant in most specifications, including models with alternative transformations, clustering choices, and functional forms. Including indicators for observations where WTP_R is derived by us or where assumptions about CO_2 reductions are required does not change the results (Table A.11). However, in three restrictive subsample columns that exclude the former or both of such observations, the CO_2 reduction coefficient loses statistical significance (the last columns of Tables A.22 and A.23, and the third column of Table A.23). These cases rely on much smaller samples (e.g., 28 observations, 8 studies) and therefore have larger standard errors; importantly, the estimates remain positive and in most cases large. Overall, the evidence points to a robust positive association between WTP_R and CO_2 reduction; the few non-significant cases seem mostly consistent with lower precision rather than a change in the underlying relationship.

The product price is positive and significant across all robustness checks, always at the 1% level.

Even while controlling for the GDP per capita, studies conducted in Europe are robustly positively significant, mainly at the 1% level.

We do not find significant results for colored labels, carbon-neutral labels, WTP derivation, or CO_2 reduction assumptions.

The remaining variables are mostly insignificant, or become significant in only a few of the regressions, as described in what follows. Sample size becomes significant with a negative sign in the second column of Table A.22. The coefficient for stated preference studies becomes significant at the 5% level with a positive sign in the third column of Table A.11, the third column of Table A.13, and the second column of Table A.15, and at the 1% level with a negative sign in the second column of Table A.22. The coefficient for published studies becomes negative and significant in the last column of Table A.14, the second, third, and fourth columns of Table A.22, and the second and fourth columns of Table A.23 at significance levels ranging from 1% to 10%. The coefficient for the dummy variable indicating in-person studies is significant and negative in the second and fourth columns of Tables A.22 and A.23. GDP per capita becomes positively significant in the last column of Table A.22 at the 1% level. The study year becomes positively significant in the second and fourth columns of Table A.23 and in the fourth column of Table A.22.

	OLS	Mixed Eff.	Weighted Mixed Eff.
Intercept	0.58^{*} (0.32)	0.20 (0.39)	0.11 (0.36)
CO_2 reduction	0.11^{***} (0.04)	0.10^{**} (0.05)	0.09^{**} (0.04)
Price	0.35^{***} (0.05)	0.33^{***} (0.07)	0.30^{***} (0.07)
Stated pref. method	-0.02 (0.25)	0.35 (0.28)	0.48^{**} (0.23)
In-person	-0.10 (0.23)	0.01 (0.21)	0.02 (0.18)
Sample size	-0.06 (0.08)	-0.06 (0.09)	-0.08 (0.09)
Publication	0.00 (0.22)	-0.13 (0.21)	-0.15 (0.21)
Study year	0.02 (0.10)	0.04 (0.10)	0.04 (0.09)
GDP per capita	0.07 (0.08)	0.02 (0.07)	0.01 (0.07)
Europe	0.33^{*} (0.18)	0.44^{***} (0.17)	0.48^{***} (0.17)
CO_2 reduction assump.	0.07 (0.15)	0.09 (0.19)	0.06 (0.18)
WTP derivation	-0.09 (0.12)	0.02 (0.15)	0.03 (0.15)
Number of obs.	126	126	126
Var (study random effect)		0.15	0.18
Var (product random eff.)		0.01	0.01
Adjusted-R^2	0.45	0.45	0.45
AIC	212.91	230.16	230.80
BIC	249.78	272.70	273.34
Log Likelihood	-93.45	-100.08	-100.40

$^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.1$

Table A.11: Factors associated with WTP for CO_2 reductions: robustness tests with alternative models

This table shows coefficient estimates and associated standard errors, which are indicated within parentheses. In the first column, we use an OLS model with clustered standard errors by study. In the second and third columns, we use mixed-effects models, including studies and product categories as random effects. In the third column, we use weights, which correspond to the inverse of the number of WTP_R estimates obtained from each study. The dependent variable is the unstandardized WTP for carbon emission reductions (WTP_R), which is transformed using the inverse hyperbolic sine function. CO_2 reduction, price, sample size, study year, and GDP per capita variables are z-scored.

	OLS I	OLS II	OLS III
Intercept	0.70*** (0.09)	0.51* (0.32)	0.56** (0.28)
CO_2 reduction	0.12** (0.06)	0.11*** (0.04)	0.08*** (0.03)
Price	0.38*** (0.05)	0.35*** (0.05)	0.33*** (0.07)
Colored label	0.16 (0.19)	0.03 (0.20)	0.08 (0.20)
Carbon neutral label	0.13 (0.16)	0.19 (0.22)	0.11 (0.25)
Stated pref. method		-0.01 (0.24)	-0.00 (0.21)
In-person		-0.05 (0.24)	-0.07 (0.25)
Sample size		-0.08 (0.08)	-0.08 (0.09)
Publication		-0.03 (0.23)	-0.17 (0.20)
Study year		0.01 (0.10)	0.06 (0.09)
GDP per capita		0.08 (0.08)	0.01 (0.07)
Europe		0.37*** (0.16)	0.54*** (0.18)
CO_2 reduction assump.			0.03 (0.17)
WTP derivation			0.01 (0.15)
Number of obs.	126	126	126
Adjusted-R^2	0.40	0.46	0.53
AIC	218.84	211.85	233.36
BIC	235.86	248.73	275.90
Log Likelihood	-103.42	-92.93	-101.68

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

Table A.12: Factors associated with WTP for CO_2 reductions: OLS model, robustness tests with additional variables

This table shows coefficient estimates and associated standard errors, which are indicated within parentheses. We use an OLS model with clustered standard errors by study. The dependent variable is the (unstandardized) WTP for CO_2 emission reductions (WTP_R), which is transformed using the inverse hyperbolic sine function. CO_2 reduction, price, sample size, study year, and GDP per capita variables are z-scored.

	Mixed Eff. I	Mixed Eff. II	Mixed Eff. III
Intercept	0.74*** (0.11)	0.23 (0.35)	0.09 (0.36)
CO_2 reduction	0.09* (0.05)	0.10* (0.05)	0.09* (0.04)
Price	0.35*** (0.06)	0.32*** (0.06)	0.29*** (0.07)
Colored label	0.08 (0.16)	0.04 (0.16)	0.11 (0.17)
Carbon neutral label	0.01 (0.19)	0.12 (0.21)	0.09 (0.27)
Stated pref. method		0.34 (0.27)	0.50** (0.24)
In-person		0.02 (0.21)	0.03 (0.19)
Sample size		-0.08 (0.10)	-0.09 (0.10)
Publication		-0.14 (0.21)	-0.15 (0.22)
Study year		0.05 (0.09)	0.04 (0.10)
GDP per capita		0.03 (0.07)	0.03 (0.08)
Europe		0.45*** (0.16)	0.50*** (0.17)
CO_2 reduction assump.			-0.00 (0.24)
WTP derivation			0.03 (0.15)
Number of obs.	126	126	126
Var (study random effect)	0.16	0.14	0.19
Var (product random eff.)	0.01	0.01	0.03
AIC	216.88	229.64	236.84
BIC	239.57	272.19	285.05
Log Likelihood	-100.44	-99.82	-101.42

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

Table A.13: Factors associated with WTP for CO_2 reductions: mixed effects model, robustness tests with additional variables

This table shows coefficient estimates and associated standard errors, which are indicated within parentheses. We use mixed-effects models, including studies and product categories as random effects. The dependent variable is the unstandardized WTP for carbon emission reductions (WTP_R), which is transformed using the inverse hyperbolic sine function. CO_2 reduction, price, sample size, study year, and GDP per capita variables are z-scored.

	OLS	WLS I	WLS II
		(w = inv. number obs.)	(w = sample size)
Intercept	0.58* (0.32)	0.57** (0.28)	1.21*** (0.29)
CO_2 reduction	0.11*** (0.04)	0.09*** (0.03)	0.10*** (0.02)
Price	0.35*** (0.05)	0.33*** (0.07)	0.29*** (0.08)
Stated pref. method	-0.02 (0.25)	-0.00 (0.21)	-0.27 (0.22)
In-person	-0.10 (0.23)	-0.09 (0.26)	-0.33 (0.25)
Sample size	-0.06 (0.08)	-0.07 (0.08)	-0.06 (0.04)
Publication	0.00 (0.22)	-0.16 (0.19)	-0.44** (0.20)
Study year	0.02 (0.10)	0.06 (0.09)	0.11 (0.12)
GDP per capita	0.07 (0.08)	-0.00 (0.07)	-0.00 (0.12)
Europe	0.33* (0.18)	0.52*** (0.17)	0.46*** (0.11)
CO_2 reduction assump.	0.07 (0.15)	0.10 (0.13)	-0.13 (0.10)
WTP derivation	-0.09 (0.12)	0.01 (0.14)	-0.02 (0.09)
Number of obs.	126	126	126
Adjusted R^2	0.50	0.57	0.41
AIC	212.91	230.12	306.73
BIC	249.78	266.99	343.61
Log Likelihood	0.45	0.53	0.36

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

Table A.14: Factors associated with WTP for CO_2 reductions: OLS and WLS models, robustness tests with weights

This table shows coefficient estimates and associated standard errors, which are indicated within parentheses. We use an OLS and WLS models with clustered standard errors by study. This table shows coefficient estimates, and associated standard errors, which are indicated within parentheses. The standard errors are clustered across studies. In the first column, we do not weigh the outcome variable. In the second column, we weigh based on the inverse of the number of estimates derived or obtained from each study. In the last column, we use the sample size as the weight. The dependent variable is the (unstandardized) WTP for CO_2 emission reductions (WTP_R), which is transformed using the inverse hyperbolic sine function. CO_2 reduction, price, sample size, study year, and GDP per capita variables are z-scored.

	Mixed Eff.	Weighted Mixed Eff. I (w = inv. number obs.)	Weighted Mixed Eff. II (w = sample size)
Intercept	0.20 (0.39)	0.11 (0.36)	0.97 (0.63)
CO_2 reduction	0.10^{**} (0.05)	0.09^{**} (0.04)	0.11^{***} (0.04)
Price	0.33^{***} (0.07)	0.30^{***} (0.07)	0.28^{***} (0.08)
Stated pref. method	0.35 (0.28)	0.48^{**} (0.23)	-0.10 (0.55)
In-person	0.01 (0.21)	0.02 (0.18)	-0.26 (0.27)
Sample size	-0.06 (0.09)	-0.08 (0.09)	-0.08 (0.09)
Publication	-0.13 (0.21)	-0.15 (0.21)	-0.29 (0.22)
Study year	0.04 (0.10)	0.04 (0.09)	0.13 (0.10)
GDP per capita	0.02 (0.07)	0.01 (0.07)	0.03 (0.07)
Europe	0.44^{***} (0.17)	0.48^{***} (0.17)	0.44^{***} (0.13)
CO_2 reduction assump.	0.09 (0.19)	0.06 (0.18)	-0.11 (0.20)
WTP derivation	0.02 (0.15)	0.03 (0.15)	-0.01 (0.15)
Number of obs.	126	126	126
Var (study random effect)	0.15	0.18	0.10
Var (country random effect)	0.01	0.02	0.01
AIC	230.16	230.80	324.34
BIC	272.70	273.34	366.88
Log Likelihood	-100.08	-100.40	-147.17

$^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.1$

Table A.15: Factors associated with WTP for CO_2 reductions: mixed effects and weighted mixed effects models, robustness tests with weights

This table shows coefficient estimates and associated standard errors, which are indicated within parentheses. We use mixed-effects models, including studies and product categories as random effects. In the first column, we do not weigh the outcome variable. In the second column, we weigh based on the inverse of the number of estimates derived or obtained from each study. In the last column, we use the sample size as the weight. The dependent variable is the (unstandardized) WTP for CO_2 emission reductions (WTP_R), which is transformed using the inverse hyperbolic sine function. CO_2 reduction, price, sample size, study year, and GDP per capita variables are z-scored.

	OLS I (not transformed)	OLS II (inv. hyperbolic sine trans.)	OLS III (log. trans.)
Intercept	0.78 (0.64)	0.58* (0.32)	-1.50* (0.89)
CO_2 reduction	0.20* (0.10)	0.11*** (0.04)	0.29*** (0.09)
Price	0.82*** (0.11)	0.35*** (0.05)	0.64*** (0.16)
Stated pref. method	-0.05 (0.54)	-0.02 (0.25)	-0.18 (0.47)
In-person	-0.31 (0.45)	-0.10 (0.23)	-0.36 (0.53)
Sample size	-0.26 (0.19)	-0.06 (0.08)	0.01 (0.19)
Publication	0.31 (0.40)	0.00 (0.22)	-0.30 (0.64)
Study year	0.21 (0.21)	0.02 (0.10)	-0.28 (0.32)
GDP per capita	0.14 (0.16)	0.07 (0.08)	-0.04 (0.24)
Europe	0.71** (0.34)	0.33* (0.18)	1.19** (0.57)
CO_2 reduction assump.	-0.27 (0.35)	0.07 (0.15)	0.58 (0.51)
WTP derivation	-0.14 (0.20)	-0.09 (0.12)	0.20 (0.49)
Number of obs.	126	126	123
Adjusted R^2	0.55	0.50	0.38
AIC	399.33	212.91	437.14
BIC	436.20	249.78	473.70
Log Likelihood	-186.67	-93.45	-205.57

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

Table A.16: Factors associated with WTP for CO_2 reductions: OLS model, robustness tests with transformations of the dependent variable

This table shows coefficient estimates and associated standard errors, which are indicated within parentheses. We use an OLS model with clustered standard errors by study. 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 CO_2 emission reductions (WTP_R), which is transformed using the inverse hyperbolic sine function. CO_2 reduction, price, sample size, study year, and GDP per capita variables are z-scored.

	Mixed Eff. I (not transformed)	Mixed Eff. II (inv. hyperbolic sine trans.)	Mixed Eff. III (log. trans.)
Intercept	0.33 (0.81)	0.20 (0.39)	-2.19** (0.92)
CO_2 reduction	0.25** (0.10)	0.10** (0.05)	0.19* (0.11)
Price	0.82*** (0.13)	0.33*** (0.07)	0.58*** (0.16)
Stated pref. method	0.44 (0.59)	0.35 (0.28)	0.69 (0.61)
In-person	-0.09 (0.44)	0.01 (0.21)	0.10 (0.50)
Sample size	-0.22 (0.19)	-0.06 (0.09)	0.02 (0.24)
Publication	0.05 (0.42)	-0.13 (0.21)	-0.43 (0.56)
Study year	0.23 (0.20)	0.04 (0.10)	-0.07 (0.25)
GDP per capita	0.05 (0.15)	0.02 (0.07)	0.01 (0.18)
Europe	0.85** (0.35)	0.44*** (0.17)	1.14*** (0.38)
CO_2 reduction assump.	-0.24 (0.38)	0.09 (0.19)	0.51 (0.48)
WTP derivation	0.01 (0.32)	0.02 (0.15)	0.23 (0.34)
Number of obs.	126	126	123
Var (study random effect)	0.50	0.15	1.18
Var (product random effect)	0.00	0.01	0.19
AIC	411.77	230.16	394.93
BIC	454.32	272.70	437.12
Log Likelihood	-190.89	-100.08	-182.47

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

Table A.17: Factors associated with WTP for CO_2 reductions: mixed effects model, robustness tests with transformations of the dependent variable

This table shows coefficient estimates and associated standard errors, which are indicated within parentheses. We use mixed-effects models, including studies and product categories as random effects. 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 CO_2 emission reductions (WTP_R), which is transformed using the inverse hyperbolic sine function. CO_2 reduction, price, sample size, study year, and GDP per capita variables are z-scored.

	OLS I (clst. by study)	OLS II (clst. by study & product)	OLS III (clst. by study & country)
Intercept	0.58^{*} (0.32)	0.56^{***} (0.07)	0.58^{*} (0.30)
CO_2 reduction	0.11^{***} (0.04)	0.11^{***} (0.02)	0.11^{**} (0.05)
Price	0.35^{***} (0.05)	0.35^{***} (0.04)	0.35^{***} (0.04)
Stated pref. method	-0.02 (0.25)	-0.03 (0.13)	-0.02 (0.23)
In-person	-0.10 (0.23)	-0.11 (0.14)	-0.10 (0.26)
Sample size	-0.06 (0.08)	-0.06 (0.15)	-0.06 (0.09)
Publication	0.00 (0.22)	-0.01 (0.16)	0.00 (0.25)
Study year	0.02 (0.10)	0.02 (0.04)	0.02 (0.12)
GDP per capita	0.07 (0.08)	0.06 (0.06)	0.07 (0.08)
Europe	0.33^{*} (0.18)	0.35^{*} (0.21)	0.33^{*} (0.18)
CO_2 reduction assump.	0.07 (0.15)	0.09 (0.08)	0.07 (0.21)
WTP derivation	-0.09 (0.12)	-0.08 (0.09)	-0.09 (0.11)
Number of obs.	126	126	126
Adjusted R^2	0.45	0.45	0.45
AIC	212.91	212.91	212.91
BIC	249.78	249.78	249.78
Log Likelihood	-93.45	-93.45	-93.45

$^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.1$

Table A.18: Factors associated with WTP for CO_2 reductions: OLS model, robustness tests with alternative cluster variables

This table shows coefficient estimates and associated standard errors, which are indicated within parentheses. In the first column, we use an OLS model with standard errors clustered by studies. In the second column, the standard errors of the OLS model are clustered by both study and product category. In the second column, the study year variable is not included due to the insufficient variation within the study and product clusters. In the third column, the standard errors are clustered by study and country. The dependent variable is the (unstandardized) WTP for CO_2 emission reductions (WTP_R), which is transformed using the inverse hyperbolic sine function. CO_2 reduction, price, sample size, study year, and GDP per capita variables are z-scored.

	Mixed Eff. I	Mixed Eff. II	Mixed Eff. III
	(study r.e.)	(study & product r.e.)	(study & country r.e.)
Intercept	0.24 (0.38)	0.20 (0.39)	0.24 (0.38)
CO_2 reduction	0.11** (0.05)	0.10** (0.05)	0.11** (0.05)
Price	0.36*** (0.06)	0.33*** (0.07)	0.36*** (0.06)
Stated pref. method	0.31 (0.28)	0.35 (0.28)	0.31 (0.28)
In-person	0.02 (0.21)	0.01 (0.21)	0.02 (0.21)
Sample size	-0.06 (0.09)	-0.06 (0.09)	-0.06 (0.09)
Publication	-0.14 (0.21)	-0.13 (0.21)	-0.14 (0.21)
Study year	0.04 (0.10)	0.04 (0.10)	0.04 (0.10)
GDP per capita	0.02 (0.07)	0.02 (0.07)	0.02 (0.07)
Europe	0.44*** (0.17)	0.44*** (0.17)	0.44*** (0.17)
CO_2 reduction assump.	0.10 (0.19)	0.09 (0.19)	0.10 (0.19)
WTP derivation	0.03 (0.15)	0.02 (0.15)	0.03 (0.15)
Number of obs.	126	126	126
Var (study random effect)	0.14	0.15	0.14
Var (product random eff.)		0.01	
Var (country random effect)			0.00
AIC	228.40	230.16	230.40
BIC	268.11	272.70	272.95
Log Likelihood	-100.20	-100.08	-100.20

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

Table A.19: Factors associated with WTP for CO_2 reductions: mixed effects model, robustness tests with alternative random effects

This table shows coefficient estimates and associated standard errors, which are indicated within parentheses. We use mixed-effects models. For the first column, we include studies as random effects. In the second column, we include both studies and product categories as random effects. In the third column, we include studies and countries as random effects. The dependent variable is the (unstandardized) WTP for CO_2 emission reductions (WTP_R), which is transformed using the inverse hyperbolic sine function. CO_2 reduction, price, sample size, study year, and GDP per capita variables are z-scored.

	OLS I	OLS II	OLS III
Intercept	0.80*** (0.09)	0.57* (0.32)	0.55* (0.31)
CO_2 reduction	0.33** (0.16)	0.25** (0.12)	0.26* (0.15)
CO_2 reduction^2	-0.04* (0.02)	-0.03 (0.02)	-0.03 (0.02)
Price	0.35*** (0.05)	0.33*** (0.05)	0.33*** (0.05)
Stated pref. method		-0.02 (0.24)	-0.02 (0.24)
In-person		-0.10 (0.24)	-0.10 (0.23)
Sample size		-0.05 (0.08)	-0.05 (0.08)
Publication		0.01 (0.22)	0.00 (0.22)
Study year		0.03 (0.09)	-0.01 (0.10)
GDP per capita		0.06 (0.08)	0.06 (0.08)
Europe		0.35* (0.18)	0.32* (0.19)
CO_2 reduction assump.			0.11 (0.18)
WTP derivation			-0.03 (0.12)
Number of obs.	126	126	126
Adjusted R^2	0.42	0.46	0.46
AIC	213.68	209.45	212.45
BIC	227.86	243.49	252.16
Log Likelihood	-101.84	-92.73	-92.22

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

Table A.20: Factors associated with WTP for CO_2 reductions: OLS model, robustness tests with alternative functional form of CO_2 reduction

This table shows coefficient estimates and associated standard errors, which are indicated within parentheses. We use an OLS model with clustered standard errors by study. The dependent variable is the (unstandardized) WTP for CO_2 emission reductions (WTP_R), which is transformed using the inverse hyperbolic sine function. CO_2 reduction, price, sample size, study year, and GDP per capita variables are z-scored. CO_2 reduction^2 variable is obtained by squaring the z-scored CO_2 reduction variable.

	Mixed Eff. I	Mixed Eff. II	Mixed Eff. III
Intercept	0.80*** (0.09)	0.32 (0.35)	0.20 (0.39)
CO_2 reduction	0.29** (0.12)	0.22* (0.12)	0.25** (0.13)
CO_2 reduction^2	-0.04* (0.02)	-0.02 (0.02)	-0.03 (0.02)
Price	0.34*** (0.06)	0.31*** (0.06)	0.33*** (0.06)
Stated pref. method		0.32 (0.27)	0.34 (0.27)
In-person		0.01 (0.21)	0.03 (0.21)
Sample size		-0.06 (0.09)	-0.05 (0.09)
Publication		-0.12 (0.21)	-0.14 (0.21)
Study year		0.05 (0.09)	0.02 (0.10)
GDP per capita		0.03 (0.07)	0.01 (0.07)
Europe		0.42*** (0.16)	0.42** (0.17)
CO_2 reduction assump.			0.14 (0.19)
WTP derivation			0.08 (0.16)
Number of obs.	126	126	126
Var (study random effect)	0.15	0.14	0.15
Var (product random eff.)	0.00	0.01	0.00
AIC	214.83	229.69	236.43
BIC	234.68	269.40	281.81
Log Likelihood	-100.41	-100.85	-102.21

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

Table A.21: Factors associated with WTP for CO_2 reductions: mixed effects model, robustness tests with alternative functional form of CO_2 reduction

This table shows coefficient estimates and associated standard errors, which are indicated within parentheses. We use mixed-effects models, including studies and product categories as random effects. The dependent variable is the unstandardized WTP for carbon emission reductions (WTP_R), which is transformed using the inverse hyperbolic sine function. CO_2 reduction, price, sample size, study year, and GDP per capita variables are z-scored. CO_2 reduction^2 variable is obtained by squaring the z-scored CO_2 reduction variable.

	OLS I (original)	OLS II (no CO_2 assump.)	OLS III (no WTP derivation)	OLS IV (neither)
Intercept	0.51 (0.33)	1.57*** (0.23)	0.78* (0.43)	1.70*** (0.15)
CO_2 reduction	0.11*** (0.04)	0.08* (0.04)	0.10*** (0.03)	0.03 (0.02)
Price	0.35*** (0.05)	0.24*** (0.03)	0.33*** (0.07)	0.29*** (0.05)
Stated pref. method	0.00 (0.24)	-0.60*** (0.11)	0.01 (0.28)	
In-person	-0.08 (0.24)	-0.83*** (0.19)	-0.27 (0.32)	-0.65*** (0.17)
Sample size	-0.05 (0.08)	-0.17*** (0.04)	-0.09 (0.07)	-0.05 (0.06)
Publication	0.01 (0.23)	-0.35** (0.15)	-0.45** (0.20)	-0.85*** (0.06)
Study year	0.04 (0.09)	0.15 (0.10)	0.02 (0.11)	0.48*** (0.07)
GDP per capita	0.06 (0.08)	0.04 (0.05)	-0.13 (0.12)	0.32*** (0.05)
Europe	0.37** (0.17)	0.62*** (0.11)	0.56*** (0.20)	0.47*** (0.03)
Number of obs.	126	55	73	28
Number of studies	37	14	24	8
Adjusted R^2	0.46	0.78	0.51	0.79
AIC	209.92	51.26	120.70	39.72
BIC	241.12	73.34	145.90	53.05
Log Likelihood	-93.96	-14.63	-49.35	-9.86

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

Table A.22: Factors associated with WTP for CO_2 reductions: OLS model, robustness tests with subsets of the data

This table shows coefficient estimates and associated standard errors, which are indicated within parentheses. We use an OLS model with clustered standard errors by study. Each column presents OLS outputs based on different subsets of data. The first column is based on the complete set of observations. The second column excludes observations for which we need to make assumptions regarding the amount of CO_2 reduction through external calculators or other third-party sources. The third column is based on data where WTP_R values are obtained directly from the studies, without any additional calculations. The fourth column combines these criteria, excluding both observations with CO_2 reduction assumptions and derived WTP values. The dependent variable is the (unstandardized) WTP for CO_2 emission reductions (WTP_R), which is transformed using the inverse hyperbolic sine function. CO_2 reduction, price, sample size, study year, and GDP per capita variables are z-scored.

	Mixed Eff. I (original)	Mixed Eff. II (no CO_2 assump.)	Mixed Eff. III (no WTP derivation)	Mixed Eff. IV (neither)
Intercept	0.26 (0.35)	1.62*** (0.37)	0.19 (0.52)	1.58*** (0.54)
CO_2 reduction	0.10** (0.05)	0.15** (0.07)	0.09 (0.07)	0.10 (0.09)
Price	0.32*** (0.06)	0.46*** (0.07)	0.31*** (0.08)	0.43*** (0.09)
Stated pref. method	0.34 (0.27)	-0.36 (0.26)	0.64 (0.40)	
In-person	0.00 (0.21)	-0.62*** (0.19)	-0.19 (0.25)	-0.59** (0.29)
Sample size	-0.07 (0.09)	0.06 (0.09)	-0.10 (0.11)	0.08 (0.15)
Publication	-0.12 (0.21)	-0.44** (0.21)	-0.41 (0.27)	-0.88* (0.46)
Study year	0.06 (0.09)	0.31** (0.12)	0.08 (0.12)	0.45** (0.20)
GDP per capita	0.02 (0.07)	0.13 (0.09)	-0.08 (0.11)	0.23 (0.17)
Europe	0.44*** (0.16)	0.49*** (0.13)	0.50** (0.20)	0.48** (0.20)
Number of obs.	126	55	73	28
Number of studies	37	14	24	8
Var (study random effect)	0.14	0.00	0.14	0.00
Var (product random eff.)	0.01	0.24	0.00	0.13
AIC	222.89	83.06	147.34	65.21
BIC	259.76	109.16	177.12	81.20
Log Likelihood	-98.44	-28.53	-60.67	-20.60

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

Table A.23: Factors associated with WTP for CO_2 reductions: mixed effects model, robustness tests with subsets of the data

This table shows coefficient estimates and associated standard errors, which are indicated within parentheses. We use mixed effects models, including studies and product categories as random effects. Each column presents mixed effects model outputs based on different subsets of data. The first column is based on the complete set of observations. The second column excludes observations for which we need to make assumptions regarding the amount of CO_2 reduction through external calculators or other third-party sources. The third column is based on data where WTP_R values are obtained directly from the studies, without any additional calculations. The fourth column combines these criteria, excluding both observations with CO_2 reduction assumptions and derived WTP values. The dependent variable is the (unstandardized) WTP for CO_2 emission reductions (WTP_R), which is transformed using the inverse hyperbolic sine function. CO_2 reduction, price, sample size, study year, and GDP per capita variables are z-scored.

A.4 Publication bias

We assess whether publication bias affects the WTP measures, by implementing the FAT-PET-WLS procedure (Stanley and Doucouliagos, 2014). Less than half of the studies report sufficient information to recover standard errors, which is a common issue in meta-analyses (Nelson and Kennedy, 2009). Therefore, we proxy precision with sample size, as often done in other meta-analyses (Florax et al., 2005; Tunçel and Hammitt, 2014; Mattmann et al., 2016; Penn and Hu, 2019).

Because multiple estimates can originate from the same underlying sample within a study, we aggregate observations at the sample level within each study, yielding 52 observations from 37 studies. Figure A.14 displays estimates of $\mathrm{WTP}_{\mathrm{R}}$, $\mathrm{WTP}_{\mathrm{kg}}$, $\mathrm{WTP}_{\mathrm{CN}}$, and $\mathrm{WTP}_{\mathrm{CN\%}}$ against the precision proxy $\sqrt{n_{ij}}$, thereby distinguishing between published and unpublished studies. There is no clear relationship between precision and WTP.

We test for publication bias via the FAT-PET-WLS specification (Stanley and Doucouliagos, 2014). Weighting is necessary to counteract the issue of heteroskedasticity of the error term.

Let Y_{ij} denote the WTP measure for sample i from study j and n_{ij} is the number of individuals in each sample:

$$Y_{ij}\sqrt{n_{ij}} = \beta_0\sqrt{n_{ij}} + \beta_1 + \nu_{ij}, \tag{1}$$

We test $H_0 : \beta_1 = 0$ to assess whether or not there is publication selection bias. Standard errors are clustered by study.

Table A.24 summarizes the results. The intercept β_1 for $\mathrm{WTP}_{\mathrm{kg}}$ is $7.81\,[-20.82, 36.44]$, which is statistically insignificant, indicating that there is no evidence of publication bias. We also test for publication bias for the remaining three

WTP measures, WTP_{R}, WTP_{CN}, and $\text{WTP}_{\text{CN\%}}$, and find insignificant intercepts, confirming that also here there is no evidence of publication bias. Overall, the FAT diagnostics do not indicate any publication bias and do not change our conclusions.

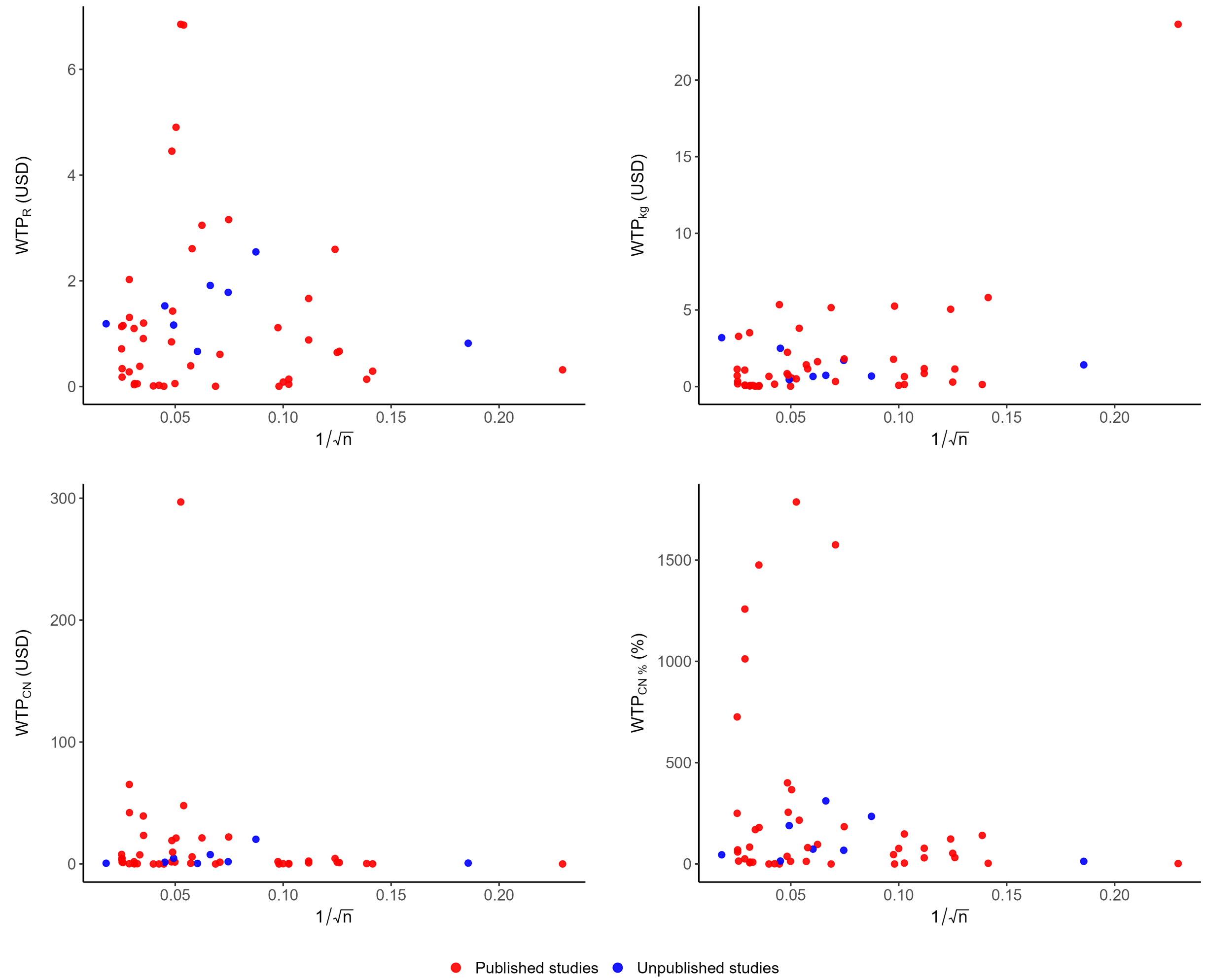


Figure A.14: WTP estimates and study sample size

This plot displays WTP estimates against $1/\sqrt{n}$ (inverse square root of the sample size). To maintain readability, extreme observations are excluded using 95th-percentile cutoffs on both axes. subsample is no longer analyzed. The non-standardized measure WTP$_R$ denotes 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 share of the product price consumers would pay extra for carbon neutrality.

Measure	N	β_1 [95% CI]
WTP_{kg} (USD)	52	7.81 [-20.82, 36.44]
WTP_{R} (USD)	52	11.74 [-3.29, 26.77]
WTP_{CN} (USD)	52	116.35 [-231.81, 464.52]
$\text{WTP}_{\text{CN\%}}$ (%)	52	-640.71 [-5392.20, 4110.78]

Table A.24: Publication bias test

β_1 is the intercept in the FAT-PET-WLS regression $Y_i\sqrt{n_i} = \beta_0\sqrt{n_i}+\beta_1+\epsilon_i$; where $H_0 : \beta_1 = 0$ is used as a test of whether or not there is publication selection. N is the number of study-sample effect sizes. Confidence intervals use study-clustered robust standard errors.

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. Amazon is a co-founder and participant, starting this 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. For the purpose of this paper, we focus exclusively on carbon-neutral labels. Independent organizations, namely Climate Impact Partners (previously named Natural Capital Partners), SCS Global Services, Climate Partner, Carbon Fund, and Carbon Trust offer carbon-neutral certifications.

There are three different ways for consumers to identify carbon-neutral labeled products on Amazon. First, they can search for any product on the platform and identify those with the "Sustainably recognized" badge. By clicking on this badge, they can see detailed information about whether the product is carbon-neutral certified or not. Second, consumers can navigate to the Climate Pledge Friendly page, choose a carbon-neutral certification and then filter all products labeled as such. Third, users may select a carbon-neutral product without knowing that it is, and then view the certificate on its product page. Figure B.1 illustrates an example of a product certified as carbon neutral by Climate Partner on Amazon.com.

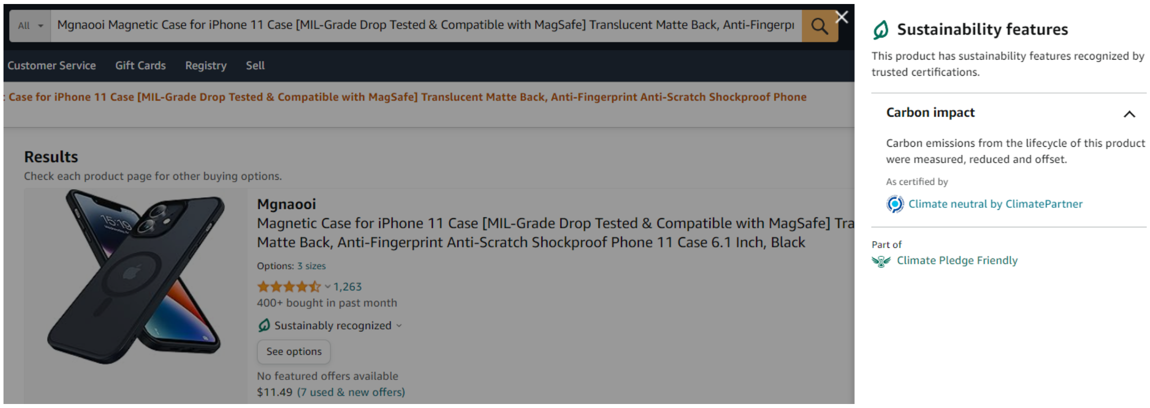


Figure B.1: A product certified carbon neutral by Climate Partner on Amazon.com

Amazon uses the term "Climate Pledge Friendly labels" to refer to various aspects of sustainability, not just those related to carbon neutrality. These other sustainability labels cover various aspects, including energy efficiency, recycling, organic certification, fair trade, animal welfare, and CO_2 reduction.[6] We focus on carbon-neutral labels, in particular excluding a related label implying much less commitment, the "Reducing CO_2" label.

[6]The list of Climate Pledge Friendly labels evolves over time. As of March 2023, the labels focusing on sustainability aspects other than carbon neutrality on Amazon.com included: BIFMA LEVEL, Blue Angel, Bluesign, Certified Animal Welfare Approved, Compact by Design, Cradle to Cradle Certified, ECOLOGO, ENERGY STAR Most Efficient, EPEAT, EWG Verified, Fair Trade Certified, Fairtrade International, Fair for Life, The Forest Stewardship Council, Global Organic Textile Standard, Global Recycled Standard, GreenCircle Certified, Green Seal, Higg Index Materials, Made in Green by Oeko-Tex, MADE SAFE, Natrue, Nordic Swan Ecolabel, Organic Content Standard 100, Organic Content Standard Blended, Pre-owned Certified, Rainforest Alliance, Recycled Claim Standard 100, Recycled Claim Standard Blended, Reducing CO_2, Regenerative Organic Certified, Responsible Wool Standard, Soil Association, STANDARD 100 by OEKO-TEX, TCO Certified, USDA Organic, U.S. EPA Safer Choice, and WaterSense.

B.2 Treated and control products

Table B.1, summarizes the restrictions used to identify changes in treatment status and the corresponding control products, as explained in Section 2.2.

Category	Restrictions
All products	Sufficient price data: More than 25% of price observations are available.
	Sufficient availability: ‘Currently unavailable’ less than 50% of the time.
Control products	Never treated: No carbon-neutral label for the entire time series.
	No other labels: Cannot have additional Climate Pledge Friendly labels that we identify and track at the start of the panel (e.g., organic, faitrade).
	Category matching: Matched to treated product categories. Higher-level categories used if fewer than 10 suitable controls are available.
Treated products	Initial untreated sequence: At least 3 weekly untreated observations before treatment.
	Treatment: Status changes from 0 to 1 (receives a carbon-neutral label).
	Consistent treatment: Treated at least 90% of the time.
	Frequent availability: Meets the 50% availability threshold after receiving the treatment.
	No other labels: No additional Climate Pledge Friendly labels that we identify and track at the start of the panel (e.g., organic, fairtrade).

Table B.1: Restrictions to define treated and control products

This table shows the sample restrictions used to identify changes in treatment status and suitable controls from our product panel across Amazon’s three marketplaces.

B.3 Changes in treatment status

Tables B.2, B.3, and B.4 present the number of treated products that received a carbon-neutral label during the observation period, along with their corresponding control products, for each product category across the three marketplaces, reporting only the most general categories (the finest-level categories are then controlled for in the estimations). We successfully scraped data for the United States from March 2023 through November 2024, and from May 2024 through November 2024 for the United Kingdom and Germany.

Table B.5 shows that treated and control products are balanced on the initial price at the start of the panel.

Tables B.6, B.7, and B.8 provide detailed information on the timing of changes in products' treatment status for the United States, United Kingdom, and Germany, including ASINs,[7] product categories (as defined by Amazon), the dates the products were first identified as carbon-neutral, and the product prices at the start and at the end of the panel.

[7] ASIN numbers can be added after "amazon.com/dp/," "amazon.co.uk/dp/," " amazon.de/dp/" to find a specific product on the respective sites for the United States, United Kingdom, and Germany.

Category	Treated	Control
Beauty & Personal Care	12	304
Cell Phones & Accessories	53	2864
Electronics	91	1716
Grocery & Gourmet Food	1	225
Health & Household	14	932
Musical Instruments	1	37
Office Products	1	356
Safety & Security	2	25
Tools & Home Improvement	9	42
Toys & Games	3	49
Video Games	20	976
Total	207	7526

Table B.2: Number of treated and control products by category (United States)

This table presents the number of treated products (products receiving carbon-neutral labels) and control products (without a label) by category for the U.S. market.

Category	Treated	Control
Accessories	2	665
Arts & Crafts	1	277
Gardening	2	77
Headphones, Earphones & Accessories	4	833
Hi-Fi & Home Audio	1	490
Microphones	2	96
Mobile Phones & Communication	28	2654
Sports	2	423
Wearable Technology	8	361
Total	50	5876

Table B.3: Number of treated and control products by category (United Kingdom)

This table presents the number of treatment products (products receiving carbon-neutral labels) and control products (without a label) by category for the U.K. market.

Category	Treatment	Control
Computer & Accessories	45	2660
Electronics & Photo	30	1814
Games	5	437
Health & Personal Care	2	358
Stationery & Office Supplies	1	84
Toys	1	98
Total	84	5451

Table B.4: Number of treated and control products by category (Germany)

This table presents the number of treated products (products receiving carbon-neutral labels) and control products (without a label) by first-level category for the German market.

	Treated	Control	T-stat (Welch p)
Initial Price	31.2	31.54	-0.167 (p=0.867)

Table B.5: Balance

The table reports the mean initial prices for treated products (those receiving carbon-neutral labels) and control products (without a label). The two-sample t-test is used to test covariate balance between the two groups.

Product ASIN	Category	First Treated (yyyy-mm-dd)	Price in Mar 2023 (USD)	Price in Nov 2024 (USD)
B00M48YNOU	Grocery & Gourmet Food	2023-04-03	12.48	21.99
B0771VVJRW	Beauty & Personal Care	2023-04-10	19.99	19.99
B0B6V9D89F	Cell Phones & Accessories	2023-04-10	13.06	6.99
B0BF9N2RP2	Cell Phones & Accessories	2023-04-24	14.66	14.24
B095BZT4SD	Electronics	2023-05-08	11.99	8.26
B09NKJ5MCV	Electronics	2023-05-08	15.32	8.34
B09NNJYGB4	Video Games	2023-05-08	229.62	156.35
B08M5L57KT	Electronics	2023-05-08	23.99	22.24
B07M91R8PN	Electronics	2023-05-08	17.99	16.99
B0B5KDNTWS	Health & Household	2023-05-15	58.00	50.16
B09W36YKY7	Health & Household	2023-05-15	42.99	42.99
B09W35DHLH	Health & Household	2023-05-15	36.99	31.81
B0948ZFQFR	Electronics	2023-05-22	25.99	24.04
B09W363MVD	Health & Household	2023-05-22	42.99	36.79
B09CTLNCFG	Electronics	2023-06-12	19.99	18.99
B0B1BSLRGT	Cell Phones & Accessories	2023-06-19	33.29	22.79
B08J3K4N15	Electronics	2023-06-19	23.99	26.49
B007N3H26M	Electronics	2023-06-19	56.99	46.66
B0073UBRP2	Electronics	2023-06-19	23.99	25.64
B014G1G10Q	Beauty & Personal Care	2023-06-19	27.95	25.46
B0BHMKVF1P	Video Games	2023-06-26	31.66	23.90
B0BL66ZW9H	Video Games	2023-06-26	59.89	56.33
B0BL67RHS6	Video Games	2023-06-26	183.76	148.98
B0BL6G3NRJ	Video Games	2023-06-26	136.36	107.84
B0BHMMH9KM	Video Games	2023-06-26	34.99	28.16
B07GSLHXXQ	Electronics	2023-07-03	9.98	10.23
B0B1TVD3HK	Electronics	2023-07-03	20.99	19.99
B0B1TQTNMC	Electronics	2023-07-03	20.99	19.59
B0BLRGQF3M	Cell Phones & Accessories	2023-07-03	9.98	15.98
B093PT44N1	Electronics	2023-07-10	30.99	24.29
B0BJFFGLHM	Electronics	2023-07-10	27.66	29.99
B07GZFJ4G5	Cell Phones & Accessories	2023-07-24	36.37	37.32

Table B.6: Timing of the changes in treatment status (United States)

Product ASIN	Category	First Treated (yyyy-mm-dd)	Price in Mar 2023 (USD)	Price in Nov 2024 (USD)
B08L3WX26S	Electronics	2023-07-24	24.99	19.94
B09FDJFJ6Z	Electronics	2023-07-24	7.99	6.40
B07RQRMGKB	Electronics	2023-07-24	11.32	9.74
B08GJ3F11N	Beauty & Personal Care	2023-07-24	11.99	9.99
B085ZXC2HS	Cell Phones & Accessories	2023-07-24	15.99	14.99
B09YFH1C8X	Beauty & Personal Care	2023-07-24	15.09	16.99
B086JBZW48	Health & Household	2023-07-31	12.97	14.99
B08PHY1PJF	Health & Household	2023-07-31	12.99	8.66
B089LDX88M	Cell Phones & Accessories	2023-07-31	15.03	11.99
B09L9RKN7W	Health & Household	2023-07-31	10.99	9.99
B08P27Y27M	Health & Household	2023-07-31	12.99	10.79
B0BLK79BZ2	Electronics	2023-08-14	28.95	23.99
B0BGHM8SY4	Electronics	2023-08-14	11.90	8.88
B09HKX6HRB	Electronics	2023-08-28	10.99	8.52
B08BR4V18G	Electronics	2023-08-28	14.99	14.99
B086QW23YD	Electronics	2023-08-28	12.99	12.48
B0BBSP2JNQ	Beauty & Personal Care	2023-08-28	19.92	21.75
B09J1DFTTV	Electronics	2023-09-04	19.91	17.99
B0BGHRM5DV	Electronics	2023-09-04	18.99	15.99
B093T7GQWB	Electronics	2023-09-04	18.79	9.95
B074KV9TT4	Electronics	2023-09-04	37.32	27.39
B088RHCSG3	Electronics	2023-09-04	14.99	12.96
B09J1FYF9V	Electronics	2023-09-04	20.95	22.47
B0BLTDYG2B	Cell Phones & Accessories	2023-09-11	14.99	14.71
B08XQQ5XTZ	Cell Phones & Accessories	2023-09-18	27.66	16.99
B0831BF1FH	Cell Phones & Accessories	2023-09-18	28.49	23.99
B08883JK8Y	Electronics	2023-09-18	33.99	29.86
B08K8S4ZDW	Electronics	2023-09-18	45.99	41.49
B095GJDXNG	Electronics	2023-09-18	31.99	27.32
B08RDF9B3F	Cell Phones & Accessories	2023-09-18	12.38	16.99
B09PR1BTM7	Tools & Home Improvement	2023-09-18	15.99	13.66
B08GG42WXY	Tools & Home Improvement	2023-09-18	11.19	8.79

Table B.6: Timing of the changes in treatment status (United States)

Product ASIN	Category	First Treated (yyyy-mm-dd)	Price in Mar 2023 (USD)	Price in Nov 2024 (USD)
B0BGN9R72N	Tools & Home Improvement	2023-09-18	10.99	8.09
B0BHH7M4YJ	Cell Phones & Accessories	2023-09-18	9.99	8.62
B09PV827TS	Electronics	2023-09-18	31.99	27.99
B0BHHVN541	Cell Phones & Accessories	2023-09-18	9.99	8.62
B0BM4QL882	Cell Phones & Accessories	2023-09-18	9.99	8.99
B07Y9G18V7	Electronics	2023-09-18	36.32	29.99
B0BK99PT9K	Electronics	2023-09-18	32.99	28.49
B0BC21JFYH	Cell Phones & Accessories	2023-09-18	10.99	8.62
B0BM4LPT4Y	Cell Phones & Accessories	2023-09-25	9.99	8.99
B08K8DNVB4	Cell Phones & Accessories	2023-10-02	43.88	36.25
B0B96PKNVL	Video Games	2023-10-16	20.32	18.66
B0B66RHD7B	Video Games	2023-10-16	28.49	27.99
B01M11FLUJ	Office Products	2023-10-30	14.17	9.97
B016XTADG2	Electronics	2023-11-06	25.99	25.99
B01MTB55WH	Electronics	2023-11-06	36.66	33.99
B07Z4RF1D3	Electronics	2023-11-06	16.73	16.15
B0B1MCHS14	Electronics	2023-11-13	26.99	15.49
B096BCMK8N	Electronics	2023-11-13	27.32	16.39
B087LRK3H4	Electronics	2023-11-13	17.99	12.99
B093C2B4K3	Electronics	2023-11-13	19.32	16.99
B082Y6YDZZ	Electronics	2023-11-20	64.98	58.45
B01BT02Q88	Beauty & Personal Care	2023-11-20	14.99	14.99
B0BLBQ9G2C	Cell Phones & Accessories	2023-11-20	26.99	26.99
B0BRC415HH	Cell Phones & Accessories	2023-11-20	21.99	20.99
B0BTRTFK4S	Cell Phones & Accessories	2023-11-20	26.99	26.99
B07J4TNYV8	Electronics	2023-11-20	139.99	128.32
B0B2BSQQL7	Electronics	2023-11-20	89.89	79.99
B0BQB8JNFB	Cell Phones & Accessories	2023-11-20	23.99	24.69
B0BP7HG18T	Electronics	2023-11-20	64.99	61.72
B07JR1XZ78	Electronics	2023-11-20	84.99	71.66
B07QXV6N1B	Cell Phones & Accessories	2023-11-27	21.99	22.32
B0BJZ5VMD6	Cell Phones & Accessories	2023-11-27	26.99	26.99

Table B.6: Timing of the changes in treatment status (United States)

Product ASIN	Category	First Treated (yyyy-mm-dd)	Price in Mar 2023 (USD)	Price in Nov 2024 (USD)
B0874M3KW4	Electronics	2023-11-27	69.99	46.99
B07ZCRWPPV	Electronics	2023-12-04	66.99	62.52
B08SJDXF73	Electronics	2023-12-11	10.99	9.97
B0BRKVSXG4	Electronics	2023-12-18	109.99	106.36
B07CSBYNWG	Beauty & Personal Care	2023-12-25	19.99	16.95
B0B7DP9CGN	Health & Household	2023-12-25	24.69	24.30
B09P37WCS4	Electronics	2024-01-22	15.99	15.79
B09X9JCLR7	Video Games	2024-01-29	29.99	26.46
B09P5BBPVY	Video Games	2024-01-29	29.99	27.22
B09YR1J35N	Electronics	2024-02-05	27.99	26.99
B09WDH6K1T	Toys & Games	2024-02-05	40.32	46.66
B0BJ2D5X2R	Cell Phones & Accessories	2024-02-05	74.10	59.20
B0BHZ6MWC1	Cell Phones & Accessories	2024-02-05	68.40	59.20
B0BHZ84Z9C	Cell Phones & Accessories	2024-02-05	68.40	59.20
B0BQ35Q43S	Cell Phones & Accessories	2024-02-05	74.10	49.60
B0BQ2L5KJJ	Cell Phones & Accessories	2024-02-05	94.73	56.86
B0BN1P1KKL	Cell Phones & Accessories	2024-02-05	68.40	53.65
B0BRY2FPKM	Cell Phones & Accessories	2024-02-05	74.10	59.20
B08FTDWPTX	Electronics	2024-02-12	11.99	11.69
B088NGVY4C	Electronics	2024-02-12	12.78	11.19
B0BRXY8RH7	Cell Phones & Accessories	2024-02-12	64.60	54.57
B089PYQQSQ	Electronics	2024-02-19	17.97	17.07
B09ZQQPNXD	Beauty & Personal Care	2024-02-19	11.99	11.54
B07HC4NBQ8	Video Games	2024-02-19	30.89	29.52
B08SJ5Z8JL	Video Games	2024-02-19	19.99	18.32
B01NAI2TXC	Video Games	2024-02-19	55.79	55.36
B0BHSVQXHG	Cell Phones & Accessories	2024-02-19	59.93	62.00
B0BQ2QJCQQ	Cell Phones & Accessories	2024-02-26	77.90	50.45
B07VCS8QTK	Electronics	2024-03-04	17.99	12.83
B09BN32Y86	Electronics	2024-03-04	11.32	7.89
B0B9SK4WD3	Cell Phones & Accessories	2024-03-04	10.98	16.98
B09JLLD5QH	Electronics	2024-03-11	15.95	9.61

Table B.6: Timing of the changes in treatment status (United States)

Product ASIN	Category	First Treated (yyyy-mm-dd)	Price in Mar 2023 (USD)	Price in Nov 2024 (USD)
B08YNKKB7M	Electronics	2024-03-11	18.79	9.95
B09R6JP7K5	Electronics	2024-03-11	18.99	15.99
B0BJV4888V	Electronics	2024-03-11	14.99	10.49
B0B3R73C5F	Electronics	2024-03-11	19.99	15.99
B09JBBPC9K	Electronics	2024-03-11	17.95	15.79
B0BGH6L5B6	Electronics	2024-03-11	18.99	14.99
B09KXSJZ6K	Electronics	2024-03-11	21.99	20.66
B09KZFH1JP	Electronics	2024-03-11	22.99	21.99
B09J4RQFK7	Electronics	2024-03-11	25.99	24.17
B084FSYC1B	Toys & Games	2024-03-11	19.99	29.99
B082ZYNMC8	Health & Household	2024-03-18	9.49	9.66
B08FFFGHJF	Toys & Games	2024-03-18	22.24	27.99
B07H8TJMX7	Electronics	2024-06-03	10.40	9.98
B07SQP1GHC	Electronics	2024-06-03	35.99	35.99
B0BJ7GST13	Cell Phones & Accessories	2024-06-03	13.98	16.98
B0B9SP1CZ2	Cell Phones & Accessories	2024-06-03	11.98	16.98
B093L2Y8KQ	Electronics	2024-06-03	9.95	7.74
B09VPBF8NY	Video Games	2024-06-03	19.99	19.99
B07PMBCTSY	Electronics	2024-06-03	66.66	55.32
B09BYJLZ16	Electronics	2024-06-03	32.66	24.99
B0B63LNZBW	Electronics	2024-06-03	29.99	13.99
B09MHFSSFB	Tools & Home Improvement	2024-06-03	11.67	10.99
B07L2LS9SK	Electronics	2024-06-03	33.96	32.26
B0B73JCBRZ	Electronics	2024-06-03	19.99	20.99
B09HQFYY88	Tools & Home Improvement	2024-06-03	11.32	10.83
B09YRVDWCP	Tools & Home Improvement	2024-06-03	15.99	13.49
B09YRVVFVK	Tools & Home Improvement	2024-06-03	15.99	12.99
B09ZPCC1J3	Tools & Home Improvement	2024-06-03	15.99	12.24
B09ZPDMMRW	Tools & Home Improvement	2024-06-03	15.99	12.24
B0BMLFV2DJ	Electronics	2024-06-03	25.99	24.26
B09TDHLXMZ	Electronics	2024-06-03	28.49	27.99

Table B.6: Timing of the changes in treatment status (United States)

Product ASIN	Category	First Treated (yyyy-mm-dd)	Price in Mar 2023 (USD)	Price in Nov 2024 (USD)
B07P7MB88J	Electronics	2024-06-03	35.14	34.19
B09BN47YHV	Electronics	2024-06-03	22.99	35.64
B08R5CCRFD	Electronics	2024-06-03	43.98	37.99
B0BBG5RRXF	Electronics	2024-06-03	28.49	27.35
B0B2K2SMH7	Cell Phones & Accessories	2024-06-03	13.99	14.91
B09SW6L7H8	Cell Phones & Accessories	2024-06-03	15.99	12.24
B0BPYJWMP7	Cell Phones & Accessories	2024-06-03	16.98	17.98
B095VLRB2J	Electronics	2024-06-03	32.99	27.99
B0BK1T5PF4	Cell Phones & Accessories	2024-06-03	16.98	17.98
B08VVWRFLS	Electronics	2024-06-03	46.99	47.48
B0B8X44B4Y	Cell Phones & Accessories	2024-06-03	15.99	13.29
B07TS6R1SF	Electronics	2024-06-03	30.79	32.66
B0921JJMZT	Electronics	2024-06-03	15.99	13.06
B09ZTXVNVD	Cell Phones & Accessories	2024-06-03	28.99	16.19
B01H6GUCCQ	Video Games	2024-06-17	25.99	21.91
B0B16VD9RQ	Beauty & Personal Care	2024-06-17	19.99	19.98
B09Q7LTBTR	Beauty & Personal Care	2024-06-17	34.18	27.55
B081JP3MJK	Video Games	2024-06-17	33.99	28.86
B0BG21S94B	Electronics	2024-06-24	52.49	48.66
B0BNPBTJDP	Video Games	2024-06-24	42.99	37.85
B07KCRTN9Q	Video Games	2024-07-08	44.99	37.96
B098S48QWM	Electronics	2024-07-22	10.58	9.98
B01MTVC775	Electronics	2024-07-29	56.99	49.10
B0BPCHQBS7	Electronics	2024-07-29	119.99	99.99
B076Q6442Z	Beauty & Personal Care	2024-08-05	7.98	6.99
B0811RYZ2J	Cell Phones & Accessories	2024-08-12	17.99	15.99
B0811RH5MF	Cell Phones & Accessories	2024-08-12	16.99	13.19
B08F79BQD3	Cell Phones & Accessories	2024-08-12	16.99	15.74
B07L793HPW	Cell Phones & Accessories	2024-08-12	17.99	13.29
B09D941CFQ	Cell Phones & Accessories	2024-08-12	16.99	16.64
B07GBXVX7W	Cell Phones & Accessories	2024-08-12	15.99	16.99

Table B.6: Timing of the changes in treatment status (United States)

Product ASIN	Category	First Treated (yyyy-mm-dd)	Price in Mar 2023 (USD)	Price in Nov 2024 (USD)
B07THZ6MVP	Cell Phones & Accessories	2024-08-12	16.99	11.42
B09D952JQQ	Cell Phones & Accessories	2024-08-12	17.99	18.24
B0BCJ8Q1QN	Cell Phones & Accessories	2024-08-12	18.99	17.99
B08M636GG3	Cell Phones & Accessories	2024-08-12	16.42	16.99
B0BBKW53L3	Cell Phones & Accessories	2024-08-12	22.99	8.99
B01K2UMMI0	Beauty & Personal Care	2024-08-19	24.99	22.39
B08L3K9LC6	Health & Household	2024-08-19	19.99	32.80
B081S71B77	Health & Household	2024-08-19	19.97	23.95
B0932BCM2T	Musical Instruments	2024-08-26	31.30	30.75
B07XVCP7F5	Video Games	2024-08-26	66.99	55.59
B08JCV3J5P	Video Games	2024-08-26	79.99	75.97
B07R1R1MKW	Health & Household	2024-08-26	17.97	23.39
B08FDPW8KR	Electronics	2024-09-09	35.32	35.99
B0B979GR4Z	Electronics	2024-09-16	31.32	27.49
B00N1YTJRC	Health & Household	2024-09-23	38.37	41.74
B0B6BW56FF	Safety & Security	2024-10-07	8.99	8.35
B0B6BVHS4W	Safety & Security	2024-10-07	9.99	8.99

Table B.6: Timing of the changes in treatment status (United States)

Product ASIN	Category	First Treated (yyyy-mm-dd)	Price in May 2024 (GBP)	Price in Nov 2024 (GBP)
B0773F8S74	Mobile Phones & Communication	2024-06-18	15.99	15.99
B0C3C8M5X6	Accessories	2024-07-16	9.99	9.99
B09BW1T7X2	Headphones, Earphones & Accessories	2024-07-16	129.95	119.71
B09BW1QVVT	Headphones, Earphones & Accessories	2024-07-16	129.95	119.71
B0CD226VG1	Arts & Crafts	2024-07-30	6.29	6.73
B0BZCMKWGV	Mobile Phones & Communication	2024-08-06	12.99	12.99
B0CNVGVM3R	Headphones, Earphones & Accessories	2024-08-06	32.99	30.99
B0CNVHKVVL	Headphones, Earphones & Accessories	2024-08-06	29.99	40.49
B07D6N526S	Hi-Fi & Home Audio	2024-08-06	10.99	19.99
B09996WC24	Mobile Phones & Communication	2024-08-06	13.99	13.46
B09D952JQQ	Mobile Phones & Communication	2024-08-06	11.89	14.96
B07GBXVX7W	Mobile Phones & Communication	2024-08-06	12.99	13.24
B08F7Q8Y5W	Mobile Phones & Communication	2024-08-06	13.99	13.08
B081H1N3PJ	Mobile Phones & Communication	2024-08-06	13.99	13.29
B07Z1CVWD2	Mobile Phones & Communication	2024-08-06	19.99	19.99
B099968ZQK	Mobile Phones & Communication	2024-08-06	13.99	13.21
B07TFD7KR3	Mobile Phones & Communication	2024-08-06	13.99	12.99
B09D94T83V	Mobile Phones & Communication	2024-08-06	14.99	14.43
B0BCHZFSFD	Mobile Phones & Communication	2024-08-06	13.99	10.92
B0CHRFQPCC	Mobile Phones & Communication	2024-08-06	13.59	15.99
B0BCJ4KZWG	Mobile Phones & Communication	2024-08-06	12.99	12.99
B0BN54PK3X	Mobile Phones & Communication	2024-08-06	13.99	11.24
B0BN5HTP3K	Mobile Phones & Communication	2024-08-06	15.99	15.19
B08R78YY9M	Mobile Phones & Communication	2024-08-06	13.99	13.99
B08DHT9KJZ	Wearable Technology	2024-08-06	7.99	6.80
B0BZH6ZF7M	Sports	2024-08-06	15.99	16.99
B0C8N8D6GF	Sports	2024-08-06	17.99	16.14
B0CB5XH9J5	Mobile Phones & Communication	2024-08-06	23.99	24.53
B09L4GBWDV	Wearable Technology	2024-08-13	7.99	6.80
B0CCN9Q27D	Gardening	2024-08-13	65.13	32.28
B0C8N7MKF6	Mobile Phones & Communication	2024-08-13	12.99	12.12
B08ZXQLJN9	Accessories	2024-08-13	19.99	21.49

Table B.7: Timing of the changes in treatment status (United Kingdom)

Product ASIN	Category	First Treated (yyyy-mm-dd)	Price in MaY 2024 (GBP)	Price in Nov 2024 (GBP)
B0CHLXSBND	Mobile Phones & Communication	2024-08-13	29.40	21.16
B0BHYKBQLP	Gardening	2024-08-13	29.22	28.94
B0BK84XP9K	Microphones	2024-08-27	49.99	46.24
B09B3LJVFJ	Microphones	2024-08-27	36.99	35.60
B0CHNSY4S8	Mobile Phones & Communication	2024-09-17	43.99	37.49
B0CHYL54H8	Mobile Phones & Communication	2024-09-17	33.43	41.79
B0CHYKQQ6S	Mobile Phones & Communication	2024-09-17	43.99	41.79
B0BDFDRCKV	Wearable Technology	2024-09-24	6.58	7.29
B09H2JD8F8	Wearable Technology	2024-09-24	6.49	7.58
B08GCNLQT6	Wearable Technology	2024-09-24	6.49	7.58
B0BPNYZ8NN	Wearable Technology	2024-09-24	6.49	7.62
B0BPNT6XYY	Wearable Technology	2024-09-24	6.49	7.62
B09KN7CNRZ	Wearable Technology	2024-09-24	6.49	7.58
B0CHYBKQPM	Mobile Phones & Communication	2024-10-15	16.99	16.34
B0C273FR2T	Mobile Phones & Communication	2024-10-15	17.99	17.84
B082SNXJ4G	Mobile Phones & Communication	2024-10-15	21.99	20.89
B0915H9JD8	Mobile Phones & Communication	2024-10-15	19.99	19.17
B0CB1C69BY	Mobile Phones & Communication	2024-10-15	16.98	17.73

Table B.7: Timing of the changes in treatment status (United Kingdom)

Product ASIN	Category	First Treated (yyyy-mm-dd)	Price in May 2024 (EUR)	Price in Nov 2024 (EUR)
B096FX9226	Electronics & Photo	2024-06-19	21.99	20.52
B09KLYT52T	Electronics & Photo	2024-06-19	9.99	9.99
B0C9ZVN154	Computer & Accessories	2024-06-26	49.99	45.96
B0C748DZRH	Electronics & Photo	2024-06-26	22.99	32.99
B0C7Q55ZM5	Computer & Accessories	2024-06-26	26.99	19.44
B0C6KF5HKT	Computer & Accessories	2024-06-26	16.59	14.79
B0CD7LYR4C	Computer & Accessories	2024-06-26	24.64	26.99
B09VB3WXQS	Computer & Accessories	2024-06-26	13.99	12.73
B0CTQ2346R	Computer & Accessories	2024-06-26	30.99	26.05
B0B31FVQPQ	Computer & Accessories	2024-06-26	16.99	15.52
B0C68N2BH1	Computer & Accessories	2024-06-26	16.99	15.91
B0BW95FDB6	Computer & Accessories	2024-06-26	19.99	18.97
B09X1H9VNZ	Computer & Accessories	2024-06-26	15.99	15.99
B09X1FZQPX	Computer & Accessories	2024-06-26	23.99	24.99
B0C9DJK1QX	Computer & Accessories	2024-06-26	14.09	13.50
B0CMCGLT21	Computer & Accessories	2024-06-26	39.67	45.99
B0CTQBG9YP	Computer & Accessories	2024-06-26	28.99	25.54
B0BVLY3JNJ	Computer & Accessories	2024-06-26	17.99	15.99
B0CTQ94TV3	Computer & Accessories	2024-06-26	39.99	35.09
B0C3LB86PN	Computer & Accessories	2024-06-26	54.99	44.99
B0BVLX7BXW	Computer & Accessories	2024-06-26	16.09	14.72
B0CGZVDMKG	Computer & Accessories	2024-07-10	55.99	46.63
B0BM5XSKDR	Computer & Accessories	2024-07-17	9.99	25.77
B075V27G2R	Computer & Accessories	2024-07-17	11.19	12.59
B07F2YJRN2	Computer & Accessories	2024-07-17	55.38	43.63
B0C3L93F2Q	Stationery & Office Supplies	2024-07-24	25.49	27.74
B08M5PSFWF	Computer & Accessories	2024-07-24	7.89	9.46
B0CSYMR7GZ	Electronics & Photo	2024-07-24	32.38	37.80
B0CH7VQJKH	Games	2024-08-07	23.95	19.32
B07JNJGM1G	Electronics & Photo	2024-08-07	13.98	12.50
B07GBXVX7W	Electronics & Photo	2024-08-07	13.95	13.45
B09996WC24	Electronics & Photo	2024-08-07	13.56	15.95

Table B.8: Timing of the changes in treatment status (Germany)

Product ASIN	Category	First Treated (yyyy-mm-dd)	Price in May 2024 (EUR)	Price in Nov 2024 (EUR)
B0CH346J32	Games	2024-08-07	23.98	19.99
B0CN8LRLLH	Games	2024-08-07	39.99	39.99
B0CN8GG24V	Games	2024-08-07	39.99	37.19
B0BR5JG23N	Games	2024-08-07	19.99	19.99
B0CL6LL5SF	Electronics & Photo	2024-08-14	12.74	14.99
B0CPDZT72H	Electronics & Photo	2024-08-14	12.74	13.87
B08ZXQLJN9	Computer & Accessories	2024-08-14	29.99	29.99
B01MY4L8BV	Health & Personal Care	2024-08-21	9.95	9.95
B0BLND9W1C	Electronics & Photo	2024-09-04	17.68	14.09
B0873358VL	Computer & Accessories	2024-10-02	15.99	20.47
B07D5QDZTY	Computer & Accessories	2024-10-02	15.99	21.74
B0CN8G45K1	Electronics & Photo	2024-10-02	59.99	55.93
B0CGM1DJZ8	Computer & Accessories	2024-10-02	36.97	43.24
B0CGLXNPHL	Computer & Accessories	2024-10-02	47.99	58.13
B073RY7XD7	Computer & Accessories	2024-10-02	14.99	19.49
B0CGR7H7BT	Computer & Accessories	2024-10-02	41.62	55.89
B0CGHRZD4Q	Computer & Accessories	2024-10-02	45.96	48.52
B0CGHF5G95	Computer & Accessories	2024-10-02	47.97	61.49
B09XR315M4	Computer & Accessories	2024-10-02	59.01	42.59
B0CPPDCGBT	Computer & Accessories	2024-10-02	47.95	62.78
B0CB3DRLCT	Electronics & Photo	2024-10-16	15.99	15.93
B0B3MKD39C	Electronics & Photo	2024-10-16	23.99	24.19
B0C273FR2T	Electronics & Photo	2024-10-16	19.99	17.99
B0CB1C69BY	Electronics & Photo	2024-10-16	19.99	18.99
B0C3C9GCGY	Computer & Accessories	2024-10-16	10.99	12.99
B0C3C8CWYQ	Computer & Accessories	2024-10-16	10.99	12.99
B08V8NPY3Y	Electronics & Photo	2024-10-16	16.99	16.99
B0BV6NT6CH	Computer & Accessories	2024-10-23	10.99	25.95
B08NSJR3TN	Computer & Accessories	2024-10-23	55.91	60.57
B09GG64C6G	Toys	2024-10-30	17.99	17.09
B0CL94BQ56	Electronics & Photo	2024-10-30	17.97	11.64
B0749MNW3N	Health & Personal Care	2024-11-06	8.49	9.99

Table B.8: Timing of the changes in treatment status (Germany)

Product ASIN	Category	First Treated (yyyy-mm-dd)	Price in May 2024 (EUR)	Price in Nov 2024 (EUR)
B0BVRD97MT	Electronics & Photo	2024-11-06	6.95	6.43
B09VH599VG	Electronics & Photo	2024-11-06	6.89	6.69
B09X777HXL	Electronics & Photo	2024-11-06	6.89	6.68
B09F3P3DQD	Electronics & Photo	2024-11-06	6.95	6.84
B0CJMJS3DS	Electronics & Photo	2024-11-06	6.89	6.67
B0BVVN31X8	Computer & Accessories	2024-11-06	10.95	8.99
B09ZYJB6RB	Electronics & Photo	2024-11-06	6.89	6.95
B09F3RCJJR	Electronics & Photo	2024-11-06	6.95	6.69
B0BMQPWBK6	Electronics & Photo	2024-11-06	6.89	6.43
B0C4LRY247	Electronics & Photo	2024-11-06	6.95	6.95
B0BD5J9M98	Electronics & Photo	2024-11-06	6.95	6.68
B0C4LTQZ62	Electronics & Photo	2024-11-06	6.89	6.95
B09FYBKN69	Computer & Accessories	2024-11-06	9.89	9.31
B09FYCQDTK	Computer & Accessories	2024-11-06	9.89	9.11
B09QT5H713	Computer & Accessories	2024-11-06	9.89	9.23
B09QT6M1WS	Computer & Accessories	2024-11-06	9.89	8.99
B0CG1R72SM	Computer & Accessories	2024-11-06	17.99	15.99
B0C84Q8TFV	Computer & Accessories	2024-11-06	17.95	17.95
B09X768KKV	Electronics & Photo	2024-11-06	6.89	6.95
B0BD5D5JHQ	Electronics & Photo	2024-11-06	6.89	6.69

Table B.8: Timing of the changes in treatment status (Germany)

B.4 Carbon footprint estimation of quasi-natural experiments

Information about a product's mitigated carbon footprint (that is, the amount reduced or offset) may be readily available on Amazon or can be estimated via external sources. Overall, we rely on four sources for carbon footprint estimation: the product's Amazon webpage, ClimatePartner's webpage, Carbon Catalogue (Meinrenken et al., 2022) and the Idemat database (Stichting Sustainability Impact Metrics, 2024). In practice, to estimate a product's carbon footprint we follow these steps. First, we check whether carbon footprint information is available on the product's Amazon page or ClimatePartner's page. ClimatePartner lists some of its product footprint information on the product webpage and allows consumers to search for a product's carbon footprint using its identification number on the company's website. If not, we verify whether the exact product or a similar one is listed in the Carbon Catalogue. If it is, we rely on that figure. Otherwise, we identify the product's main material (often specified first in online descriptions) and consult the Idemat database for relevant data, combining these two databases. Because carbon footprint data is typically provided in terms of carbon dioxide (or equivalent) emissions per kilogram of product, we multiply the reported figure by the product's actual weight to determine its total carbon footprint. Caveats apply. In particular, we could not estimate the carbon footprint for 8 out of 207 quasi-natural experiments in the US, 1 out of 50 experiments in the UK, and 8 out of 84 experiments in Germany.

B.5 Difference-in-difference analysis

This section presents the output of the difference-in-difference model (Callaway and Sant'Anna, 2021) described in Section 3.2. Tables B.9 and B.10 report the dynamic and calendar effects for the United States, respectively.

Months -18 to 0 (Pre-treatment)				Months 1 to 19 (Post-treatment)			
Months	Estimate (%)	Lower 95% CI	Upper 95% CI	Months	Estimate (%)	Lower 95% CI	Upper 95% CI
-18	-1.16	-5.05	2.73	1	-0.93	-2.82	0.97
-17	-4.80	-25.12	15.52	2	0.37	-2.07	2.81
-16	-1.15	-3.76	1.47	3	-0.30	-2.71	2.12
-15	0.09	-1.54	1.71	4	-0.67	-3.41	2.06
-14	-0.58	-3.22	2.05	5	-1.82	-4.98	1.33
-13	0.44	-1.69	2.56	6	-3.04	-7.10	1.02
-12	-0.08	-1.87	1.71	7	-2.64	-6.78	1.50
-11	0.18	-1.26	1.63	8	-2.25	-6.66	2.15
-10	0.28	-1.08	1.64	9	-3.39	-7.69	0.90
-9	-0.91	-2.61	0.79	10	-3.78	-9.22	1.67
-8	1.65	0.15	3.15	11	-3.67	-9.25	1.90
-7	-1.02	-3.09	1.05	12	-2.57	-8.58	3.44
-6	1.93	-0.14	4.00	13	-2.69	-8.96	3.58
-5	-0.35	-1.99	1.29	14	-4.67	-10.52	1.17
-4	-0.50	-1.79	0.79	15	-5.75	-13.39	1.90
-3	-0.40	-1.65	0.85	16	-4.60	-14.78	5.58
-2	-0.16	-1.72	1.41	17	-5.77	-19.34	7.80
-1	-1.10	-2.49	0.30	18	-6.55	-29.68	16.58
0	0.14	-1.20	1.47	19	10.46	-51.74	72.67

Table B.9: Dynamic effects (US)

This table presents the effect of carbon-neutral labels on product price changes, expressed in percentages, relative to the product's price in March 2023 on Amazon's U.S. marketplace. Furthermore, the plot displays the upper and lower 95% confidence intervals based on 1,000 bootstrap samples. The control group is defined as products without a carbon-neutral label. The control variables include the product categories and the product's initial price at the beginning of the panel.

Time	Estimate (%)	Lower 95% CI	Upper 95% CI
April 2023	3.17	-3.12	9.46
May 2023	-0.53	-4.31	3.24
June 2023	1.00	-2.39	4.38
July 2023	-1.06	-4.14	2.03
August 2023	-1.88	-6.59	2.82
September 2023	-0.58	-3.54	2.37
October 2023	-0.72	-4.90	3.47
November 2023	-0.85	-5.16	3.46
December 2023	-0.12	-4.71	4.46
January 2024	-2.39	-6.48	1.71
February 2024	-1.56	-5.49	2.36
March 2024	-2.71	-7.04	1.63
April 2024	-2.29	-6.94	2.37
May 2024	-2.87	-7.08	1.35
June 2024	-1.73	-4.94	1.48
July 2024	-1.14	-4.28	2.00
August 2024	-1.17	-4.09	1.75
September 2024	-2.43	-5.51	0.65
October 2024	-2.23	-5.55	1.08
November 2024	-4.59*	-8.00	-1.19

Table B.10: Calendar Effects (US)

This table presents the effect of carbon-neutral labels on product price changes, expressed in percentages, relative to the product's price in March 2023 on Amazon's U.K. marketplace. Furthermore, the plot displays the upper and lower 95% confidence intervals based on 1,000 bootstrap samples. The control group is defined as products without a carbon-neutral label. The control variables include the product categories and the product's initial price at the beginning of the panel.

B.6 Robustness tests

This section presents a list of robustness tests for the main estimation using data from Amazon's United States marketplace.

First, Figure B.2 illustrates the results of relaxing the condition that the carbon-neutral label should appear in more than 90% of observations after treatment. Second, Figure B.3 shows the estimation results using unbalanced data for the United States. Third, Figure B.4 shows the results excluding products with Climate Pledge Friendly or Small Business labels introduced after March 2023. Fourth, Figure B.5 shows the results excluding control variables. Fifth, Figure B.6 shows results controlling for the initial number of ratings, in addition to the product's initial price and product categories.

We also list two additional robustness estimations using alternative outcome variables. First, Figure B.7 shows the results using absolute price level as the outcome variable. Second, B.8 shows the results using the number of ratings as the outcome variable.

A discussion of these additional findings is provided in Section 3.2 in the main body of the text.

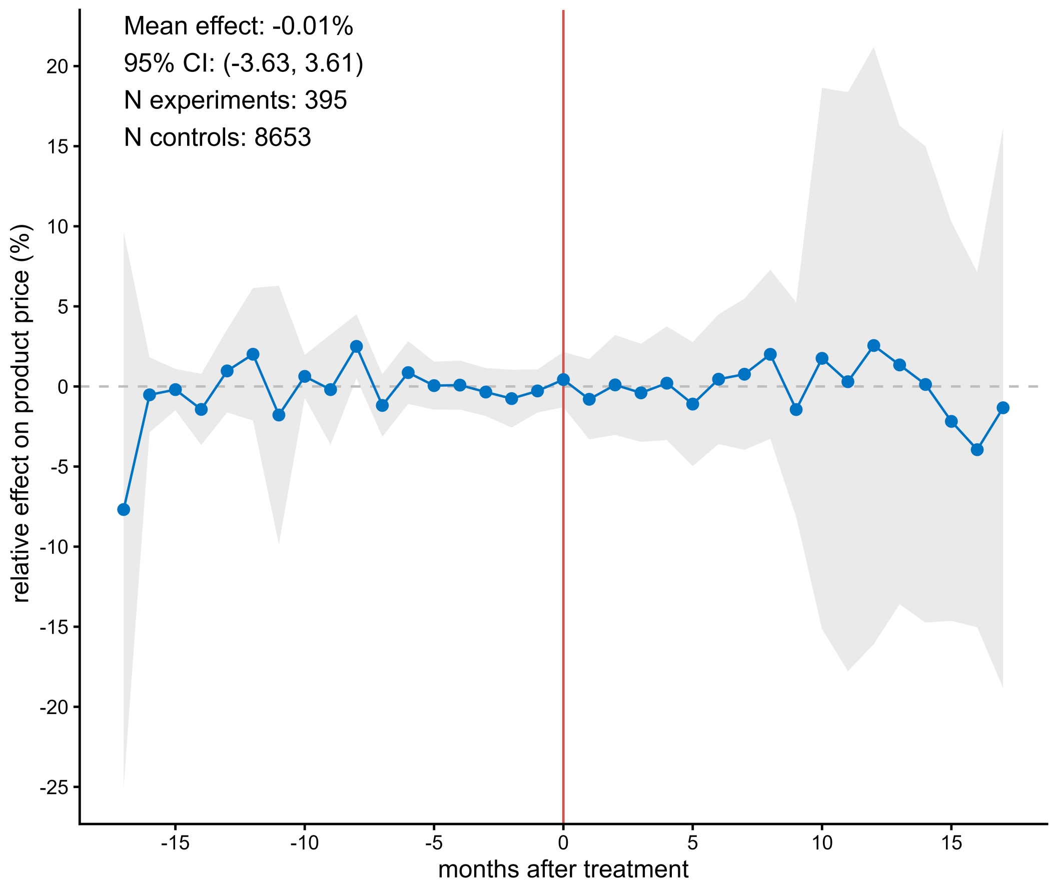


Figure B.2: The effect of carbon-neutral label when removing label consistency constraint (United States)

This plot shows the dynamic treatment effect in percentages relative to the product's price at baseline. Vertical red line marks treatment onset. The shaded area indicates a 95% confidence interval of treatment effect based on 1,000 bootstrap samples that control for multiple hypothesis testing. The control variables include product categories and the product's initial price at the beginning of the panel.

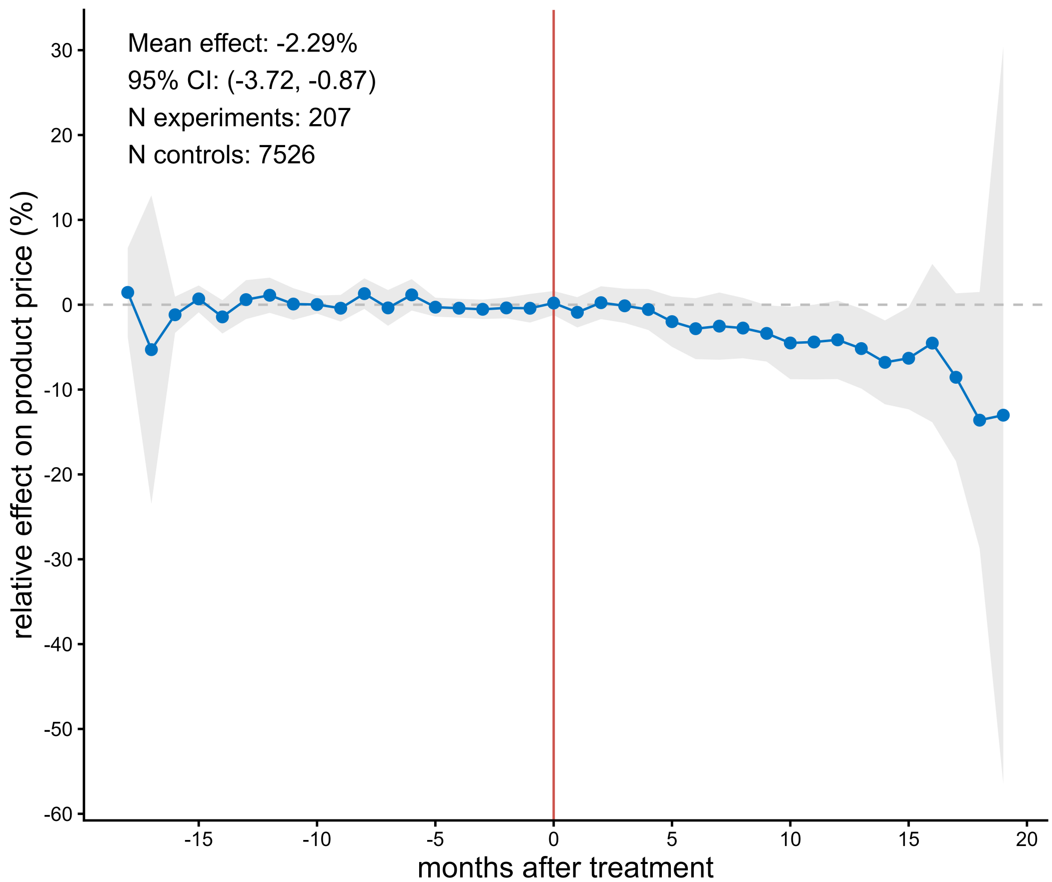


Figure B.3: Effect of carbon-neutral label using unbalanced data option for estimation (United States)

This plot shows the dynamic treatment effect in percentages relative to the product's price at baseline. Vertical red line marks treatment onset. The shaded area indicates a 95% confidence interval of treatment effect based on 1,000 bootstrap samples that control for multiple hypothesis testing.

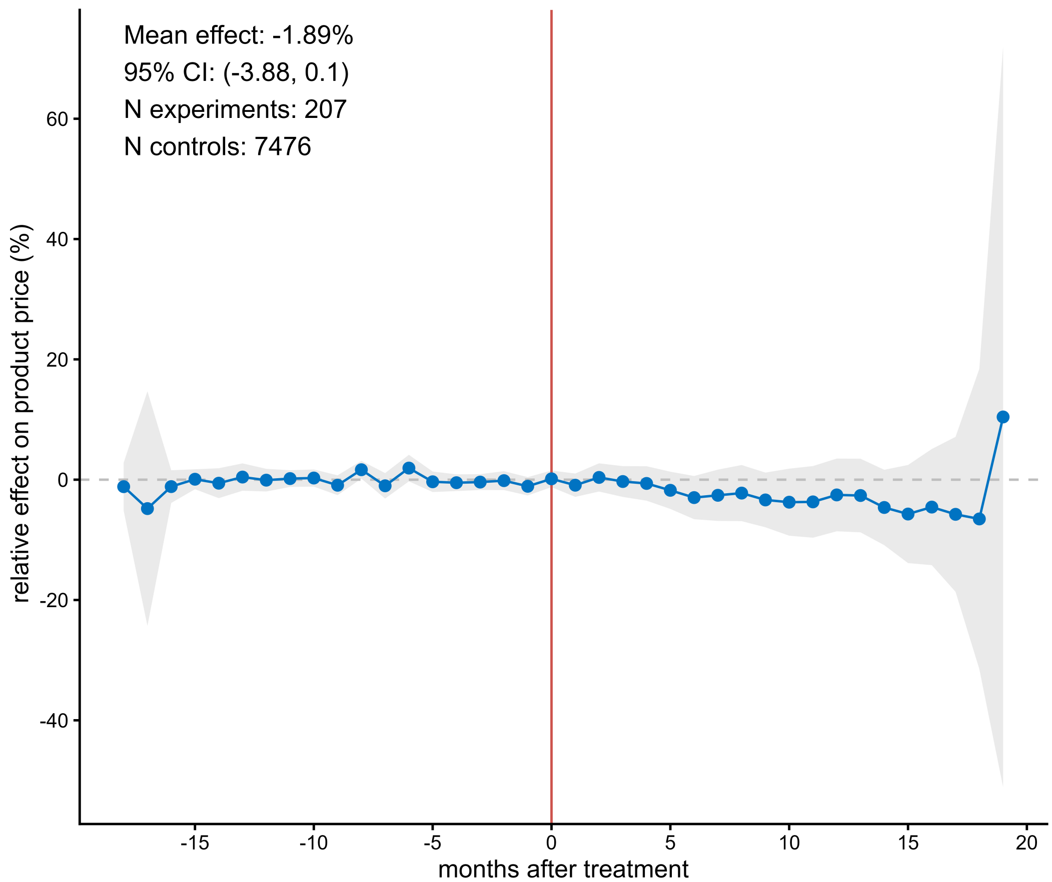


Figure B.4: Effect of carbon-neutral label excluding new Climate Pledge Friendly labels and Small Business labels (United States)

This plot shows the dynamic treatment effect in percentages relative to the product's price at baseline. Vertical red line marks treatment onset. The shaded area indicates a 95% confidence interval of treatment effect based on 1,000 bootstrap samples that control for multiple hypothesis testing. The control variables include product categories and the product's initial price at the beginning of the panel.

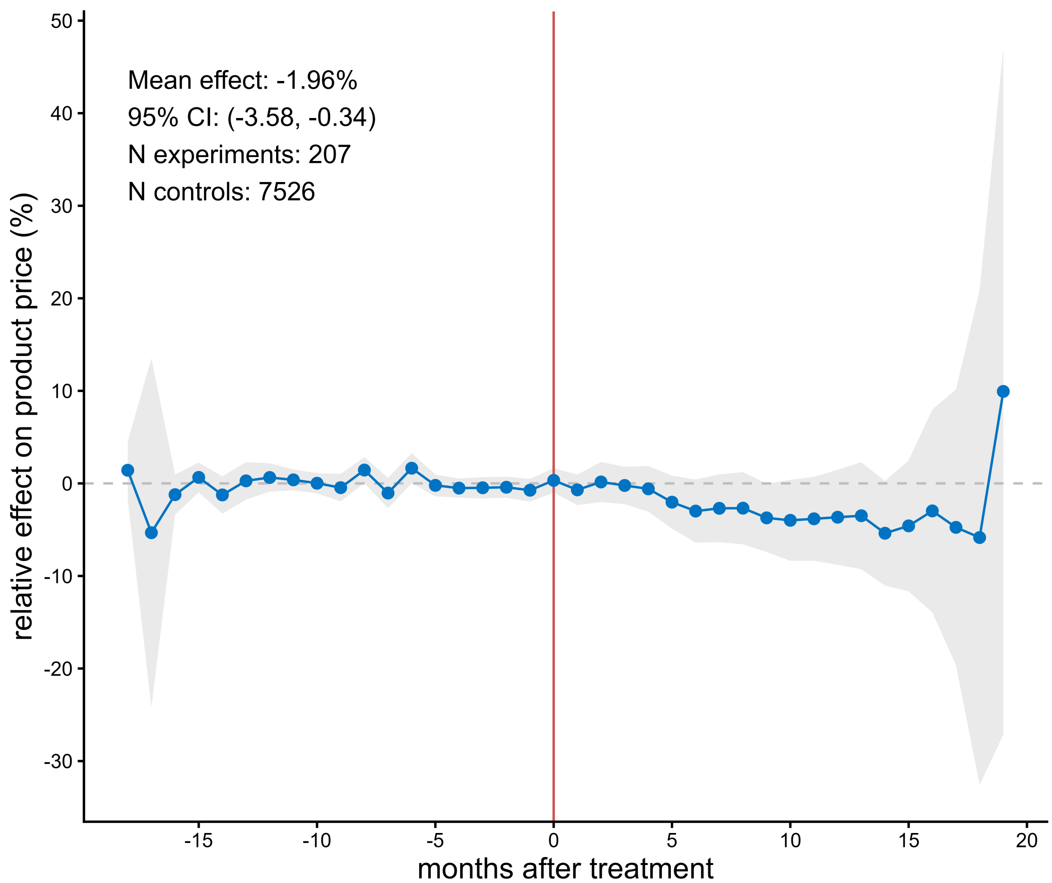


Figure B.5: Effect of carbon-neutral label without control variables (United States)

This plot shows the dynamic treatment effect in percentages relative to the product's price at baseline. Vertical red line marks treatment onset. The shaded area indicates a 95% confidence interval of the treatment effect based on 1,000 bootstrap samples that control for multiple hypothesis testing.

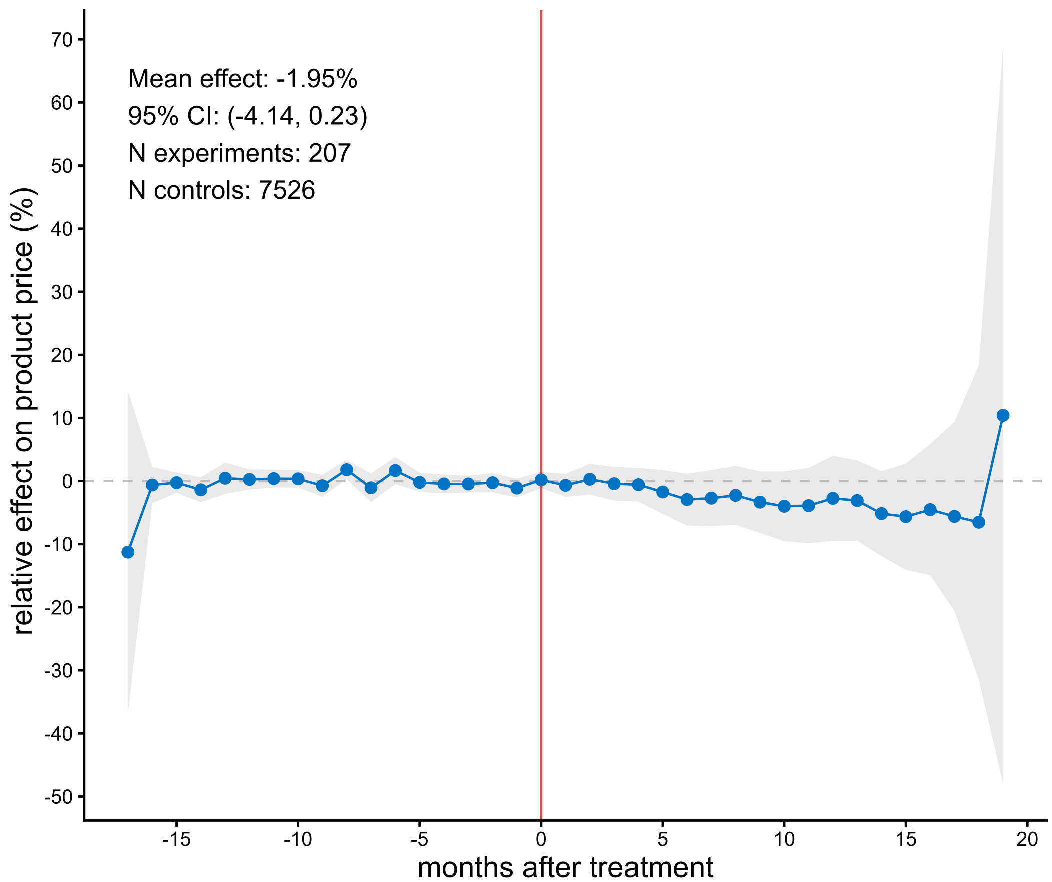


Figure B.6: Effect of carbon-neutral label with the initial number of ratings as an additional control variable (United States)

This plot shows the dynamic treatment effect in percentages relative to the product's price at baseline. Vertical red line marks treatment onset. The shaded area indicates a 95% confidence interval of the treatment effect based on 1,000 bootstrap samples that control for multiple hypothesis testing. The control variables include product categories, the product's initial price, and the initial number of ratings at the beginning of the panel.

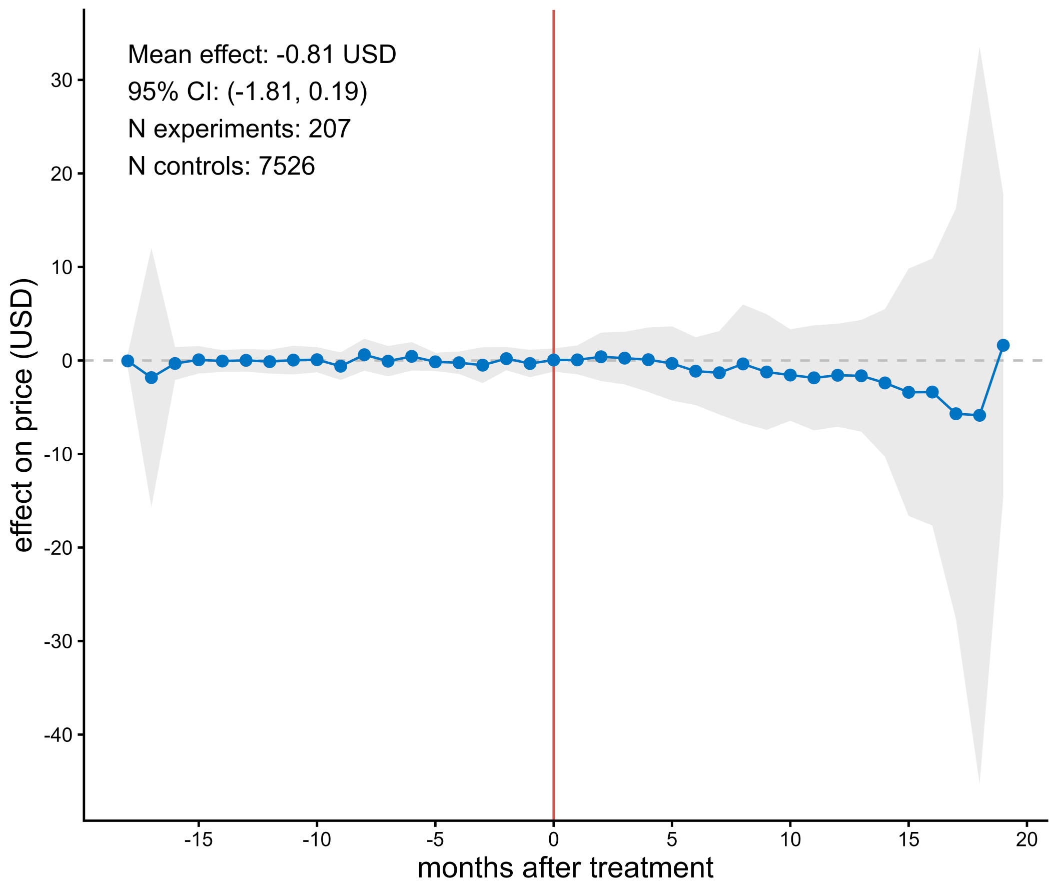


Figure B.7: Effect of carbon-neutral label using absolute price level as outcome variable (United States)

This plot shows the dynamic treatment effect in USD. Vertical red line marks treatment onset. The shaded area indicates a 95% confidence interval of treatment effect based on 1,000 bootstrap samples that control for multiple hypothesis testing. The control variables include product categories and the product's initial price at the beginning of the panel.

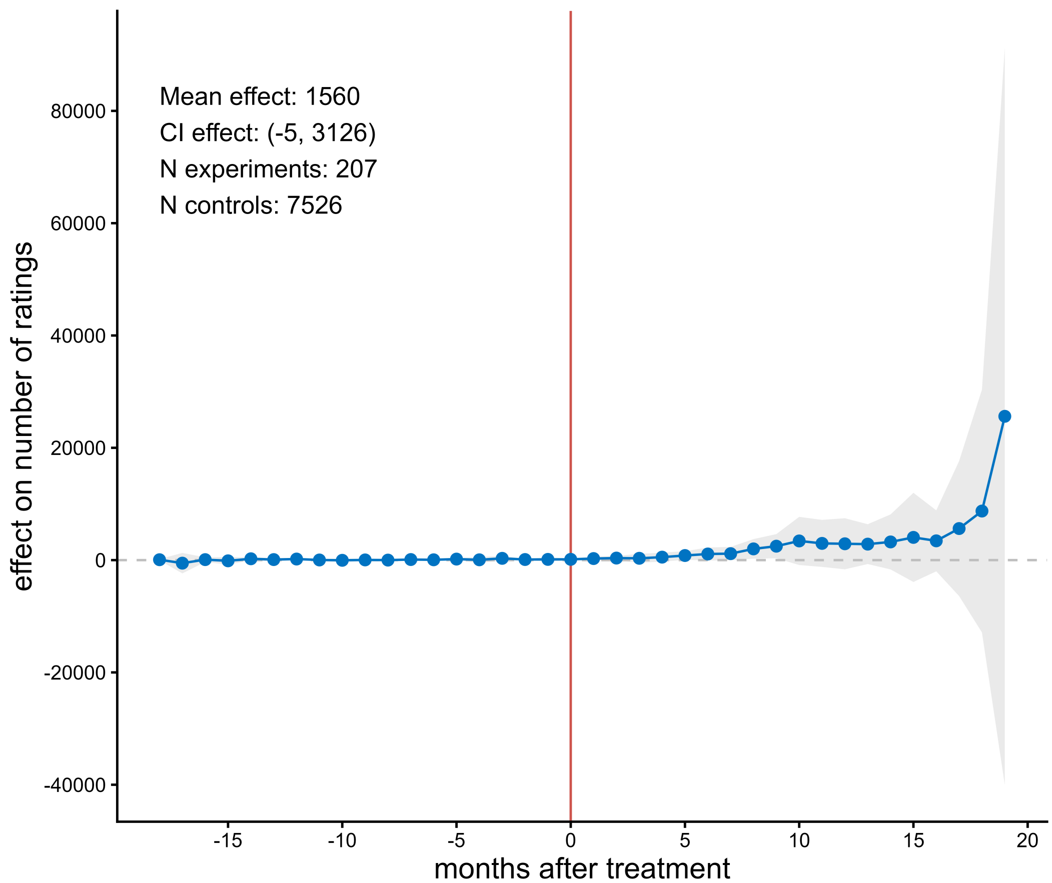


Figure B.8: Effect of carbon-neutral label using the number of ratings as the outcome variable (US)

This plot shows the dynamic treatment effect of carbon-neutral label on the rating count in March 2023. Vertical red line marks treatment onset. The shaded area indicates a 95% confidence interval of treatment effect based on 1,000 bootstrap samples that control for multiple hypothesis testing. The control variables include product categories.

B.7 Results for the United Kingdom and Germany

This section presents event-study plots using product price changes as the outcome for the United Kingdom and Germany, and analogous estimations using the number of product ratings for these two countries.

Figures B.9 and B.11 present the dynamic effects of the carbon-neutral label on product price changes; while Figures B.10 and B.12 show the event-study results using the number of ratings for the United Kingdom and Germany respectively.

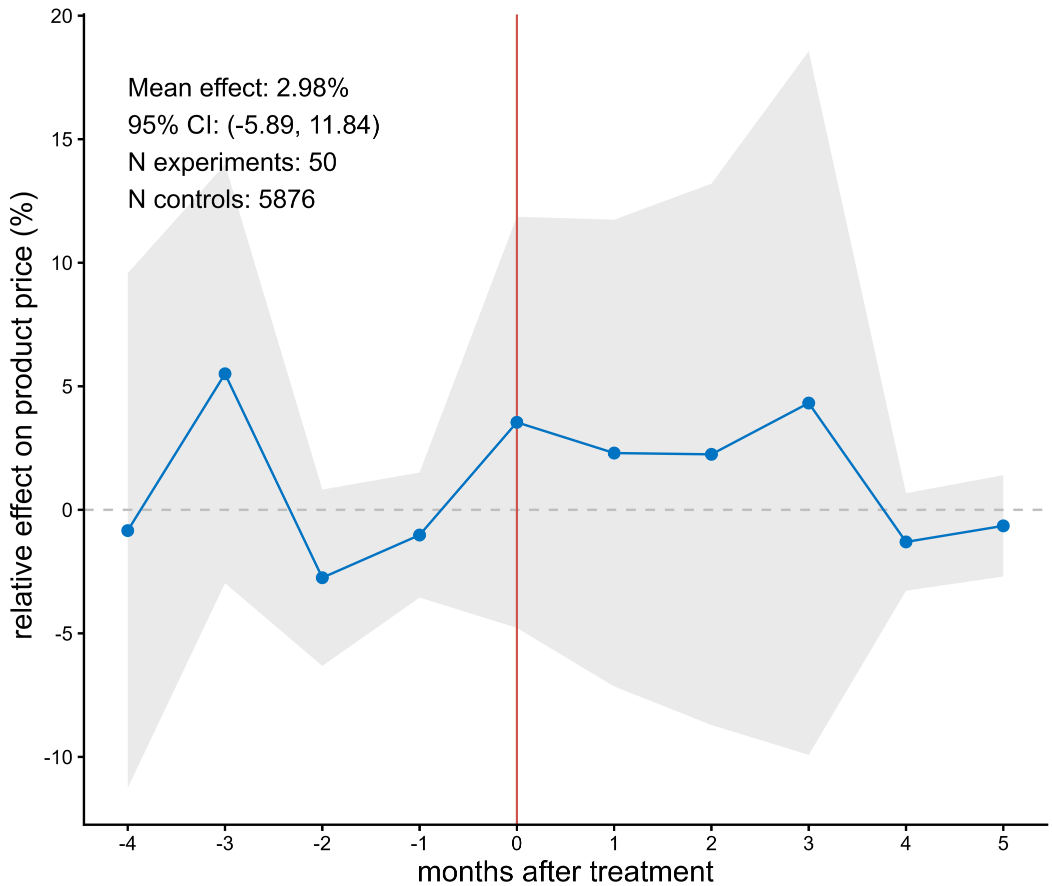


Figure B.9: Effect of carbon-neutral label (UK)

This plot shows the dynamic treatment effect in percentages relative to the product's price at baseline. Vertical red line marks treatment onset. Shaded area indicates 95% confidence interval of treatment effect based on 1,000 bootstrap samples that control for multiple hypothesis testing. The control variables include product categories and the product's initial price at the beginning of the panel.

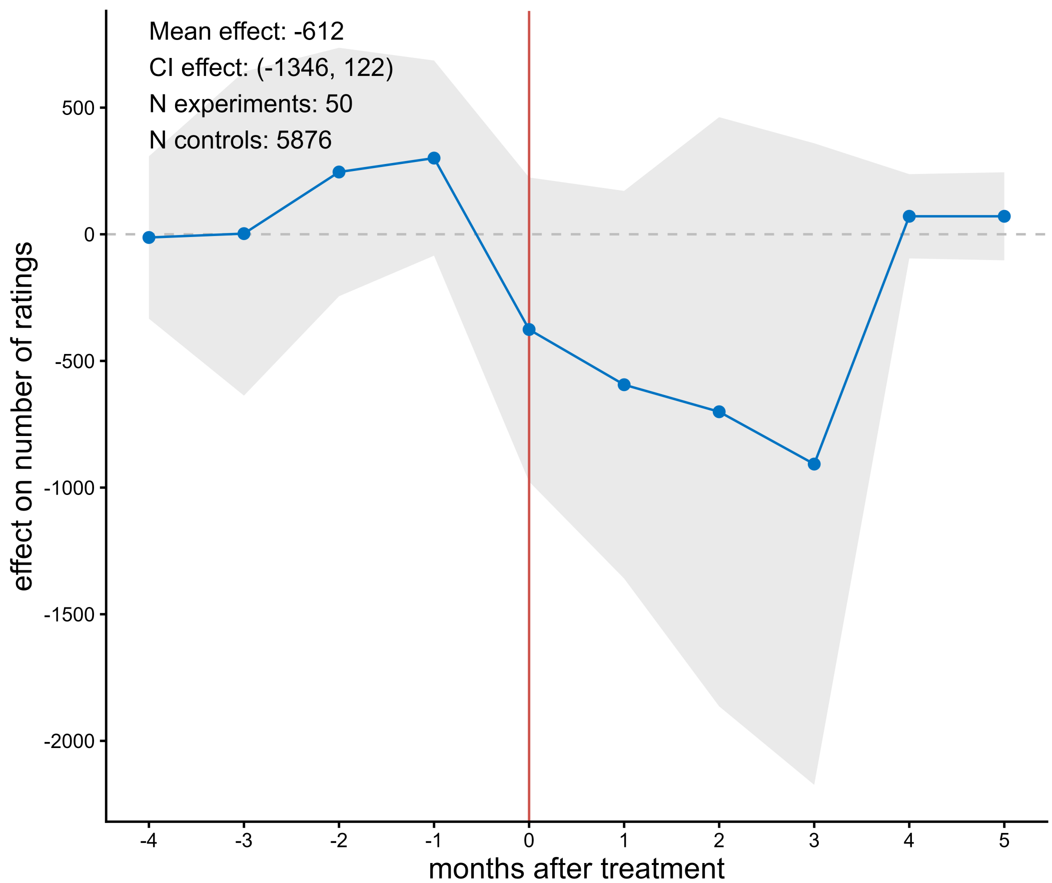


Figure B.10: Effect of carbon-neutral label using the number of ratings as the outcome variable (UK)

This plot shows the dynamic treatment effect of the carbon-neutral label on the rating count in May 2024. Vertical red line marks treatment onset. The shaded area indicates a 95% confidence interval of the treatment effect based on 1,000 bootstrap samples that control for multiple hypothesis testing. The control variables include product categories.

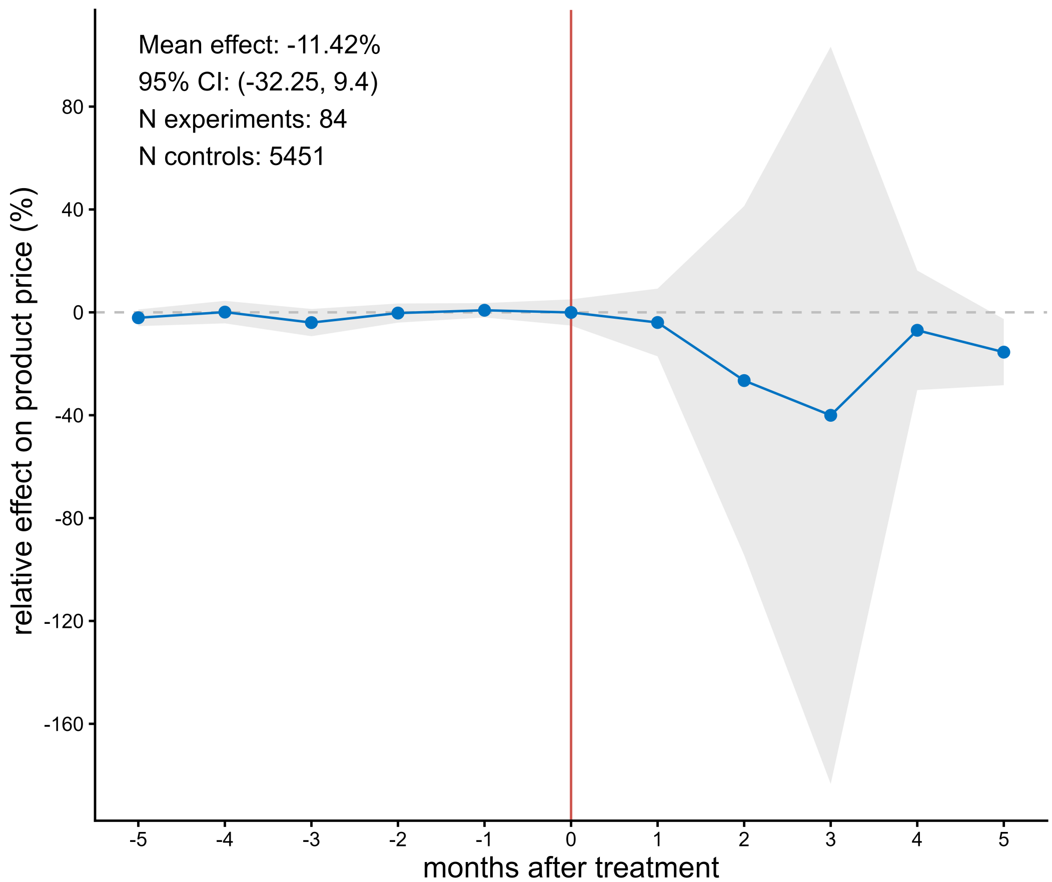


Figure B.11: Effect of carbon-neutral label (Germany)

This plot shows the dynamic treatment effect in percentages relative to the product's price at baseline. Vertical red line marks treatment onset. Shaded area indicates 95% confidence interval of the treatment effect based on 1,000 bootstrap samples that control for multiple hypothesis testing. The control variables include product categories and the product's initial price at the beginning of the panel.

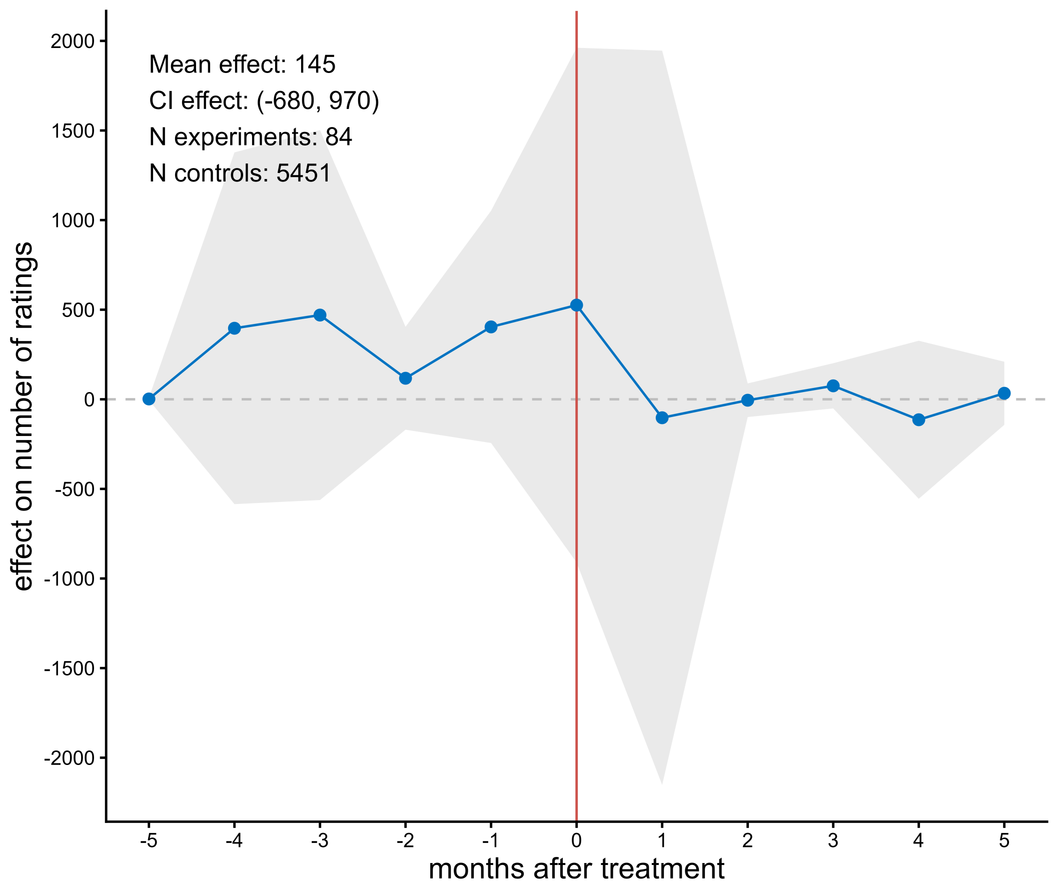


Figure B.12: Effect of carbon-neutral label using the number of ratings as the outcome variable (Germany)

This plot shows the dynamic treatment effect of carbon-neutral label on the rating count in May 2024. Vertical red line marks treatment onset. The shaded area indicates a 95% confidence interval of treatment effect based on 1,000 bootstrap samples that control for multiple hypothesis testing. The control variables include product categories.

B.8 Heterogeneity analyses

This section examines whether treatment effects vary across a variety of dimensions– price ranges, product categories, carbon intensity, and label certifiers– using the same outcome (percentage price change relative to the initial price) as in the main analysis for the United States. Our aim is to assess whether the main conclusion that consumers do not value carbon-neutral labels is meaningfully affected when considering subgroups of products as well.

Figure B.13 distinguishes between products falling within the price range observed in the meta-analysis (USD 0.09–22.15) and those above it. Consumers may value the same amount of carbon reductions more for expensive goods, relative to cheaper ones, a point that we discuss when presenting results from the meta-analysis. Based on Figure B.13, our conclusions are unchanged. Either way, consumers do not value carbon-neutral labels. The estimates for the two subgroups are not statistically different. The estimates are -1.56% [-5.59, 2.46] for products within the meta-analysis price range and -2.49% [-4.85, -0.13] for those above, respectively.

Figure B.14 provides estimates for the different product categories provided by Amazon: Electronics -5.33% [-7.22, -3.44], Cell Phones & Accessories 2.28% [-2.39, 6.94], Video Games -4.92% [-11.36, 1.53], Health & Household -5.96% [-9.76, -2.16], and Beauty & Personal Care -1.58% [-6.17, 3.02]. Once more, our main conclusions are confirmed. In no case there is evidence that consumers value carbon-neutral labels. Confidence intervals across categories overlap and include the overall estimate (-1.91%). Note that in the case of Health & Household products, the treated sample is small (N = 14).

Figure B.15 groups products by carbon intensity. We define product carbon intensity as a product's carbon footprint (kg CO_2) divided by its weight (kg). We rank treated products by this measure and split them at the median into 'Low' and 'High' carbon-intensity groups. A category is labeled Low (High) only if all experiments in that category fall in that group; categories with both levels are marked 'Mixed' and excluded, and all control products (as well as 7 treated products with missing carbon intensity information) get their category's Low/High label. The carbon-intensity ranges for the Low and High groups are, respectively, 0.40–4.52 kg CO_2/kg (Low) and 4.82–723 kg CO_2/kg (High). Here too, we find that consumers do not value carbon-neutral labels. Point estimates are -2.98% [-5.92, -0.05] for products with high carbon intensity and -1.49% [-6.14, 3.17] for products with low carbon intensity.

Finally, Figure B.16 compares products grouped according to the third-party certifiers certifying them. Also in this case, we conclude that consumers do not value carbon-neutral labels. The effect for CarbonFree Certified (Carbonfund) is -3.23% [-5.86, -0.60], for ClimatePartner -1.34% [-3.98, 1.30], and for all other certifiers -4.05% [-10.46, 2.36]. Confidence intervals overlap substantially across certifiers.

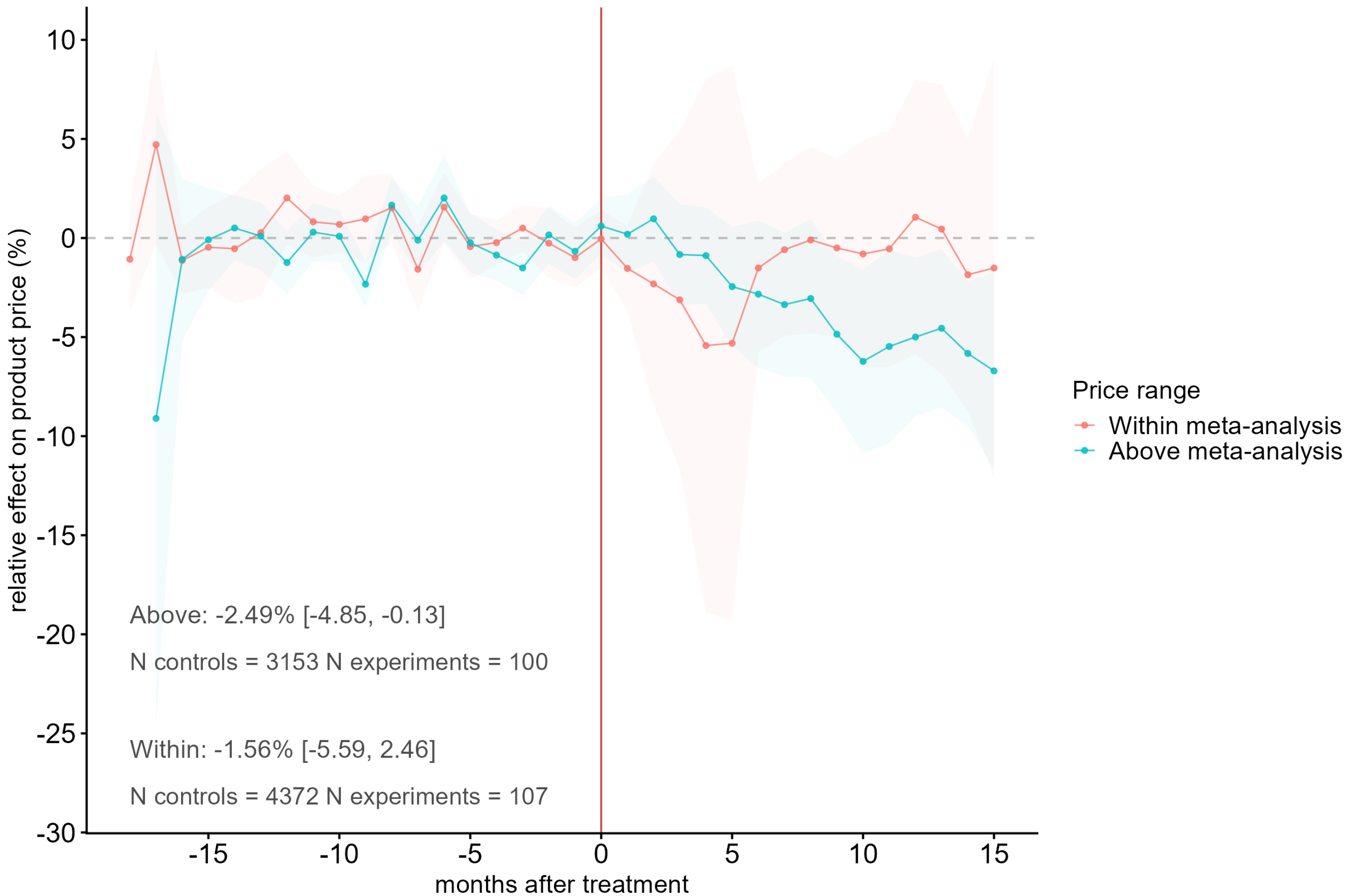


Figure B.13: Heterogeneous effect of the carbon-neutral label on product price changes: prices within and above the meta-analysis range (US)

This plot shows the dynamic treatment effect of the carbon-neutral label on product prices relative to March 2023. Prices are restricted to the meta-analysis range (USD 0.09-22.15) and above; no observations fall below this range. Vertical red line marks treatment onset. The shaded area indicates a 95% confidence interval of the treatment effect based on 1,000 bootstrap samples that control for multiple hypothesis testing. The control variables include product categories and the initial price of products. In the heterogeneity analysis, the event-study plot is trimmed at period 15 because subsequent months in the panel have very small sample sizes by construction.

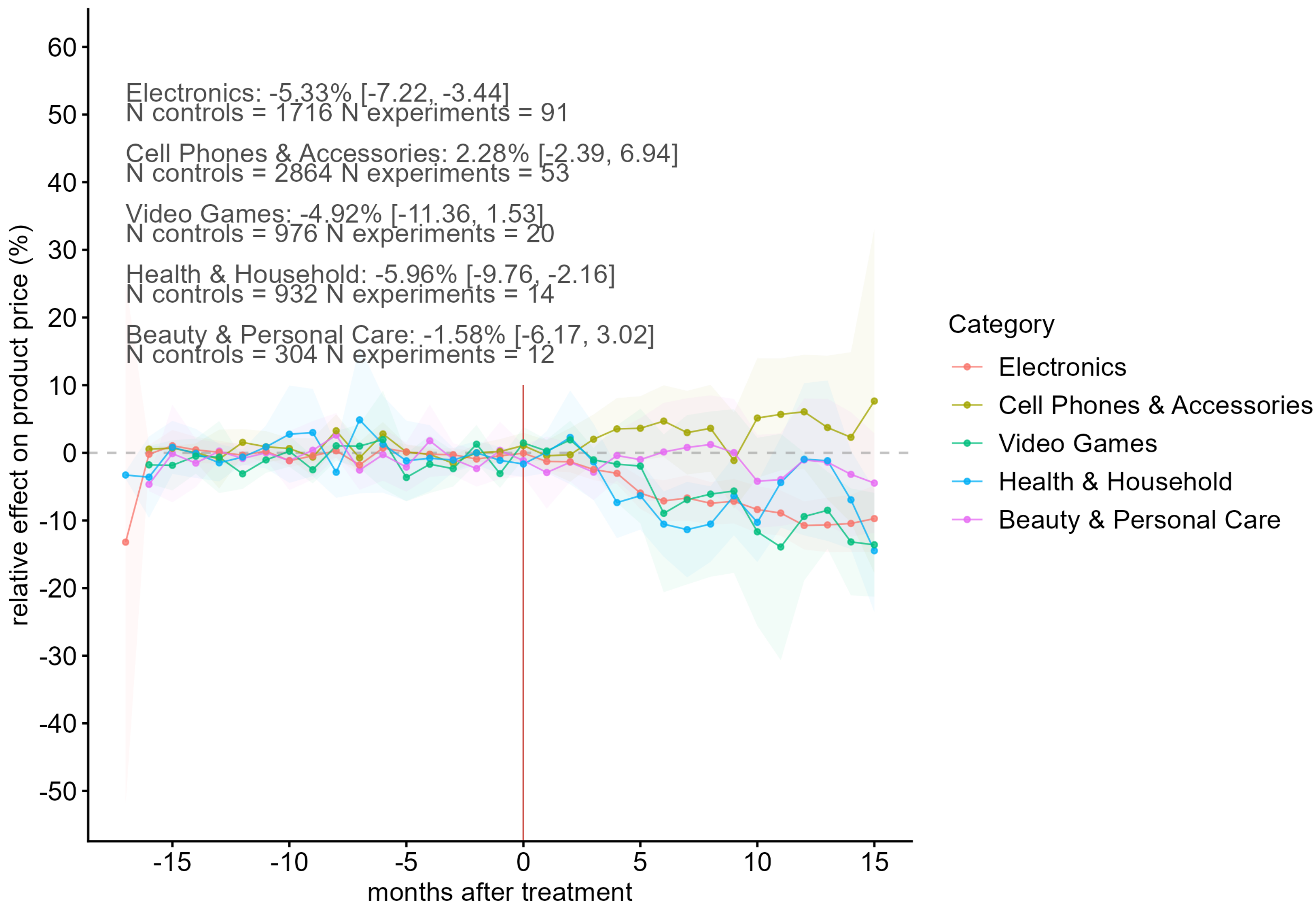


Figure B.14: Heterogeneous effect of carbon-neutral label on product's price change: product categories (US)

This plot shows the dynamic treatment effect of the carbon-neutral label on product prices relative to March 2023 by product categories with 10 or more treated products. Vertical red line marks treatment onset. The shaded area indicates a 95% confidence interval of the treatment effect based on 1,000 bootstrap samples that control for multiple hypothesis testing. The control variables include product categories and the initial price of products. In the heterogeneity analysis, the event-study plot is trimmed at period 15 because subsequent months in the panel have very small sample sizes by construction, limiting the ability to study heterogeneity.

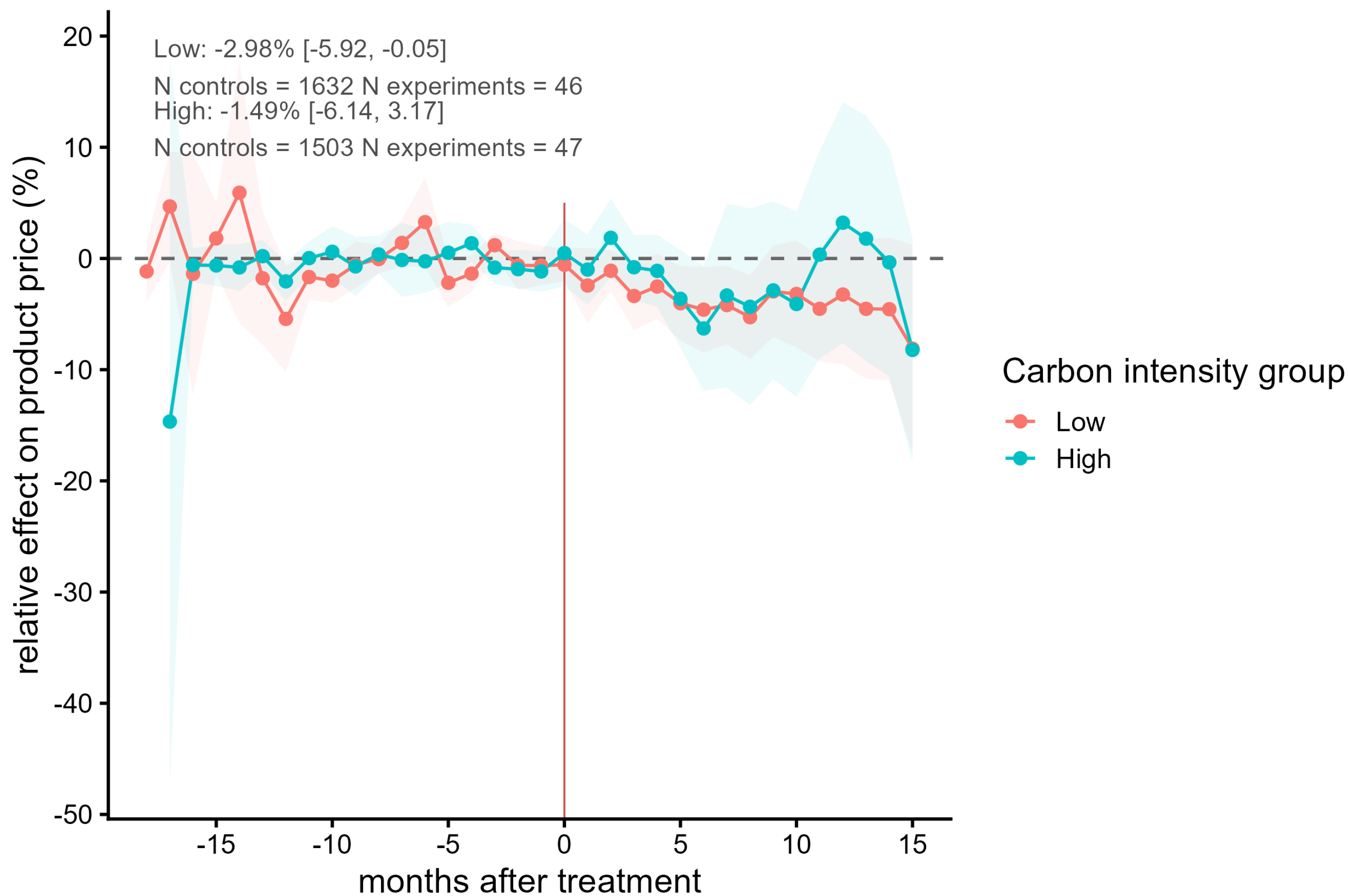


Figure B.15: Heterogeneous effect carbon-neutral label on product's price change: high and low carbon-intensive product categories (US)

This plot displays the dynamic treatment effect of the carbon-neutral label on products' price change relative to its price in March 2023, with different carbon intensity categories. Carbon-intensity heterogeneity is constructed by ranking experiment-level carbon intensities (carbon footprint per kilogram of product) and splitting the distribution into two groups (Low, High). A category is labeled Low (High) only if all experiments in that category fall in that group; categories with mixed groups are excluded. Control group products get the Low/High label of their category. Low categories: Accessories, Adapters, Backpacks, Black, Cloths & Towelettes, Covers, Dolls, Gloves, Headsets, Hubs, Keyboard Cases, Non-Sterile Gloves, Screen Protectors, Sleeves, USB Cables, Wrist Rests. High categories: Chargers & Power Adapters, Charging Stations, Cradles, Creams & Moisturizers, Elderberry, Eyes, Face Mists, FM Transmitters, Gaming Keyboards, Gels, Hair Brushes, Keyboards, Laptop Accessories, Menstrual Cups, Mice, Omega-3, Pore Cleansing Strips, Portable Bluetooth Speakers, Sports & Outdoor Play, Stylus Pens, Underwater Photography. The shaded area indicates a 95% confidence interval of the treatment effect based on 1,000 bootstrap samples that control for multiple hypothesis testing. The control variables include product categories and the initial price of products. In the heterogeneity analysis, the event-study plot is trimmed at period 15 because subsequent months in the panel have very small sample sizes by construction, limiting the ability to study heterogeneity

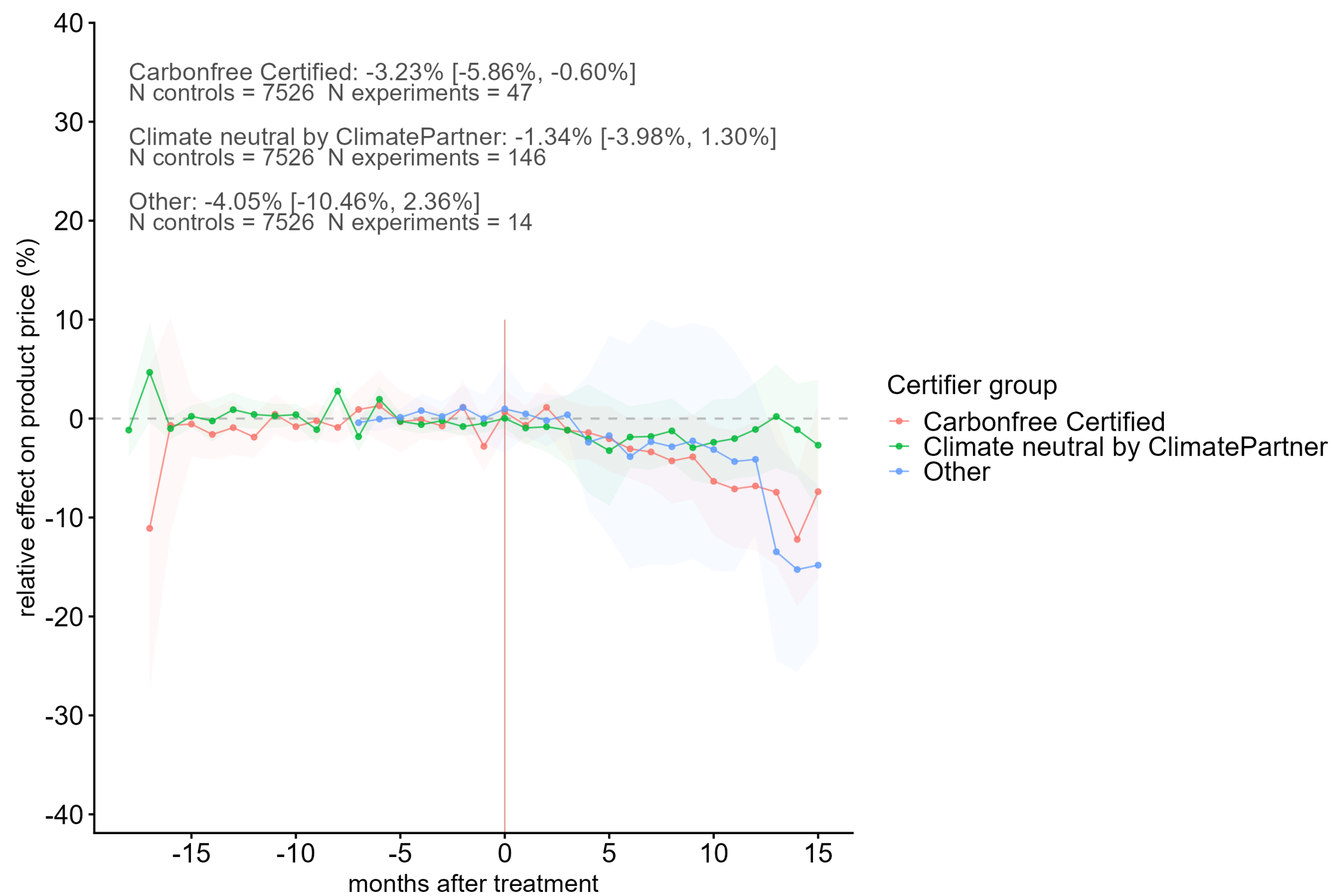


Figure B.16: Heterogeneous effect of carbon-neutral label on product's price change: label certifiers (US)

This plot displays the dynamic treatment effect of the carbon-neutral label on products' price change relative to its price in March 2023, with different carbon-neutral label certifiers. Certifiers with at least 10 treated products are displayed individually; all remaining certifiers are grouped together as 'Other', which includes Carbon Neutral by Carbon Trust and Carbon Neutral Certified by SCS Global Services. Control variables include product categories. The shaded area indicates a 95% confidence interval of the treatment effect based on 1,000 bootstrap samples that control for multiple hypothesis testing. The control variables include product categories and the initial price of products. In the heterogeneity analysis, the event-study plot is trimmed at period 15 because subsequent months in the panel have very small sample sizes by construction, limiting the ability to study heterogeneity

B.9 Customer reviews

In this section, we examine the content of customer reviews. We are interested in assessing whether consumers talk about carbon neutrality. Since carbon neutrality is a rather technical term, we consider additional keywords and then proceed by searching keywords in the corpus of reviews. The first page of reviews were scraped every week from May to November 2024 from Amazon's marketplace in the United States and from March to November 2024 in the United Kingdom and in Germany. We use a list of 40 keywords, as provided in this section. We collected 201,673 unique reviews for the United States, 90,617 reviews for the United Kingdom, and 285,426 unique reviews for Germany.

Tables B.11, B.12, and B.13 show occurrences of keywords for always-treated products, which already had a carbon-neutral label at the beginning of the panel, and never-treated products without a carbon-neutral label. For always-treated products, we further exclude reviews posted before the panel start date in each country to ensure we focus on reviews written when the products had the label. We proceed in this way to capture customers talking about products that we can confidently consider carbon neutral at the time of the review.

We report the occurrence of each keyword, as well as the total occurrence of the 40 keywords that we selected, providing overall shares for always-treated and never-treated units at the bottom of the table. Keyword frequencies are very low for both always-treated and never-treated products: United States, 0.114% and 0.028%; United Kingdom, 0.040% and 0.016%; Germany, 0.134% and 0.082%, respectively. That is, while treated products attract marginally more talk of climate-friendly features, the overall level is negligible. Further, the presence of similar values in control and treated products, as in the case of 'sustainable' features, points to product characteristics other than the labels that we are interested in driving the marginal coverage that we document. Overall, the summary statistics provided in this section confirm our main conclusions: consumers do not really value carbon-neutral products.

Keyword	Always treated products (US)	Never treated products (US)
CO_2 neutral†	0/63276	0/138397
Carbon Neutral Certified by SCS Global Services	0/63276	0/138397
Carbon Neutral by Carbon Trust	0/63276	0/138397
Carbon Trust	0/63276	0/138397
CarbonNeutral product by Climate Impact Partners	0/63276	0/138397
CarbonNeutral product by Natural Capital Partners	0/63276	0/138397
Carbonfree	0/63276	0/138397
Carbonfree Certified	0/63276	0/138397
Carbonfund	0/63276	0/138397
Carbonfund.org	0/63276	0/138397
Climate Impact Partners	0/63276	0/138397
Climate neutral by ClimatePartner	0/63276	0/138397
ClimatePartner	0/63276	0/138397
Natural Capital Partners	0/63276	0/138397
SCS Global Services	0/63276	0/138397
carbon credits	0/63276	0/138397
carbon footprint	1/63276	2/138397
carbon offsetting	0/63276	0/138397
carbon dioxide†	1/63276	0/138397
carbon neutral†	15/63276	2/138397
carbon reducing †	0/63276	0/138397
climate change	0/63276	0/138397
climate friendl*	0/63276	0/138397
climate pledge friendl*	0/63276	0/138397
corporate social responsibility	0/63276	0/138397
eco-label*	0/63276	0/138397
emissions	0/63276	0/138397
environment friendly†	0/63276	1/138397
environmentally friendl*	26/63276	3/138397
global warming	0/63276	0/138397
greenhouse gas	0/63276	0/138397
low carbon †	0/63276	0/138397
nature friendly†	0/63276	0/138397
net zero†	0/63276	0/138397
offsetting	0/63276	0/138397
reducing CO_2†	0/63276	0/138397
renewable energy	0/63276	0/138397
sustainabl*	29/63276	31/138397
zero carbon	0/63276	0/138397
zero emissions	0/63276	0/138397
Total (%)	**0.114%**	**0.028%**

Table B.11: Keyword occurrences (US)

This table shows keyword occurrences in always-treated and never-treated product reviews in Amazon's US marketplace, scraped between May 2024 and November 2024. Words marked with "*" denote wildcards, allowing any continuation of the stem (e.g., "sustainabl*" matches "sustainability" and "sustainable"). Terms marked with † include both hyphenated and non-hyphenated forms. For "reducing CO_2," we also cover the reversed order, i.e., "CO_2 reducing."

Keyword	Always treated products (UK)	Never treated products (UK)
CO_2 neutral†	0/17617	0/73000
Carbon Neutral Certified by SCS Global Services	0/17617	0/73000
Carbon Neutral by Carbon Trust	0/17617	0/73000
Carbon Trust	0/17617	0/73000
CarbonNeutral product by Climate Impact Partners	0/17617	0/73000
CarbonNeutral product by Natural Capital Partners	0/17617	0/73000
Carbonfree	0/17617	0/73000
Carbonfree Certified	0/17617	0/73000
Carbonfund	0/17617	0/73000
Carbonfund.org	0/17617	0/73000
Climate Impact Partners	0/17617	0/73000
Climate neutral by ClimatePartner	0/17617	0/73000
ClimatePartner	0/17617	0/73000
Natural Capital Partners	0/17617	0/73000
SCS Global Services	0/17617	0/73000
carbon credits	0/17617	0/73000
carbon footprint	0/17617	0/73000
carbon offsetting	0/17617	0/73000
carbon dioxide†	0/17617	5/73000
carbon neutral†	0/17617	0/73000
carbon reducing†	0/17617	0/73000
climate change	0/17617	0/73000
climate friendl*	0/17617	0/73000
climate pledge friendl*	0/17617	0/73000
corporate social responsibility	0/17617	0/73000
eco-label*	0/17617	0/73000
emissions	0/17617	0/73000
environment friendly†	0/17617	0/73000
environmentally friendl*	4/17617	3/73000
global warming	0/17617	0/73000
greenhouse gas	0/17617	0/73000
low carbon†	0/17617	0/73000
nature friendly†	0/17617	0/73000
net zero†	0/17617	0/73000
offsetting	0/17617	1/73000
reducing CO_2†	0/17617	0/73000
renewable energy	0/17617	0/73000
sustainabl*	3/17617	3/73000
zero carbon	0/17617	0/73000
zero emissions	0/17617	0/73000
Total (%)	**0.040%**	**0.016%**

Table B.12: Keyword occurrences (UK)

This table shows keyword occurrences in always-treated and never-treated product reviews on Amazon's UK marketplace, scraped between March 2024 and November 2024. Words marked with "*" denote wildcards, allowing any continuation of the stem (e.g., "sustainabl*" matches "sustainability" and "sustainable"). Terms marked with † include both hyphenated and non-hyphenated forms. For "reducing CO_2," we also cover the reversed order, i.e., "CO_2 reducing."

Keyword	Always treated products (Germany)	Never treated products (Germany)
CO_2 neutral†	0/46375	0/239051
Carbon Neutral Certified by SCS Global Services	0/46375	0/239051
Carbon Neutral by Carbon Trust	0/46375	0/239051
Carbon Trust	0/46375	0/239051
CarbonNeutral product by Climate Impact Partners	0/46375	0/239051
CarbonNeutral product by Natural Capital Partners	0/46375	0/239051
Carbonfree	0/46375	0/239051
Carbonfree Certified	0/46375	0/239051
Carbonfund	0/46375	0/239051
Carbonfund.org	0/46375	0/239051
Climate Impact Partners	0/46375	0/239051
Climate neutral by ClimatePartner	0/46375	0/239051
ClimatePartner	0/46375	0/239051
Natural Capital Partners	0/46375	0/239051
SCS Global Services	0/46375	0/239051
carbon credits	0/46375	0/239051
carbon footprint	1/46375	0/239051
carbon offsetting	0/46375	0/239051
carbon dioxide†	0/46375	5/239051
carbon neutral†	0/46375	0/239051
carbon reducing†	0/46375	0/239051
climate change	0/46375	6/239051
climate friendl*	0/46375	6/239051
climate pledge friendl*	0/46375	6/239051
corporate social responsibility	0/46375	0/239051
eco-label*	0/46375	0/239051
emissions	0/46375	2/239051
environment friendly†	9/46375	35/239051
environmentally friendl*	16/46375	64/239051
global warming	0/46375	0/239051
greenhouse gas	0/46375	0/239051
low carbon†	0/46375	0/239051
nature friendly†	0/46375	0/239051
net zero†	0/46375	0/239051
offsetting	0/46375	0/239051
reducing CO_2†	0/46375	0/239051
renewable energy	0/46375	0/239051
sustainabl*	36/46375	73/239051
zero carbon	0/46375	0/239051
zero emissions	0/46375	0/239051
Total (%)	**0.134%**	**0.082%**

Table B.13: Keyword occurrences (Germany)

This table shows keyword occurrences in always-treated and never-treated product reviews in Amazon's Germany marketplace, scraped between March 2024 and November 2024. Words marked with "*" denote wildcards, allowing any continuation of the stem (e.g., "sustainabl*" matches "sustainability" and "sustainable"). Terms marked with † include both hyphenated and non-hyphenated forms. For "reducing CO_2," we also cover the reversed order, i.e., "CO_2 reducing."