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. Increasingly, private companies are making their operations carbon neutral. It is an empirical question how consumers value carbon-neutral products, which we address as follows. First, we provide a meta-analysis of the literature analyzing demand for products with carbon labels, based on an overall sample of 26,547 participants. The focus is on average willingness to pay for carbon reductions as well as on the characteristics of the underlying literature. Second, we leverage information on prices and product characteristics from one of the largest online marketplaces, Amazon's, to infer from revealed preferences on consumers' valuation of carbon-neutral products, through a hedonic approach. The staggered process of carbon-neutral certification leads to a series of quasi-natural experiments, which we use for identification purposes. We find that the literature, which is mainly based on stated preferences and controlled environments, suggests a positive willingness to pay for carbon neutrality of products that exceeds most estimates of the social cost of carbon. However, this finding is not supported by the hedonic approach, where we do not find evidence for a positive willingness to pay for carbon neutrality.

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

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

1 Introduction

An important question in economics relates to why people engage in pro-social behavior and to what extent society can rely on people's private motivations to ensure the provision of public goods. Climate change mitigation is such a (global) public good. While climate policy gradually 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 have decided or announced plans to make their operations, or at least part of them, carbon neutral (Rogelj et al., 2021). The main driver of these decisions is likely pressure from investors and company boards to prepare firms for a low-carbon future (Kim and Lyon, 2011). Yet, it is an open empirical question whether consumers are willing to pay more for carbon-neutral products.

This paper aims to address this question. It does so as follows. First, it collects evidence on consumers' willingness to pay (WTP) for the carbon neutrality of products from the literature. The literature that we cover includes 37 studies, providing 129 observations, and an overall sample of 27,241 participants. From this body of evidence, it is possible to estimate average WTP across studies, geographies, and samples, and compare it with the range of estimates that economists have provided for the social cost of carbon to understand at what level, if any, consumers privately internalize the climate externality. Further, with the tools of meta-analysis, it is possible to determine, at least correlationally, the study features that may lead to higher or lower WTP for carbon-neutral labels, including the key methodological difference between stated and revealed preferences.

Second, this paper uses hedonic difference in differences to complement the meta-analysis with a real-world assessment, which as described is based on surveys and experiments with population samples. In particular, we use publicly available information on prices and product characteristics from the Amazon marketplace, covering a wide range of products, tracked over several months in different countries – the United States, the United Kingdom, and Germany – to estimate WTP for the carbon neutrality of products in a hedonic framework. 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 been recently certified carbon neutral. From an empirical standpoint, the emergence of these certifications creates a multitude of quasi-natural experiments, which we leverage to causally identify consumers' WTP for the carbon neutrality of products. We collected data across the three markets over many months, retrieving data – for instance of over 38,000 products on Amazon's U.S. marketplace – on a weekly basis. In the United States, we identify 208 treated products that received carbon-neutral certification on Amazon during the observation period and 7,260 control products without such certification. In the United Kingdom, we identify 52 treated products and 6,258 control products. In Germany, we identify 92 treated products and 6,935 controls. Given the staggered nature of these certifications, we rely on recent advances in the difference in differences literature, and in particular on Callaway and Sant'Anna (2021b).

The results from the meta-analysis point to a positive WTP for carbon-neutral labels, where at USD 1986 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

[1]Of the 122 million households in the United States, more than a half possess an Amazon Prime subscription (Statista, 2022b) Further, in a month, there are about 236 million unique visitors to Amazon's marketplace, as of May 2024 (Statista, 2024). 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 have an Amazon Prime membership (Mintel, 2019). More than 75% of online German consumers made at least one purchase per month on Amazon in 2022 (Statista, 2022a).

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.

Based on the hedonic difference in differences approach, we find no evidence for a causal relationship between carbon-neutral labeling and product prices. The average WTP derived from the hedonic approach is statistically indistinguishable from zero across all three markets. Hence, the substantial WTP for the carbon neutrality of products reported in the literature is not reflected in the prices of products sold on the main online marketplace, Amazon, across three countries, Germany, the United Kingdom, and the United States. We also do not find consistent evidence for an effect of carbon-neutral labeling on the quantities sold – proxied by customer ratings. While there is some evidence for a positive trend in sales in Germany and the United States, we find no such evidence for the United Kingdom. The fact that there is some movement around customer ratings suggests, however, that relying on prices only as usually done in the willingness-to-pay literature may mask some effects, especially in the short run.

This paper contributes to multiple strands of literature. First, a body of work examining the role of corporate social responsibility (e.g. Fehr et al., 1993; Shleifer, 2004; Besley and Ghatak, 2007; Falk and Szech, 2013; Bartling et al., 2015; see also Bénabou and Tirole, 2010, and Kitzmueller and Shimshack, 2012), including with respect to reductions in CO_2 emissions (e.g. Kim and Lyon, 2011; Doda et al., 2016). Second, a broad literature on the adoption of pro-social behavior (e.g. Dawes and Thaler, 1988; Fehr et al., 1993; Fehr and Schmidt, 1999; Bénabou and Tirole, 2006; Ellingsen and Johannesson, Ellingsen and Johannesson; Andreoni and Bernheim, 2009; Ariely et al., 2009), including a recent focus on the adoption of non-normative pro-social behavior (e.g. Sparkman and Walton, 2017; Kraft-Todd et al., 2018; Bicchieri and Dimant, 2019; Mortensen et al., 2019; Spencer et al., 2019; Andreoni et al., 2020; Carattini and Blasch, 2024; Carattini et al., 2024). Third, analyses of people's cooperativeness in a global social dilemma such as climate change mitigation (see Carattini et al., 2019 for a review), including private demand for carbon offsets (Kotchen, 2009; Jacobsen, 2011; Kesternich et al., 2016; Rodemeier, 2023). Fourth, 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). Fifth, a strand of literature comparing stated and revealed preference methods and their ability to uncover actual preferences, including WTP (e.g. Arrow et al., 1993; Adamowicz et al., 1994; Bateman et al., 2002; Johnston et al., 2017). Sixth, an established literature applying hedonic methods to a wide range of questions in environmental economics and beyond (e.g. Rosen, 1974; Smith and Desvousges, 1986; Chay and Greenstone, 2005; Muehlenbachs et al., 2015; Banzhaf, 2020, 2021).

In terms of policy implications, assessing the demand for carbon-neutral products 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. While large, publicly-traded firms pledged to become carbon neutral at a time of pressure from investors, including 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 of statistically significant – and in fact of economically meaningful – WTP in actual purchasing decisions by customers across three large markets, although there is some suggestive evidence of a potential effect on quantities, if 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 shortly concludes.

2 Data and empirical approach

2.1 Meta analysis

This section describes concisely the data and empirical approach used for the meta-analysis, while pointing the reader to a set of sections in the Appendix providing more detailed information. The underlying literature and derivation procedure of WTP for reductions in CO_2 emissions is described in Section A.1 in the Appendix. In our main analyses we have in total 126 observations across 37 studies, 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 26,547 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 climate labels, excluding the cost of the product. The studies in our database focus on a variety of products, which we categorize as dairy, fruits and vegetables, meat, non-food items, oil and grain, snacks, and water and drinks. In our database, we not only have observations of reductions in CO_2 emissions, but also reductions in greenhouse gas emissions expressed as CO_2 equivalents, and we treat these equally. Additionally, we consider the term "CO_2 reduction" in a broad sense, encompassing actual CO_2 reductions, offsets, abatement, and CO_2 capture. We elaborate more on these concepts in Section A.1.3 of the Appendix.

First, we report the average WTP for CO_2 reductions and WTP for carbon neutrality based on the literature. Next, we present the distribution of the WTP measures across studies in the literature and compare the WTP for reducing CO_2 emissions by 1 kg with the social cost of carbon. Furthermore, we conduct regression analysis to understand which factors are associated with WTP for CO_2 reductions, including the amount of CO_2 reduction, product price, and method (stated versus revealed preference studies), in-person studies, sample size, published versus unpublished studies, study year, GDP per capita, and studies conducted in Europe. 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 clustered standard errors based on studies.

Our analyses include a series of robustness tests using alternative models, including a mixed effects model incorporating random effects for studies and product categories, as well as a weighted mixed effects model where weights are applied to equally weigh 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 calculations for deriving WTP from studies. The goal of these exercises is to ensure the robustness of our core results.

2.2 Hedonic model

This section describes the data used for the hedonic analyses as well as the corresponding empirical approach, while also pointing the reader to additional information in the Appendix. The goal of the hedonic model is to provide empirical evidence from revealed preferences, to be compared with the evidence, mostly from stated preference studies and controlled environments, 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 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 valuable feature. Further, over the years, Amazon has given increasing importance to carbon neutrality, among other environmental aspects, collaborating with several organizations providing labels for carbon-neutral or carbon-reduced products. More than 50 different sustainability 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. 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 based on special collections of carbon-neutral products available on Amazon.com. Next, we identify the category nodes of the carbon-neutral products that are used by Amazon to tag products of the same product category. For each category node that we identify, we scrape many untreated products without carbon-neutral labels. This process ensures that for each treated product, we obtain many control units from the same product category.

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

Our product selection strategy results in a set of 40,031 products from 27 categories on Amazon's German marketplace, 41,384 products from 264 categories on Amazon's marketplace in the United Kingdom, and 39,432 products from 64 categories on Amazon's American marketplace. From this broad set of products, we can then identify treated products, when products obtain new labels, and in turn, control products, as described shortly below.

We scrape the same set of product information for all these products each week, as displayed on Amazon's website, for IP addresses from Germany, the United Kingdom, and the United States, respectively. The data collection started in March 2023 and ended in December 2024. We scraped data from Amazon.com, the American marketplace, for this entire period. For Germany and the United Kingdom, Amazon.de and Amazon.co.uk, respectively, we have data from May 2024 until December 2024. For all markets, we have many quasi-natural experiments to leverage for empirical purposes, as just described.

Most importantly, we retrieve information about the price of the product and the treatment status of the product, which allows us to perform a staggered difference in differences analysis. The staggered adoption of carbon-neutral labels by products sold on Amazon 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 arguably comparable products with the same product category assigned by Amazon. We exclude Amazon's own products from the analysis as well as books 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, proxied by the number of ratings that a product receives, to provide a fuller picture.

For the difference in differences 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.[2] We further exclude already-treated products (2,038 for Germany,

[2] Note that it is not plausible to expect prices to be successfully scraped 100% of the time. We

1,831 for the United Kingdom, and 2,038 for the United States).

We identify 92, 52, and 208 treated products for Germany, the United Kingdom, and the United States, respectively. We identify 6,935, 6,258, and 7,260 control products for Germany, the United Kingdom, and the United States, respectively. 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 (35,445 products in Germany, 32,472 in the United Kingdom, and 23,926 in the United States), we first consider products that do not have another label (e.g. organic, fair 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 a 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. The resulting sample of control products includes 6,935 products from Germany, 6,258 products from the United Kingdom, and 5,036 products from the United States. 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.5, B.6, and B.7 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 based on difference in differences. We assume that the timing at which products get treated is plausibly random and assume (and verify) that treatment is irreversible (at least within our timeframe), leading to a difference in difference setup with staggered treatment assignment and treatment being absorbed. Our setting is also such that only a small share of products

interpolate (and extrapolate) the missing data points linearly.

receive the treatment, so that economically meaningful general equilibrium effects are unlikely.

In particular, we have a difference in differences setup with multiple time periods, variation in treatment timing, and where the parallel trend assumption holds only after controlling for different product categories and initial prices, which is why we use the doubly robust estimator of (Callaway and Sant'Anna 2021b) as implemented in the R package *did* (Callaway and Sant'Anna 2021a). Event analyses are used to verify that the conditional parallel trends assumption holds when conditioning on the top-level product category and initial price, and allow us to examine dynamic treatment effects.

We express the outcome variable in terms of the percentage change in a product's price, relative to its initial price. This approach focuses on relative rather than absolute price shifts, accounting for the broad range of products and price levels on Amazon. We, however, also provide estimates based on absolute prices. Finally, we also consider the number of ratings a product receives as a proxy for quantities (sales).

3 Empirical evidence

3.1 Descriptive evidence from the meta analysis

In this section, we describe two main findings, of descriptive nature, related to the meta-analysis. The first finding focuses on the WTP estimates for a reduction of 1 kg of CO_2 emissions, as derived from the literature that the meta-analysis covers. We then compare the average WTP with recent estimates of the social cost of carbon, taking the average WTP at face value and assessing at what level consumers are internalizing the climate externality in their provision of a global public good. 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). Secondly, we report the average WTP for carbon neutrality, which represents the WTP for reducing product's CO_2 emissions by 100% or achieving carbon neutrality.

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

We define four WTP measures. First, the measure $\mathrm{WTP_R}$ 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. To standardize WTP estimates for easier comparison with our results from the hedonic approach, we also define three additional measures. $\mathrm{WTP_{kg}}$ represents the WTP per 1 kg of CO_2 reduction, calculated by dividing $\mathrm{WTP_R}$ by the amount of CO_2 reduction in kilograms, and is expressed in USD. When comparing with estimates for the social cost of carbon, we easily convert this measure into USD per ton of CO_2. $\mathrm{WTP_{CN}}$ denotes the WTP for achieving carbon neutrality. It is calculated by multiplying $\mathrm{WTP_{kg}}$ by the baseline CO_2 emissions of the product, and is also expressed in USD. Finally, $\mathrm{WTP_{CN\%}}$ represents $\mathrm{WTP_{CN}}$ 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 $\mathrm{WTP_{CN}}$ by the price of the product.

Figure 1 shows the distribution of $\mathrm{WTP_R}$ and $\mathrm{WTP_{kg}}$ across studies, where a logarithmic x-axis is used for a better representation of the distribution of observations. As illustrated in the figure, the average $\mathrm{WTP_R}$ of study averages is USD 1.23. The

WTP_{kg} of study averages is USD 1.99 per kg of CO_2 reduction, or USD 1986 per ton of CO_2. To put these estimates in comparison, the social cost of carbon during the Obama administration has been around USD 40 per ton of CO_2 (IWG on Social Cost of Carbon, 2010, 2013), while under the Biden administration it has been at USD 51 per ton of CO_2 (IWG on Social Cost of Carbon, 2016; IWG on Social Cost of Greenhouse Gases, 2021) for several years before being raised to USD 190 per ton of CO_2 (Environmental Protection Agency, 2023). The economic literature points, however, to potentially 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 that the meta-analysis provides. Carbon prices around the world also vary widely. They have generally kept increasing over the last few years, but only a few countries, such as Sweden and Switzerland, have carbon prices above USD 100 per ton of CO_2 (World Bank, 2023), about a twentieth of the average WTP_{kg} derived from the literature that the meta-analysis covers.

Some interesting observations emerge from Figure 1. First, we observe 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 size of the circles. Third, based on Figure 1, meat products, which constitute 37% of our sample, seem to be related to a lower WTP_{kg} compared to other products. That is, study participants seem to be willing to pay less for a 1 kg CO_2 reduction in meat products compared to other products, such as water and drinks, which are responsible for less CO_2 emissions. For the breakdown of the remainder of our sample according to product categories, we refer the reader to Appendix Section A.2.

Next, we turn to the drivers of WTP in the underlying studies covered in the meta-analysis. The drivers of WTP are discussed based on Table 1, which contains our main meta-analytical results providing associations between study characteristics and WTP_R. We use OLS and cluster standard errors by studies.

Our independent variables in the first model (OLS I) include the amount of CO_2 reduction, which is z-scored, to understand whether study participants value more greater contributions to climate mitigation; and product price, which is z-scored, to assess the proportionality of WTP to product price. In the second model (OLS II) we also add methodological variables, including a dummy variable for stated preference methods, to account for potential biases such as hypothetical bias that may arise in survey studies compared to revealed preference studies, a dummy variable for in-person studies to account for differences relative to computer-based or online studies, as well as a variable for the sample size of the study that is used to estimate WTP, which is z-scored, to account for the size of the studies, as well as a dummy variable for published studies to account for potential biases in comparison to unpublished studies. Contextual controls include study year, which is z-scored, to account for potential secular trends in public awareness regarding climate change and climate labels; gross domestic product (GDP) per capita, which is z-scored, to account for the economic situation of consumers in the study country; and a dummy variable for studies conducted in Europe to control for geography-specific effects, including potential variation in environmentally-friendly lifestyles.

In the third model (OLS III) we also have 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 interpret the results from the original findings. As a robustness check, we also include dummy variables for colored labels in Appendix A.3 in Tables A.11 and A.12, which are used in the literature to distinguish between higher and lower carbon footprint options, and a dummy variable for carbon-neutral certifications compared to carbon reductions and carbon footprint certifications.

Table 1 shows that the significant coefficients remain largely unchanged across specifications. The coefficients confirm the positive and significant association between CO_2 reductions and WTP_R, indicating that participants are sensitive to the amount of CO_2 reductions implied by the climate labels. Other interesting associations also emerge. For instance, a higher product price is associated with a higher WTP. That is, comparable reductions in CO_2 emissions may be more easily accepted by study participants when the cost represents a smaller share of the overall product price, so that the relative price increase is more muted. Additionally, studies conducted in Europe (compared to America, Asia, and Africa) also seem to be associated with a higher WTP.

We do not find a robust significant association of WTP_R with the following variables: potential biases in stated preference studies versus revealed preference studies; in-person versus online or computer-assisted studies; sample size of the study; potential biases in published relative to unpublished studies; study year; GDP per capita. Similarly, we do not find a robust significant association of WTP_R with the control variables for CO_2 assumptions and WTP derivations, which are used to control for observations for which we need to make assumptions regarding the amount of CO_2 reduction and to make additional calculations to derive WTP estimates from the studies.

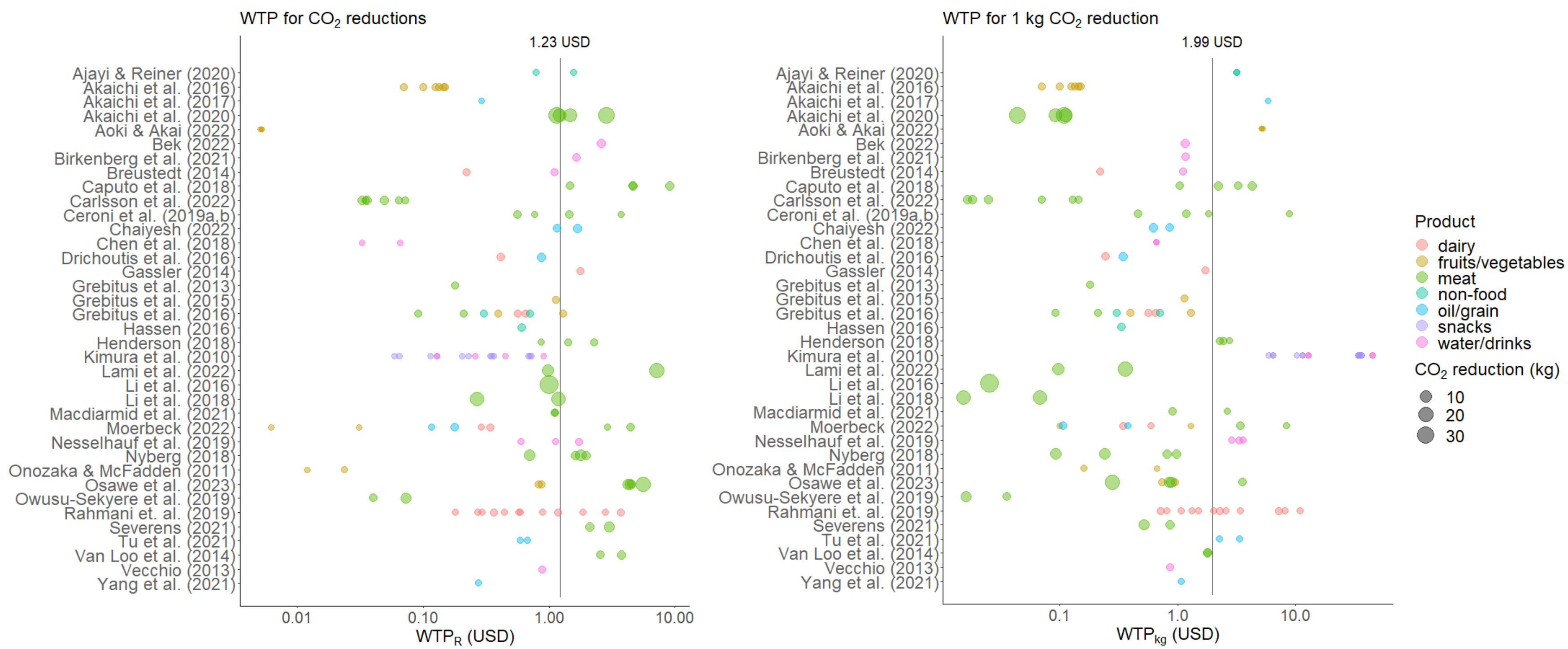

Figure 1: WTP for CO_2 reductions across studies

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.

Table 1: Factors associated with WTP for CO_2 reductions

	OLS I	OLS II	OLS III
Intercept	0.74*** (0.08)	0.52* (0.32)	0.52 (0.32)
CO_2 reduction	0.11*** (0.05)	0.10** (0.03)	0.10** (0.04)
Price	0.35*** (0.05)	0.32*** (0.05)	0.32*** (0.05)
Stated pref. method		-0.00 (0.23)	-0.01 (0.23)
In-person		-0.07 (0.23)	-0.08 (0.21)
Sample size		-0.04 (0.08)	-0.05 (0.07)
Publication		-0.02 (0.23)	-0.03 (0.22)
Study year		0.02 (0.09)	-0.02 (0.10)
GDP per capita		0.07 (0.08)	0.08 (0.08)
Europe		0.37*** (0.17)	0.32** (0.18)
CO_2 reduction assump.			-0.07 (0.12)
WTP derivation			0.15 (0.15)
Number of obs.	126	126	126
Adjusted-R^2	0.35	0.42	0.41
AIC	219.50	212.94	214.96
BIC	230.84	244.14	251.83
Log Likelihood	-105.75	-95.47	-94.48

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

This table shows coefficient estimates and associated standard errors, which are indicated within parentheses. We use an OLS model with clustered standard errors by studies. 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.

Appendix A.3 includes our battery of robustness tests. First, we present regressions with alternative models, including the mixed effects model, in Table A.10. Second, we incorporate two additional variables: carbon-neutral certification and colored labels in Tables A.11 and A.12. Third, we show WLS (weighted least squares) and weighted mixed effects models in Tables A.13 and A.14. Fourth, we compare alternative transformations of the dependent variable in Tables A.15 and A.16. Fifth, we run the OLS model with two-way clustered errors: studies and product categories or countries in Table A.17. Sixth, we conduct mixed effects regressions with random effects for countries instead of product categories in Table A.18. Seventh, we include the square of the z-scored CO_2 emission reduction variable in Tables A.19 and A.20. 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.21 and A.22.

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

3.2 Hedonic difference in differences

In this section, we describe the main findings from the hedonic analyses with 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 (2021b). 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. The pre-treatment coefficients mostly fluctuate around zero and are not statistically significant. In terms of the causal effects of carbon-neutral labels, Figure 2 suggests 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 mostly negative, except in the early and final periods, and are not statistically significant.

Note that the confidence band becomes substantially wider over time. This pattern can be explained by the fact that the number of observations thins out as one moves towards the right-hand side of the graph due to the staggered nature of treatment assignment. Overall, the average effect of a carbon-neutral label over the 19-month observation period is -1.78% (95% CI: -3.71, 0.16) of the initial product price in March 2023, and not significantly different from zero.[3][4] The average effect of carbon-neutral label on product price translates to USD -0.51 in absolute terms, given the average initial price of treated products of USD 28.42.

Our estimates are robust to a variety of robustness tests shown in Appendix B.5. First, we fully relax the restriction that the product information needs to be scraped successfully and show the carbon-neutral label in more than 90% of the observations after treatment. Relaxing this condition does not affect our conclusions, as seen in Figure B.2. The average treatment effect becomes slightly positive but remains statistically insignificant (0.16% of the price at baseline).

Second, we estimate the treatment effects using an unbalanced version of the panel without filling gaps in the scraping process by interpolating (or extrapolating). The

[3]Table B.8 in Appendix B.4 contains the coefficients describing the dynamic effects.

[4]Following good scientific practice, all dynamic effect plots and calendar effect tables show confidence bands that correct for multiple hypothesis testing with Callaway and Sant'Anna (2021b)'s use of a multiplier-type bootstrap procedure. However, our null result for the effect of carbon-neutral labels is not sensitive to the application of this correction, as shown by the average treatment effect tests for which the correction is not applied.

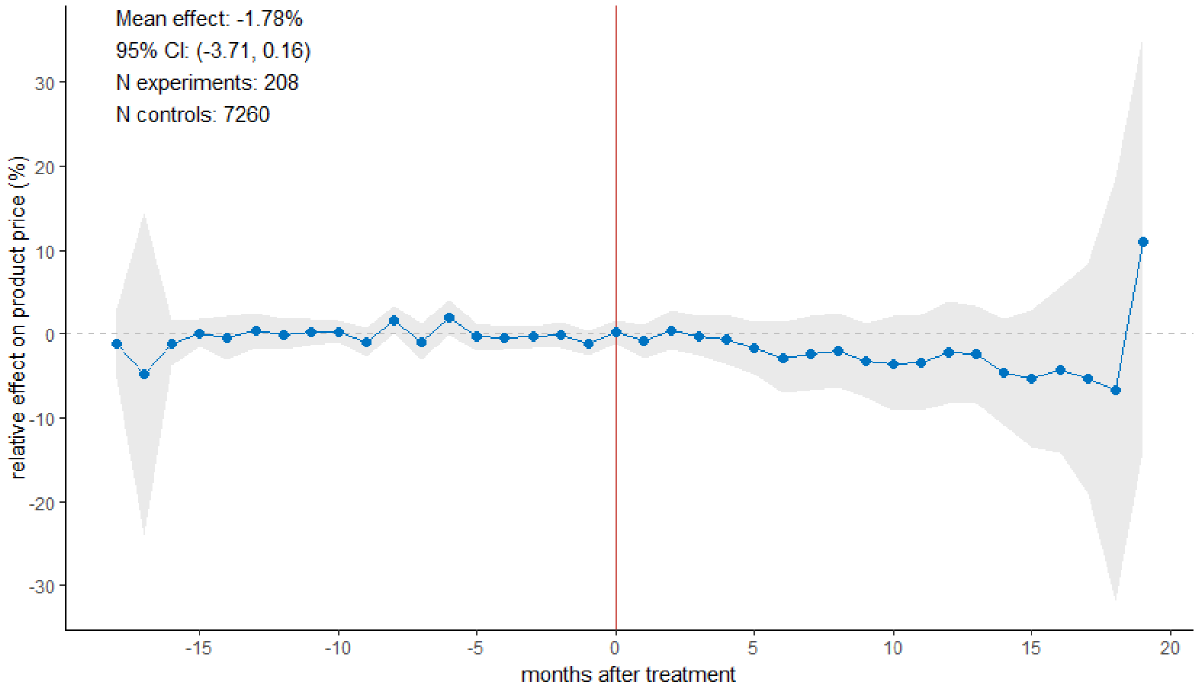

Figure 2: Effect of carbon-neutral label (US)

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.

corresponding robustness test is presented in Figure B.3, Appendix B.5. While this approach restricts the inclusion of control variables in the estimation, our conclusions remain again unchanged. The average treatment effects are, if anything, negative, 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 any products that received another label after March 2023, as well as those with a Small Business badge from the analysis.[5] This approach results in 180 treated products and 5,608 control products. Appendix B.5, Figure B.6 shows that once more, the effect of a carbon-neutral label mostly oscillates around zero and is overall statistically non-significant.

Fourth, we check the impact of removing the restriction on the minimum number of control products per treated product. The results remain the same as in the main estimation, as shown in Figure B.7 in Appendix B.5.

Lastly, a non-significant effect is observed when using the absolute price level as the dependent variable in the hedonic analysis instead of the relative price change compared to product's initial price. The average effect of a carbon-neutral label on the absolute product price over the 19-month observation period is -0.57 USD (95% CI: -3.71, 0.16), as shown in Figure B.10 Appendix B.6.

Overall, these robustness tests confirm that our main findings are not sensitive to the use of different specifications, or sample restrictions.

Since there is variation in treatment timing for treated products, dynamic effects (effects observed after certain months of treatment) differ from calendar effects (effects in specific months) and are estimated separately. As shown in Table B.9 in Appendix B.4, no specific pattern emerges from the calendar effects.

Next, we estimate treatment effects on the number of ratings as a proxy for product sales. We find a significant average effect of 1590 ratings (95% CI: 36, 3144), as shown in Table B.13 in Appendix B.6. This provides tentative evidence that a product's popularity on the platform increases when it receives a carbon neutral label.

We now turn to the United Kingdom. We perform the same sequence of analyses and thus describe our results concisely. Figure 3 presents the main results, showing the dynamic effects of receiving a carbon-neutral label on the price change of the product

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

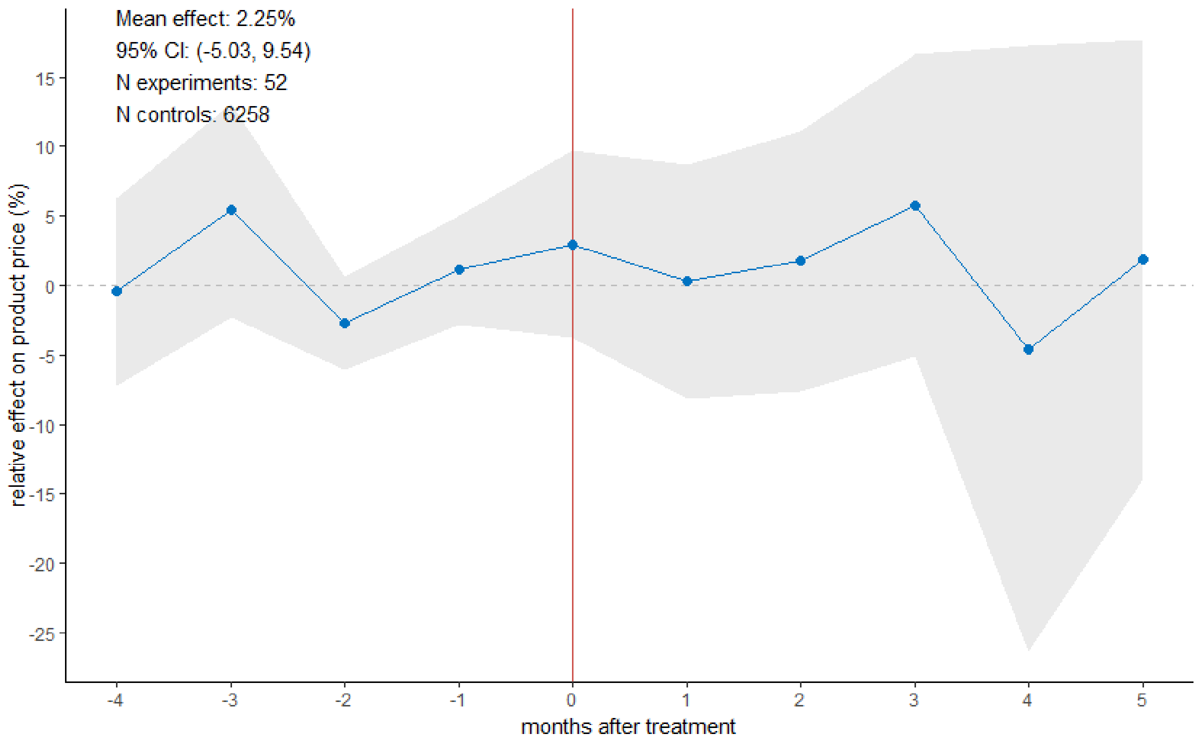

Figure 3: Effect of carbon-neutral label (UK)

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.

relative to its initial price. Also here, the pre-treatment effects mostly fluctuate around zero and are not statistically significant. The average effect of a carbon-neutral label over the five-month observation period is 2.25% (95% CI: -5.03, 9.54), and is not statistically significantly different from zero. Table B.10, Appendix B.4 provides the coefficients of the dynamic effects. The effect of a carbon-neutral label on product price translates to GBP 0.51, given that the average initial price of treated products is GBP 22.55.

As for the United States, we also subject our estimations for the United Kingdom to the same set of robustness tests. As before, our estimates are robust to using an unbalanced panel, without interpolating (and sometimes extrapolating). Table B.4 in Appendix B.4 provides the corresponding estimates. Our findings are also robust to relaxing our baseline restriction on the number of control products per treated product. Table B.8 in Appendix B.4 shows that the average treatment effect (a non-significant effect of 2.25%) and the dynamic effects remain unchanged.

The results remain qualitatively similar when using the absolute price level as the outcome variable. The average effect of a carbon-neutral label on the product price over the five-month observation period is GBP 0.97 (95% CI: -5.03, 9.54), as shown in Figure B.11, Appendix B.6.

We also do not observe a specific pattern of calendar effects in the data for the United Kingdom. Table B.11 Appendix B.4 shows the effects of having a carbon-neutral label in a particular month for all products labeled as carbon-neutral in that month.

The average treatment effect on our proxy of product sales – the number of ratings a product receives – is now negative and statistically insignificant. For the United Kingdom, we find an average effect of -442 ratings (95% CI: -1086, 203), as shown in Table B.14 in Appendix B.6.

Next, we turn to Amazon's German marketplace. Figure 4 provides the event study. Figure 4 suggests that, if anything, the effect of a carbon-neutral label is negative, but statistically insignificant. The average effect of a carbon-neutral label over the five-month observation period is -13.36% (95% CI: -39.11, 11.4), which is not statistically significantly different from zero. Table B.12 in Appendix B.4 provides more details on dynamic effects. The effect of a carbon-neutral label on product price translates to EUR -3.09 in absolute terms, given the average initial price of treated products of EUR 23.15.

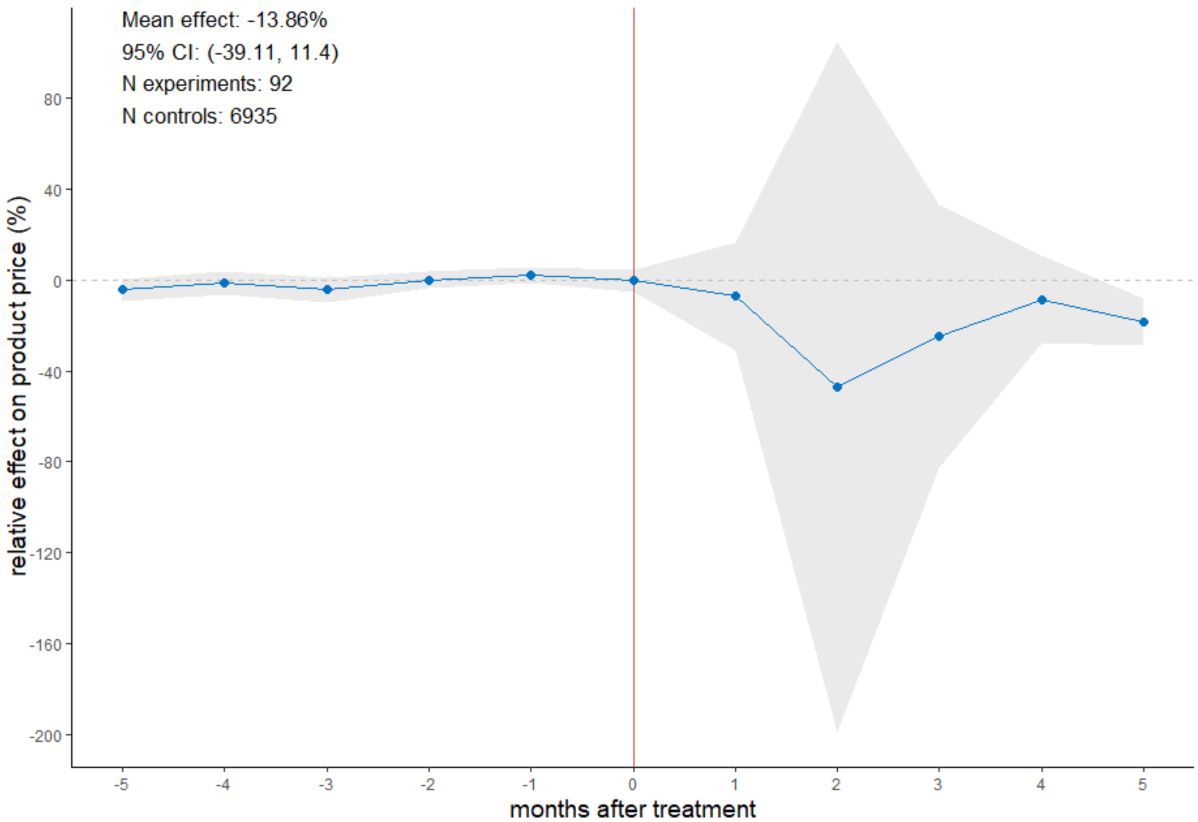

Figure 4: Effect of carbon-neutral label (Germany)

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 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.

As for the United States and the United Kingdom, we also subject our estimations for Germany to the same set of robustness tests. As before, our estimates are robust to using an unbalanced panel. Table B.5 in Appendix B.4 provides the corresponding estimates. Our estimates are also robust to relaxing our baseline restriction on the number of control products per treated product. Table B.9 in Appendix B.4 shows that the main estimate (a non-significant effect of -13.86%) and the dynamic effects remain similar.

A negative and significant average treatment effect emerges when using the absolute price level (rather than price changes) as the outcome variable in the difference-in-differences analysis. Over the five-month observation period, the average effect of a carbon-neutral label on the product price is -1.72 EUR (95% CI: -3.41, -0.03), as shown in Figure B.12 in Appendix B.6.

We also check for calendar effects using the data for Germany. Appendix B.4, Table B.13, shows the effects of having a carbon-neutral label in a particular month for all products labeled as carbon-neutral in that month. These monthly effects are mostly negative and insignificant, except for the first two months (June and July 2024), for which they are negative and significant.

We also estimate treatment effects on the number of ratings as a proxy for product sales and find a positive and significant average treatment effect of 1852 ratings (95% CI: 239, 3466), as shown in Table B.15 in Appendix B.6. Again, as for the United States we find some evidence, albeit not confirmed for the United Kingdom, indicative of an effect on quantities, based on the number of ratings as proxy.

4 Conclusions

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

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

In this paper, we analyze the demand for carbon-neutral products empirically. Our approach is twofold. First, we use a meta-analysis of existing studies in the literature assessing such demand, mostly with stated preference techniques and population samples. Second, we use online marketplaces in three different countries and their staggered introduction of carbon-neutral certified products to causally estimate the effect of carbon-neutral labels on product prices, inferring consumers' WTP for carbon-neutral labels through hedonic analyses.

The results of the meta-analysis indicate a large, positive WTP for carbon-labeled products (1.99 USD per kilogram of CO_2 reduction), which corresponds to 236% of the product's average price. The WTP for carbon-labeled 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 is mainly based on stated preference studies and controlled environments, point to a strong demand for carbon-neutral products among potential consumers, our hedonic analysis of actual market data does not support this finding. Across the three markets, we find statistically non-significant effects. If anything, point estimates are negative in two of the three markets.

The hedonic analysis of willingness to pay suggests that, based on actual market data, the potential of carbon-neutral labeling for climate change mitigation should be considered with caution. This finding contrasts with the current consensus in the stated preference literature, as summarized in our meta-analysis. At the same time, we find some tentative evidence of an effect of carbon-neutral labels on the popularity of products online. While this evidence is not conclusive, it does point to potential benefits of carbon-neutral labeling that the usual assessment of willingness to pay may not capture.

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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, such as those indicating carbon footprint, carbon reduction, or carbon neutrality. Based on the studies with (hypothetical or real) product purchases, we derive the WTP estimates for full or partial CO_2 reductions, including through offsets. As a further qualification, we 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 emissions 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. (2023)
Unspecified product	Mostafa (2016)
Multiple sustainability labels	Sporleder et al. (2014)

Table A.2: Excluded Studies and Rationales

A.1.2 List of studies and characteristics

Table A.3 describes the literature covered in the 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 climate impact information valued in the study (based on which we derive the corresponding amount of CO_2 reduction), such as carbon footprint information, carbon neutral label, or percentage of CO_2 reduction.

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

Study	No. obs.[a]	Product	Country	Method[b]	Climate impact information[c]
Ajayi and Reiner (2020)	2	Plastic bottle	United Kingdom	DCE	Percentage of carbon capture
Akaichi et al. (2016)	6	Banana	France, Netherlands, United Kingdom	DCE	Carbon footprint from transportation
Akaichi et al. (2017)	1	Rice	United States	AFE	Carbon footprint
Akaichi et al. (2020)	4	Ground beef	Spain, United Kingdom	DCE	GHG emissions
Aoki 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	Climate impact information
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	Carbon-friendly label and annual GHG emission reduction in percentages
Li et al. (2018)	2	Beef, ground beef	United States	DCE	Carbon-friendly label
Macdiarmid et al. (2021)	2	Lasagne	United Kingdom	DCE	Carbon footprint

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

Study	No. obs.	Product	Country	Method	Climate impact information
Mõerbeck (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 measures of WTP based on all studies (37) and observations (126). The non-standardized measure (WTP_R) refers to the WTP for carbon reductions, which can vary both within and between studies. This measure is directly taken or derived from studies, and converted to 2020 USD. We use this measure in our regression analysis as the outcome variable to explore factors associated with WTP.

To facilitate comparisons of WTP estimates both within and between studies, as well as with our results from the hedonic approach, we create three alternative WTP measures. The first measure is denoted as WTP_{kg}, which refers to the WTP for a 1 kg reduction in carbon emissions. This is obtained by dividing WTP_R by the respective amount of CO_2 reduction in kilograms, and is expressed in USD. The WTP for carbon neutrality, denoted as WTP_{CN}, is calculated by multiplying WTP_{kg} by the baseline CO_2 emissions of the respective product in kilograms, and is expressed in USD. This measure is derived for all observations and all studies in our database, not just those that value carbon-neutral labels. The proportion of a product's price that consumers would be willing to pay extra for carbon neutrality, denoted as $WTP_{CN\%}$, is obtained by dividing WTP_{CN} by the product's price.

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

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

   Let β_{cost} and β_{climate} be the coefficients for price and the product's climate impact attribute, respectively. MWTP for the climate impact attribute is derived using the following equation:

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

   Note that we do not derive a WTP estimate from 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 use online food/drink carbon calculators, specifically, MyEmissions and Plate up for the Planet. A few instances also involve non-food products, specifically flowers and plastic bottles. For flowers, we refer to Flowers from the Farm, an association supporting cut flower growers in the United Kingdom, and for plastic bottles, tappwater.co. Note that if the study does not specify the amount of CO_2 emission reduction, we have a 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 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 exceptions for which price information is unavailable: rice in Thailand, apple juice in Germany, and beef in the United States. We obtained rice price data from Globalproductprices.com for Chaiyesh (2022), apple juice prices from Selina Wamucii, which is an agricultural company and social enterprise, 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 Section 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 WTP_{CN} and $WTP_{CN\%}$ and plotting their distributions.

We initially collect 37 studies and 225 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.

Table A.4: WTP derivation strategy

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

Table A.4: WTP derivation strategy (continued)

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

Table A.4: WTP derivation strategy (continued)

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

Table A.4: WTP derivation strategy (continued)

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

Table A.4: WTP derivation strategy (continued)

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

Table A.4: WTP derivation strategy (continued)

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

Table A.4: WTP derivation strategy (continued)

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

Table A.4: WTP derivation strategy (continued)

Study	Details
Nyberg (2018)	The WTP for low carbon emissions and medium carbon emissions, relative to large carbon emissions, are reported in the study (Tables 10, 12, A2, and A4). Carbon emissions are categorized as low for emissions of 7 kg or less, medium for emissions between 7 kg and 11 kg, and large for emissions of more than 11 kg per portion of lasagna (0.4 kg). A high carbon-footprint lasagna, weighing 0.4 kg, contains approximately 0.08 kg of ground beef, as provided in Macdiarmid et al. (2021). Its carbon emissions amount to 1.88 kg (according to the Plate Up for the Planet calculator), which falls within the "low emissions" category defined in this study. In the meta-analysis, as we treat offsets and reductions in the same way, we assume that the carbon emissions of products can be reduced to 0 kg. Therefore, we assume average emissions of 3.5 kg for low levels (averaging 0 kg and 7 kg of carbon emissions), 9 kg for medium levels (averaging 7 kg and 11 kg of carbon emissions), and 11 kg for large levels. Respective carbon reduction levels for WTP estimates are calculated by determining the differences between low and large (7.5 kg = 11 kg - 3.5 kg) and between medium and large (2 kg = 11 kg - 9 kg) carbon emissions. We average WTP estimates from the survey results from colored labels and text-only labels.
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 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 liter of wine (1.03 kg) is obtained from the myEmissions calculator.
Yang et al. (2021)	WTP for a 38% carbon reduction is derived from the study (Table 4). The amount of carbon emissions of 1 kg rice (0.68 kg) is obtained from the myEmissions calculator. We use this information to calculate respective carbon emission reduction (0.26 kg).

A.2 Descriptive statistics

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

Figure 1 in Section 3.1 shows the distribution of WTP_R (non-standardized WTP for carbon reductions) as well as WTP_{kg} (WTP for 1 kg carbon reduction), while Figure A.1 shows the distribution of WTP_{CN} (WTP for carbon neutrality) and $WTP_{CN\%}$ (the proportion of a product's price that consumers would be willing to pay extra for carbon neutrality) across studies along with the magnitude of CO_2 reductions or baseline product emissions, as well as different product categories. Figures A.2, A.3, and A.4 display the histogram of each outcome variable, WTP_R, WTP_{kg}, WTP_{CN}, and $WTP_{CN\%}$, respectively, both with and without outliers.

	N	Mean	Std. Dev.	Min	Max
WTP_R (USD)	126	1.13	1.52	-0.09	9.06
WTP_{kg} (USD)	126	4.33	9.27	-1.38	45.28
WTP_{CN} (USD)	126	8.77	30.41	-0.13	311.56
$WTP_{CN\%}$ (%)	126	158.05	338.15	-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	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 figure 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	1.23	1.18	0.00	4.94
WTP_{kg} (USD)	37	1.99	3.94	0.02	23.73
WTP_{CN} (USD)	37	11.84	30.57	0.00	176.90
$WTP_{CN\%}$ (%)	37	235.55	422.94	0.06	1624.88
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	4	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 figure 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	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)	2.02 (2.05)	1.29 (1.95)	21.53 (47.33)	284.89 (453.08)
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: Means of WTP estimates by product category

This table displays the product categories, their respective number of observations (N), and the means of the outcome variables. Standard deviations are provided in parentheses. The third column presents the CO_2 emissions associated with the products, which vary according to the type and amount of product valued in studies. The 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	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)	1.92 (1.64)	1.25 (1.61)	24.21 (42.50)	324.62 (476.58)
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 figure displays the product categories, their respective number of studies (N), and the means of study specific means of the outcome variables. Standard deviations are provided in parentheses. The third column presents the CO_2 emissions associated with the products, which vary according to type and amount of product valued in studies. The non-standardized measure WTP_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

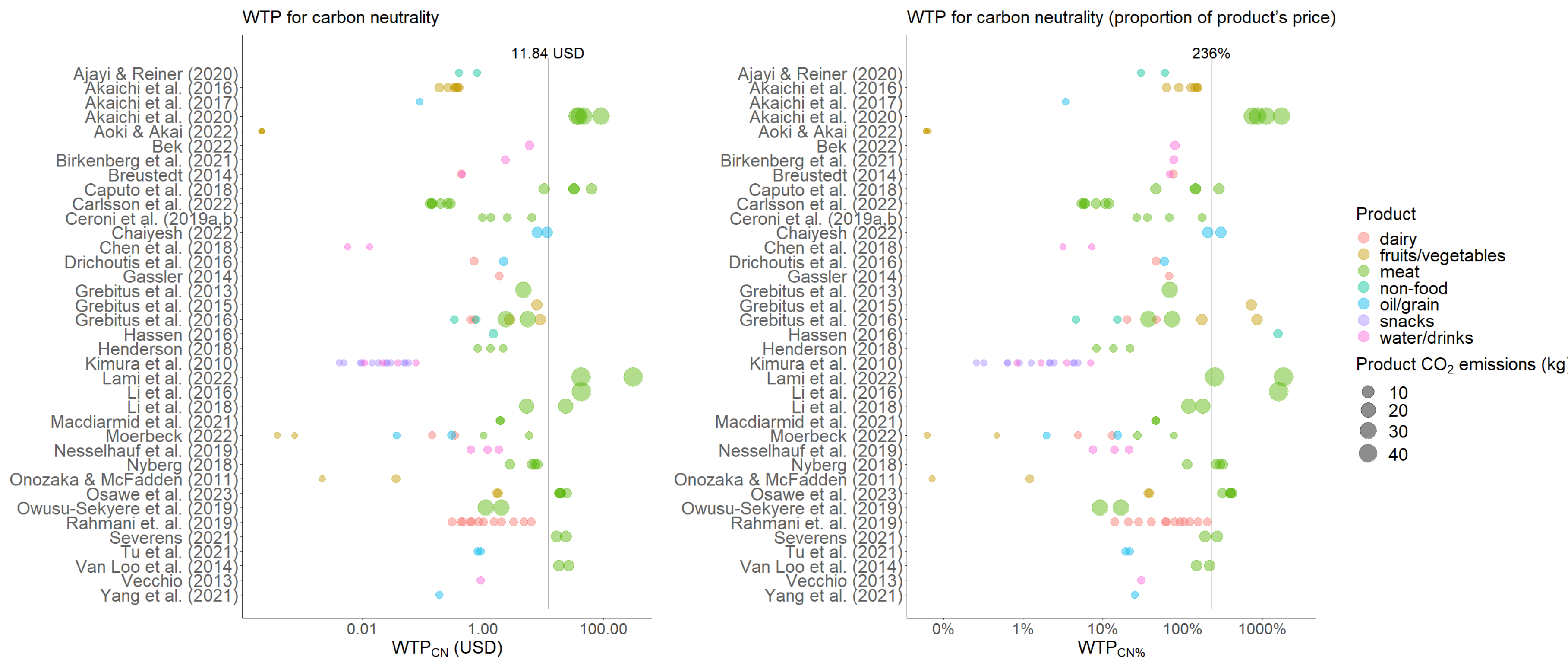


Figure A.1: WTP for carbon neutrality across studies

A logarithmic axis (base 10) is used to create this figure. The vertical lines represent the mean of study means. The left graph displays WTP_{CN} (WTP for carbon neutrality) across studies, where the size of each circle represents the baseline CO_2 emissions of the product in kilograms. 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.

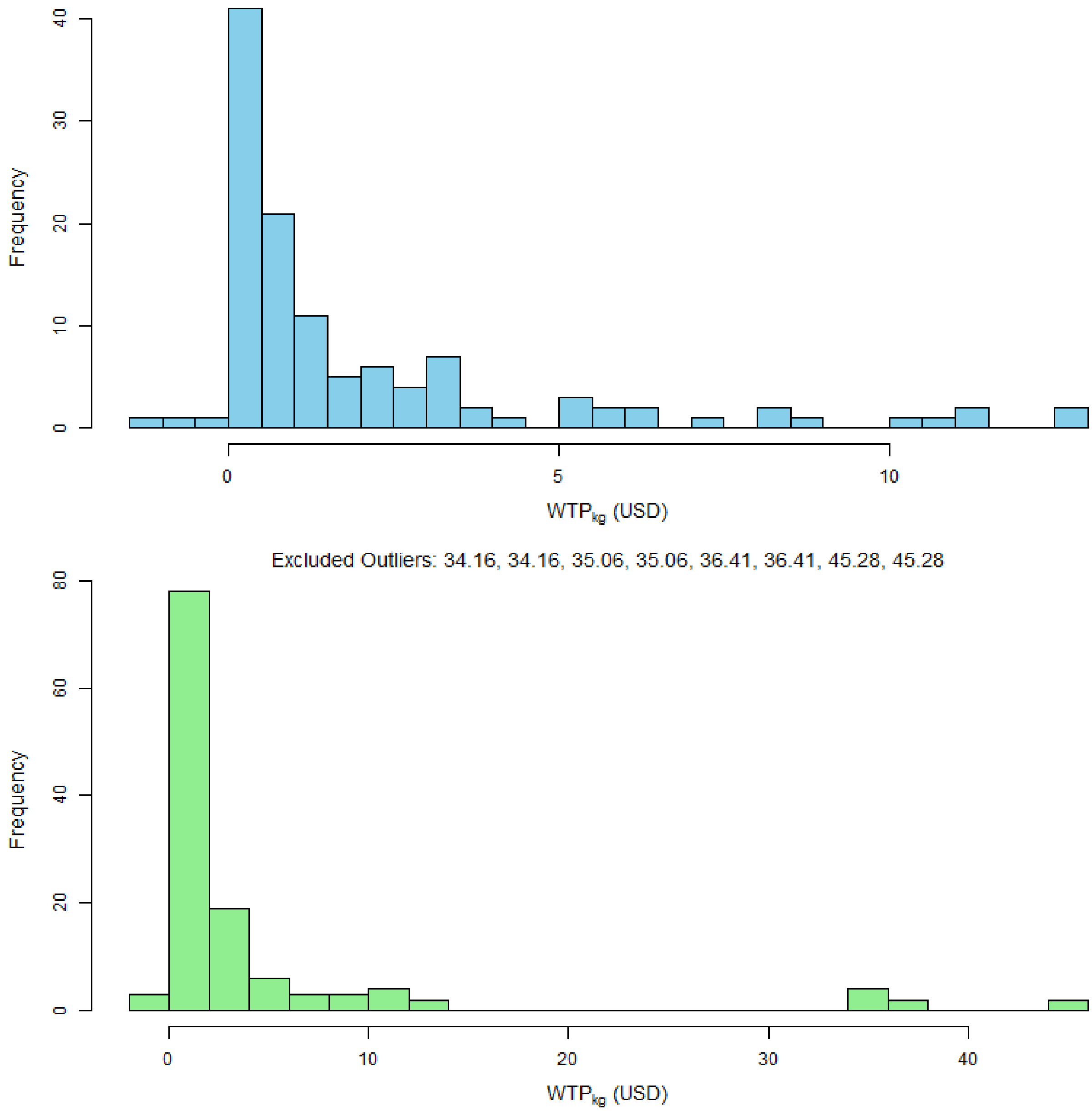


Figure A.2: WTP for 1 kg carbon reduction ($\mathrm{WTP_{kg}}$)

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

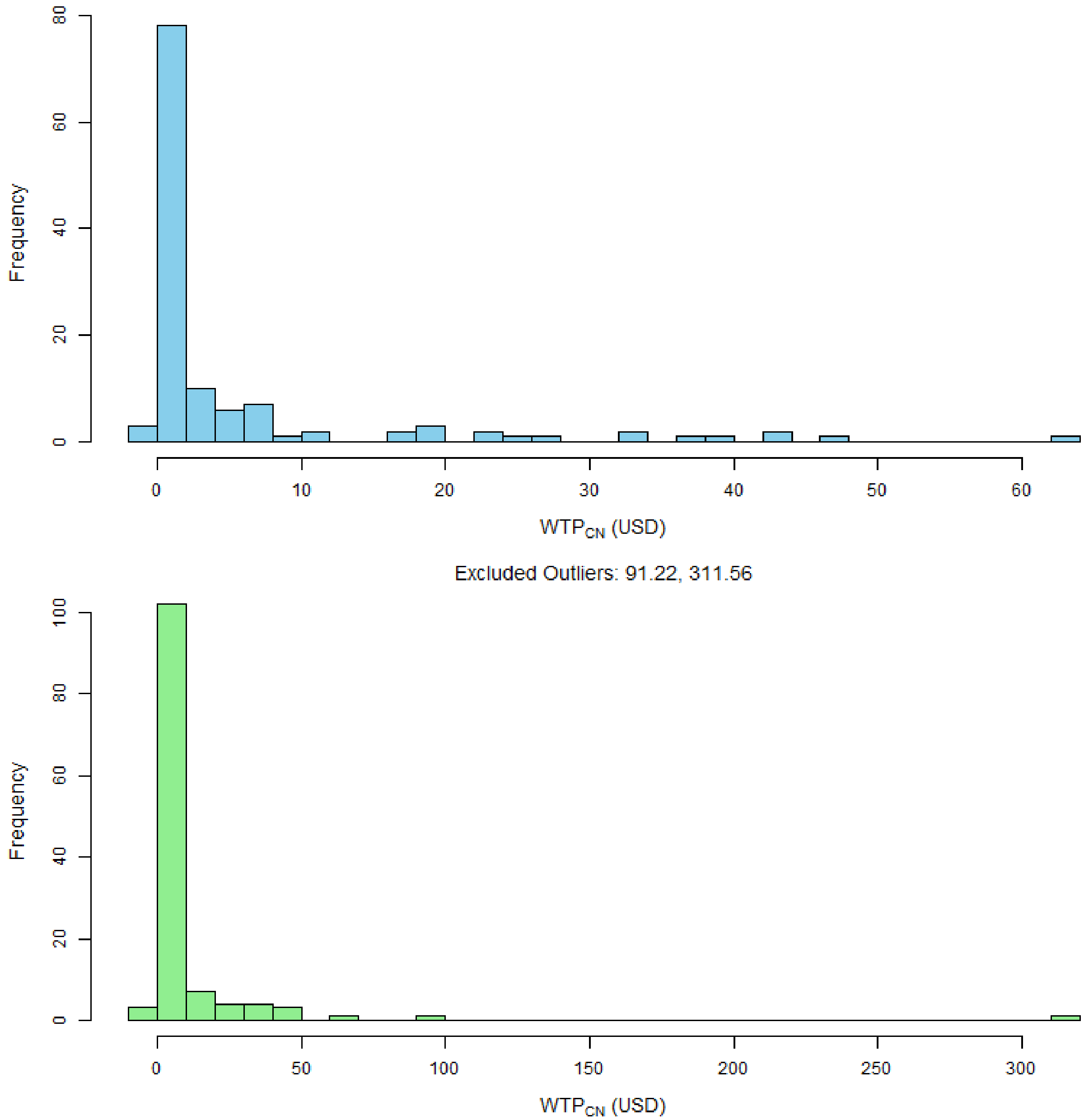


Figure A.3: WTP for carbon neutrality ($\mathrm{WTP}_{\mathrm{CN}}$)

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

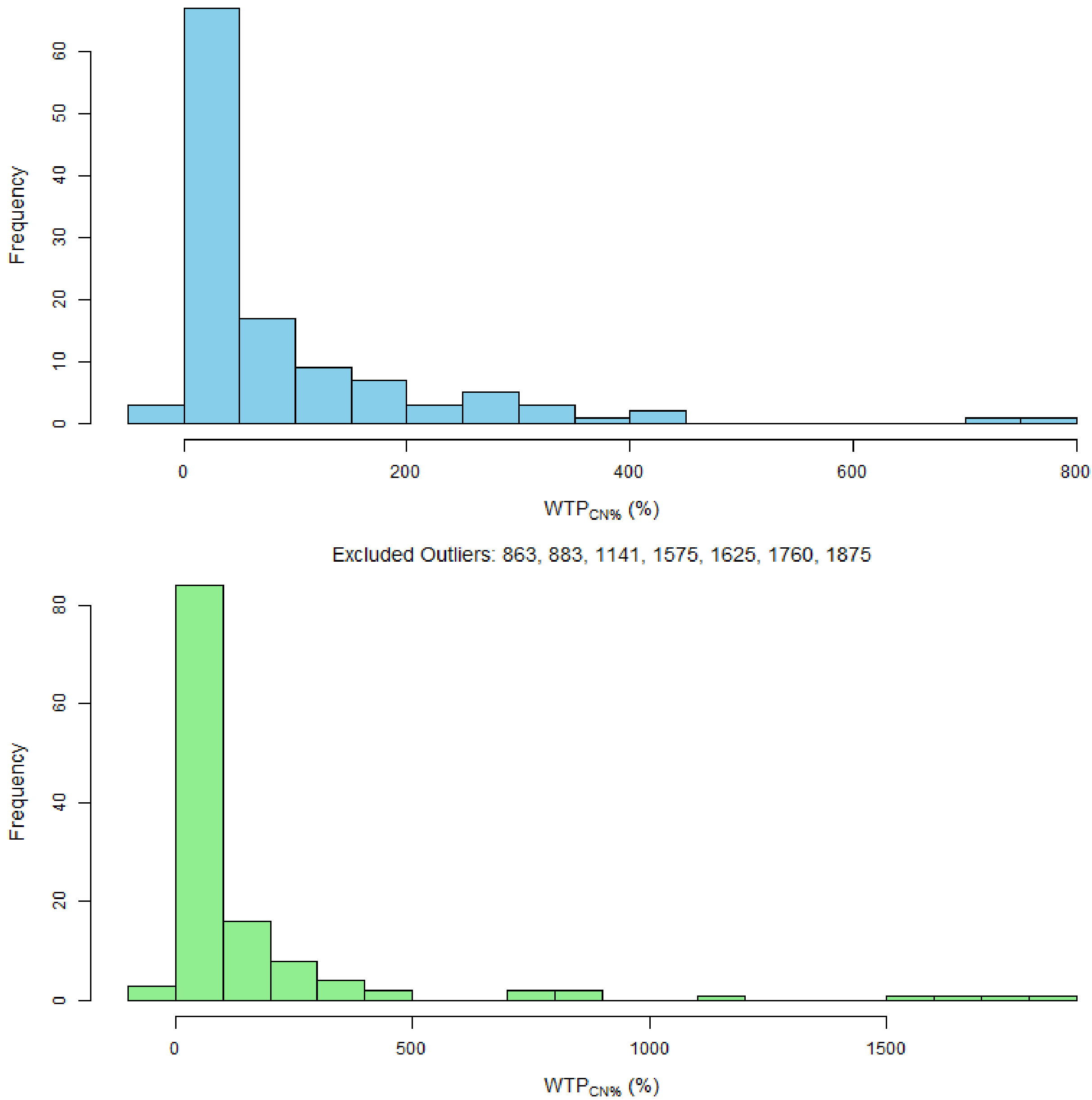
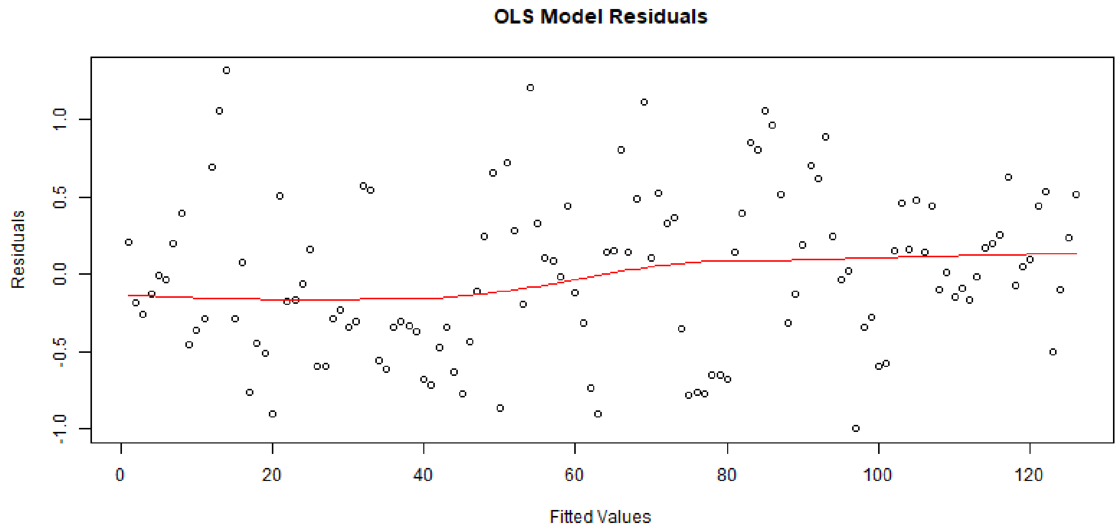


Figure A.4: The proportion of a product's price that consumers would be willing to pay extra for carbon neutrality ($WTP_{CN\%}$)

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.



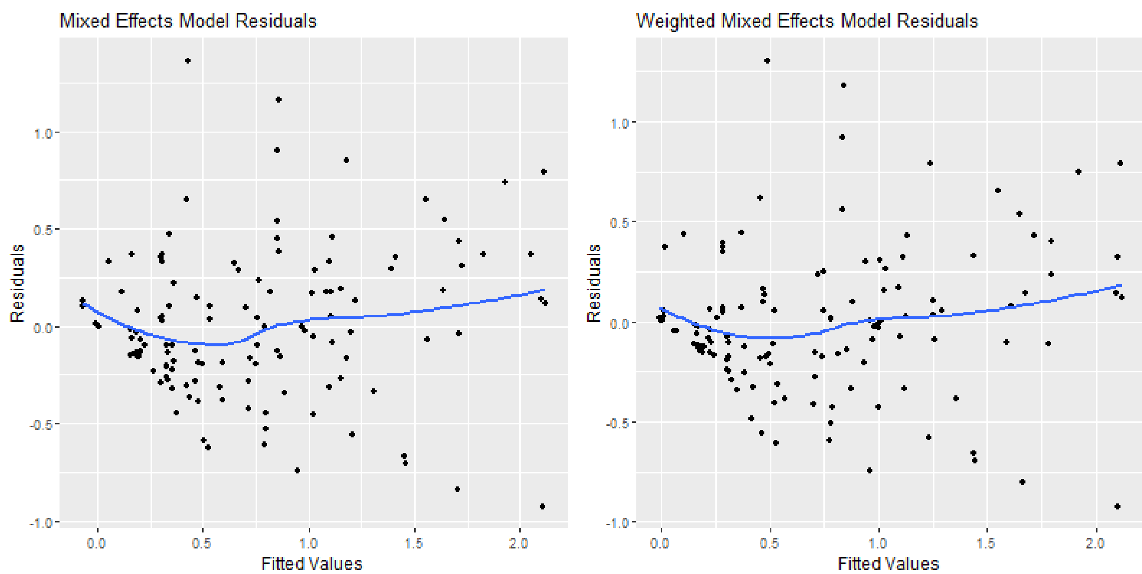


Figure A.5: Residuals versus fitted values

Table A.9: Breusch-Pagan test for OLS models presented in Table 1

Model	Breusch-Pagan Stat.	p-value
OLS I	6.32	0.04*
OLS II	25.91	0.002**
OLS III	24.64	0.01*

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

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.10 provides OLS model estimations with standard errors clustered by studies. 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.11 and A.12 include two additional variables, carbon neutral certification and colored labels, analyzed using OLS and mixed-effects models, in addition to those in our main 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 other variables, including 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 run WLS and weighted mixed-effects models in Tables A.13 and A.14, respectively. For comparison purposes, we use the unweighted model 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 the weights.

Fourth, we run OLS and mixed-effects regressions using different transformation approaches for the depenent variable in Tables A.15 and A.16, respectively. For comparison purposes, the first column shows estimations with the untransformed dependent variable. The second column displays the results based on transformation according to the inverse hyperbolic sine, and the last column uses the logarithmic transformation.

Fifth, we run the OLS model with two-way clustered errors in Table A.17. For comparison, the first column includes the 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 study countries.

Sixth, we run the mixed-effects regressions with alternative random effects as shown in Table A.18. For comparison, the first column includes the mixed-effects model with random effects for studies. The second column incorporates random effects for both studies and product categories. The third column includes random effects for studies and study countries.

Seventh, we run OLS and mixed-effects regressions, including the square of the z-scored CO_2 emission reduction variable in Tables A.19 and A.20 respectively. The first column includes the CO_2 reduction, CO_2 reduction squared, and product price variables. The second column includes additional variables such as stated preference studies, sample size, and GDP per capita. In the last column, we add control variables for CO_2 reduction assumptions and WTP derivations, as detailed in Section A.1.3.

Eighth, we run OLS and mixed-effects regressions with different subsets of observations in Tables A.21 and A.22 respectively. The first column is based on the complete set of observations. The second column displays results while omitting observations that require assumptions about the amount of CO_2 reductions. The third column includes only observations where WTP values are sourced directly from the studies, excluding those requiring further calculations or derivations. The final column shows model results that excludes both types of observations: those with CO_2 reduction assumptions and those with derived WTP values.

Based on the results presented in Tables A.10-A.22, the positive significance of the CO_2 emission reduction variable is confirmed across all robustness checks (mainly at the 5% level) except for three, which are insignificant. These exceptions are the second column of Table A.20 and the third columns of Tables A.21 and A.22. Although the latter two columns may caution us regarding the observations for which we derive WTP_R, the CO_2 emission reduction variable remains significant even when we exclude observations involving CO_2 reduction assumptions. Furthermore, when we control for observations for which we derive the WTP_R estimates, as in Table A.10, the CO_2 reduction variable is consistently significant across all models. This indicates a mostly robust and significant association between the WTP_R and the amount of CO_2 reduction.

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

Even while controlling for GDP per capita, studies conducted in Europe are robustly and positively significant at the 1% or 5% levels in all regressions, except for the last columns of Tables A.21 and A.22. However, these regressions are based on a small subset of (only 28) observations.

Confirming our main results in Table 1 from Section 3.1, we do not find significant results for sample size, colored labels, or the WTP derivation variables in any of the robustness regressions. The remaining variables are mostly insignificant but become significant in only a few of the regressions, as described in the below paragraph.

The coefficient for stated preference studies becomes significant at the 10% level with a negative sign in the second columns of Tables A.21 and A.22. The coefficient for published studies becomes negative and significant in the third column of Table A.13, the second and third columns of Table A.21, and the second column of Table A.22 at significance levels randing from 1% to 10%. The coefficient for CO_2 reduction assumptions becomes significant, albeit only at the 10% level, with a positive sign, in the second column of Table A.13 and the third column of Table A.15. The coefficient for the dummy variable indicating in-person studies is significant and negative in the second columns of Tables A.21 and A.22 at the 5% level. GDP per capita becomes positively significant in the first column of Table A.15 at the 10% level. The study year becomes negatively significant in the third column of Table A.15 at the 10% level. The coefficient for the carbon-neutral label is positive and significant at the 10% level in the second column of Table A.11.

	OLS	Mixed Eff.	Weighted Mixed Eff.
Intercept	0.52 (0.32)	0.18 (0.39)	0.14 (0.36)
CO_2 reduction	0.10** (0.04)	0.11** (0.05)	0.12*** (0.04)
Price	0.32*** (0.05)	0.32*** (0.07)	0.30*** (0.07)
Stated pref. method	-0.01 (0.23)	0.31 (0.28)	0.39 (0.24)
In-person	-0.08 (0.21)	0.04 (0.21)	0.05 (0.19)
Sample size	-0.05 (0.07)	-0.05 (0.09)	-0.06 (0.09)
Publication	-0.03 (0.22)	-0.18 (0.21)	-0.22 (0.21)
Study year	-0.02 (0.10)	-0.01 (0.10)	-0.01 (0.09)
GDP per capita	0.08 (0.08)	0.03 (0.07)	0.01 (0.07)
Europe	0.32** (0.18)	0.42** (0.17)	0.48*** (0.17)
CO_2 reduction assump.	0.15 (0.15)	0.19 (0.19)	0.17 (0.18)
WTP derivation	-0.07 (0.12)	0.04 (0.15)	0.06 (0.15)
Number of obs.	126	126	126
Var (study random effect)		0.13	0.16
Var (product random eff.)		0.01	0.01
Adjusted-R^2	0.41		
AIC	214.96	235.84	249.44
BIC	251.83	278.39	291.99
Log Likelihood	-94.48	-102.92	-109.72

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

Table A.10: 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 studies. 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	0.68*** (0.06)	0.50* (0.29)	0.49* (0.25)
CO_2 reduction	0.11*** (0.04)	0.10** (0.04)	0.07** (0.03)
Price	0.35*** (0.05)	0.32*** (0.05)	0.30*** (0.05)
Colored label	0.17 (0.15)	0.07 (0.15)	0.12 (0.15)
Carbon neutral label	0.15 (0.12)	0.26* (0.14)	0.12 (0.16)
Stated pref. method		-0.01 (0.25)	0.03 (0.18)
In-person		-0.02 (0.16)	-0.04 (0.14)
Sample size		-0.07 (0.06)	-0.07 (0.06)
Publication		-0.07 (0.14)	-0.20 (0.12)
Study year		-0.02 (0.06)	0.01 (0.06)
GDP per capita		0.11** (0.05)	0.03 (0.05)
Europe		0.36*** (0.14)	0.51*** (0.12)
CO_2 reduction assump.			0.11 (0.14)
WTP derivation			0.05 (0.11)
Number of obs.	126	126	126
Adjusted-R^2	0.35	0.42	0.46
AIC	220.81	213.25	238.32
BIC	237.83	250.12	280.86
Log Likelihood	-104.41	-93.63	-104.16

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

Table A.11: 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 studies. 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	0.71*** (0.10)	0.25 (0.35)	0.12 (0.37)
CO_2 reduction	0.10** (0.05)	0.10** (0.05)	0.13*** (0.05)
Price	0.32*** (0.06)	0.30*** (0.06)	0.29*** (0.07)
Colored label	0.11 (0.16)	0.08 (0.16)	0.14 (0.18)
Carbon neutral label	0.04 (0.19)	0.18 (0.21)	0.04 (0.27)
Stated pref. method		0.30 (0.27)	0.41 (0.25)
In-person		0.06 (0.21)	0.05 (0.20)
Sample size		-0.07 (0.10)	-0.06 (0.10)
Publication		-0.18 (0.21)	-0.22 (0.21)
Study year		0.01 (0.09)	-0.01 (0.09)
GDP per capita		0.06 (0.07)	0.02 (0.08)
Europe		0.44*** (0.16)	0.49*** (0.18)
CO_2 reduction assump.			0.12 (0.24)
WTP derivation			0.06 (0.15)
Number of obs.	126	126	126
Var (study random effect)	0.15	0.13	0.17
Var (product random eff.)	0.01	0.01	0.02
AIC	221.96	235.49	255.31
BIC	244.65	278.03	303.53
Log Likelihood	-102.98	-102.74	-110.66

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

Table A.12: 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 (w = inv. number obs.)	WLS II (w = sample size)
Intercept	0.52 (0.32)	0.50** (0.27)	1.11* (0.26)
CO_2 reduction	0.10** (0.04)	0.08*** (0.03)	0.10*** (0.02)
Price	0.32*** (0.05)	0.30*** (0.06)	0.25*** (0.08)
Stated pref. method	-0.01 (0.23)	0.03 (0.19)	-0.23 (0.19)
In-person	-0.08 (0.21)	-0.06 (0.23)	-0.31 (0.23)
Sample size	-0.05 (0.07)	-0.06 (0.07)	-0.05 (0.04)
Publication	-0.03 (0.22)	-0.20 (0.19)	-0.44*** (0.20)
Study year	-0.02 (0.10)	0.02 (0.09)	0.07 (0.12)
GDP per capita	0.08 (0.08)	0.01 (0.07)	0.00 (0.12)
Europe	0.32** (0.18)	0.49*** (0.17)	0.46*** (0.11)
CO_2 reduction assump.	0.15 (0.15)	0.19* (0.12)	-0.08 (0.10)
WTP derivation	-0.07 (0.12)	0.03 (0.14)	0.00 (0.09)
Number of obs.	126	126	126
Adjusted R^2	0.41	0.47	0.32
AIC	214.96	235.46	309.29
BIC	251.83	272.33	346.16
Log Likelihood	-94.48	-104.73	-141.64

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

Table A.13: 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 studies. 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	0.18 (0.39)	0.14 (0.36)	0.87 (0.64)
CO_2 reduction	0.11^{**} (0.05)	0.12^{***} (0.04)	0.11^{***} (0.04)
Price	0.32^{***} (0.07)	0.30^{***} (0.07)	0.25^{***} (0.08)
Stated pref. method	0.31 (0.28)	0.39 (0.24)	-0.07 (0.55)
In-person	0.04 (0.21)	0.05 (0.19)	-0.21 (0.27)
Sample size	-0.05 (0.09)	-0.06 (0.09)	-0.07 (0.09)
Publication	-0.18 (0.21)	-0.22 (0.21)	-0.31 (0.22)
Study year	-0.01 (0.10)	-0.01 (0.09)	0.08 (0.10)
GDP per capita	0.03 (0.07)	0.01 (0.07)	0.04 (0.07)
Europe	0.42^{**} (0.17)	0.48^{***} (0.17)	0.43^{***} (0.13)
CO_2 reduction assump.	0.19 (0.19)	0.17 (0.18)	-0.02 (0.20)
WTP derivation	0.04 (0.15)	0.06 (0.15)	0.02 (0.15)
Number of obs.	126	126	126
Var (study random effect)	0.13	0.16	0.10
Var (country random effect)	0.01	0.01	0.01
AIC	235.84	249.44	327.86
BIC	278.39	291.99	370.41
Log Likelihood	-102.92	-109.72	-148.93

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

Table A.14: 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	0.62 (0.62)	0.52 (0.32)	-1.57* (0.88)
CO_2 reduction	0.18** (0.10)	0.10** (0.04)	0.28*** (0.09)
Price	0.75*** (0.10)	0.32*** (0.05)	0.61*** (0.15)
Stated pref. method	-0.02 (0.51)	-0.01 (0.23)	-0.16 (0.45)
In-person	-0.23 (0.38)	-0.08 (0.21)	-0.33 (0.51)
Sample size	-0.21 (0.16)	-0.05 (0.07)	0.03 (0.19)
Publication	0.21 (0.36)	-0.03 (0.22)	-0.34 (0.64)
Study year	0.06 (0.17)	-0.02 (0.10)	-0.32* (0.32)
GDP per capita	0.18* (0.15)	0.08 (0.08)	-0.02 (0.25)
Europe	0.67** (0.31)	0.32** (0.18)	1.19*** (0.57)
CO_2 reduction assump.	0.00 (0.26)	0.15 (0.15)	0.66* (0.52)
WTP derivation	-0.08 (0.20)	-0.07 (0.12)	0.22 (0.49)
Number of obs.	126	126	123
Adjusted R^2	0.44	0.41	0.31
AIC	402.84	214.96	437.31
BIC	439.71	251.83	473.87
Log Likelihood	-188.42	-94.48	-205.66

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

Table A.15: 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 studies. For the first column, we do not transform the outcome variable. In the second column, we transform it using the inverse hyperbolic sine function. In the third column, we use logarithmic transformation, resulting in the loss of three negative observations. The dependent variable is the (unstandardized) WTP for 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 (0.78)	0.18 (0.39)	-2.25** (0.92)
CO_2 reduction	0.22** (0.10)	0.11** (0.05)	0.22* (0.11)
Price	0.75*** (0.13)	0.32*** (0.07)	0.57*** (0.16)
Stated pref. method	0.29 (0.59)	0.31 (0.28)	0.67 (0.61)
In-person	-0.05 (0.41)	0.04 (0.21)	0.15 (0.50)
Sample size	-0.17 (0.17)	-0.05 (0.09)	0.04 (0.24)
Publication	-0.02 (0.38)	-0.18 (0.21)	-0.50 (0.55)
Study year	0.07 (0.18)	-0.01 (0.10)	-0.13 (0.24)
GDP per capita	0.11 (0.13)	0.03 (0.07)	0.02 (0.18)
Europe	0.75** (0.34)	0.42** (0.17)	1.13*** (0.38)
CO_2 reduction assump.	0.05 (0.35)	0.19 (0.19)	0.62 (0.48)
WTP derivation	0.03 (0.30)	0.04 (0.15)	0.26 (0.34)
Number of obs.	126	126	123
Var (study random effect)	0.29	0.13	1.15
Var (product random effect)	0.00	0.01	0.19
AIC	421.54	235.84	396.44
BIC	464.08	278.39	438.62
Log Likelihood	-195.77	-102.92	-183.22

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

Table A.16: 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	0.52 (0.32)	0.52 (0.08)	0.52 (0.29)
CO_2 reduction	0.10** (0.04)	0.10** (0.02)	0.10** (0.05)
Price	0.32*** (0.05)	0.32*** (0.04)	0.32*** (0.04)
Stated pref. method	-0.01 (0.23)	-0.01 (0.14)	-0.01 (0.22)
In-person	-0.08 (0.21)	-0.08 (0.13)	-0.08 (0.23)
Sample size	-0.05 (0.07)	-0.05 (0.14)	-0.05 (0.08)
Publication	-0.03 (0.22)	-0.03 (0.15)	-0.03 (0.25)
Study year	-0.02 (0.10)	-	-0.02 (0.12)
GDP per capita	0.08 (0.08)	0.08 (0.07)	0.08 (0.09)
Europe	0.32** (0.18)	0.32** (0.20)	0.32** (0.17)
CO_2 reduction assump.	0.15 (0.15)	0.15 (0.07)	0.15 (0.22)
WTP derivation	-0.07 (0.12)	-0.07 (0.09)	-0.07 (0.11)
Number of obs.	126	126	126
Adjusted R^2	0.41	0.42	0.41
AIC	214.96	213.08	214.96
BIC	251.83	247.11	251.83
Log Likelihood	-94.48	-94.54	-94.48

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

Table A.17: 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 studies and product categories. 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 studies and countries. 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 (study r.e.)	Mixed Eff. II (study & product r.e.)	Mixed Eff. III (study & country r.e.)
Intercept	0.21 (0.39)	0.18 (0.39)	0.21 (0.39)
CO_2 reduction	0.12** (0.05)	0.11** (0.05)	0.12** (0.05)
Price	0.34*** (0.06)	0.32*** (0.07)	0.34*** (0.06)
Stated pref. method	0.29 (0.28)	0.31 (0.28)	0.29 (0.28)
In-person	0.05 (0.21)	0.04 (0.21)	0.05 (0.21)
Sample size	-0.04 (0.09)	-0.05 (0.09)	-0.04 (0.09)
Publication	-0.18 (0.21)	-0.18 (0.21)	-0.18 (0.21)
Study year	-0.01 (0.10)	-0.01 (0.10)	-0.01 (0.10)
GDP per capita	0.03 (0.07)	0.03 (0.07)	0.03 (0.07)
Europe	0.41** (0.17)	0.42** (0.17)	0.41** (0.17)
CO_2 reduction assump.	0.20 (0.18)	0.19 (0.19)	0.20 (0.18)
WTP derivation	0.05 (0.15)	0.04 (0.15)	0.05 (0.15)
Number of obs.	126	126	126
Var (study random effect)	0.13	0.13	0.13
Var (product random eff.)		0.01	
Var (country random effect)			0.00
AIC	233.96	235.84	235.96
BIC	273.67	278.39	278.50
Log Likelihood	-102.98	-102.92	-102.98

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

Table A.18: 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	0.77*** (0.05)	0.56* (0.07)	0.51 (0.33)
CO_2 reduction	0.27** (0.10)	0.19* (0.02)	0.21* (0.11)
CO_2 reduction^2	-0.03* (0.02)	-0.02 (0.04)	-0.02 (0.02)
Price	0.33*** (0.05)	0.31*** (0.14)	0.32*** (0.05)
Stated pref. method		-0.01 (0.13)	-0.01 (0.26)
In-person		-0.08 (0.14)	-0.07 (0.16)
Sample size		-0.04 (0.16)	-0.04 (0.06)
Publication		-0.02 (0.07)	-0.03 (0.14)
Study year		0.01 (0.19)	-0.04 (0.07)
GDP per capita		0.07 (0.08)	0.07 (0.05)
Europe		0.36** (0.09)	0.32** (0.14)
CO_2 reduction assump.			0.18 (0.14)
WTP derivation			-0.03 (0.13)
Number of obs.	126	126	126
Adjusted R^2	0.36	0.41	0.41
AIC	218.67	214.06	215.83
BIC	232.85	248.10	255.54
Log Likelihood	-104.34	-95.03	-93.91

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

Table A.19: 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 studies. 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	0.77*** (0.09)	0.32 (0.35)	0.18 (0.39)
CO_2 reduction	0.24* (0.12)	0.18 (0.12)	0.23* (0.13)
CO_2 reduction^2	-0.03 (0.02)	-0.01 (0.02)	-0.02 (0.02)
Price	0.31*** (0.06)	0.29*** (0.06)	0.32*** (0.07)
Stated pref. method		0.31 (0.27)	0.31 (0.28)
In-person		0.03 (0.21)	0.06 (0.21)
Sample size		-0.05 (0.09)	-0.04 (0.09)
Publication		-0.16 (0.21)	-0.18 (0.21)
Study year		0.02 (0.09)	-0.03 (0.10)
GDP per capita		0.05 (0.07)	0.03 (0.07)
Europe		0.42** (0.16)	0.40** (0.17)
CO_2 reduction assump.			0.23 (0.19)
WTP derivation			0.09 (0.16)
Number of obs.	126	126	126
Var (study random effect)	0.14	0.13	0.14
Var (product random eff.)	0.00	0.01	0.00
AIC	221.56	236.88	242.75
BIC	241.41	276.59	288.13
Log Likelihood	-103.78	-104.44	-105.37

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

Table A.20: 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 (no both)
Intercept	0.52^{*} (0.32)	1.25^{***} (0.19)	0.81 (0.45)	0.75 (0.27)
CO_2 reduction	0.10^{**} (0.03)	0.17^{**} (0.07)	0.08 (0.03)	0.20^{*} (0.11)
Price	0.32^{***} (0.05)	0.27^{***} (0.05)	0.29^{***} (0.06)	0.32^{***} (0.07)
Stated pref. method	-0.00 (0.23)	-0.49^{*} (0.13)	-0.01 (0.28)	
In-person	-0.07 (0.23)	-0.50^{**} (0.18)	-0.28 (0.31)	-0.25 (0.27)
Sample size	-0.04 (0.08)	-0.10 (0.03)	-0.09 (0.07)	-0.07 (0.07)
Publication	-0.02 (0.23)	-0.38^{*} (0.08)	-0.47^{**} (0.21)	-0.34 (0.18)
Study year	0.02 (0.09)	-0.11 (0.10)	-0.02 (0.10)	-0.07 (0.19)
GDP per capita	0.07 (0.08)	0.09 (0.05)	-0.13 (0.12)	0.25 (0.11)
Europe	0.37^{***} (0.17)	0.46^{***} (0.11)	0.57^{***} (0.18)	0.32 (0.16)
Number of obs.	126	55	73	28
Number of studies	37	14	24	8
Adjusted R^2	0.42	0.71	0.44	0.68
AIC	212.94	57.72	125.31	47.81
BIC	244.14	79.80	150.50	61.13
Log Likelihood	-95.47	-17.86	-51.65	-13.91

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

Table A.21: 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 studies. 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 (no both)
Intercept	0.29 (0.35)	1.35*** (0.37)	0.27 (0.54)	0.75 (0.63)
CO_2 reduction	0.10** (0.05)	0.23*** (0.07)	0.10 (0.07)	0.20* (0.11)
Price	0.30*** (0.06)	0.37*** (0.07)	0.27*** (0.08)	0.32*** (0.08)
Stated pref. method	0.31 (0.27)	-0.48* (0.28)	0.55 (0.42)	
In-person	0.03 (0.21)	-0.46** (0.21)	-0.19 (0.25)	-0.25 (0.37)
Sample size	-0.06 (0.09)	-0.04 (0.08)	-0.10 (0.11)	-0.07 (0.16)
Publication	-0.15 (0.20)	-0.47** (0.23)	-0.44 (0.27)	-0.34 (0.47)
Study year	0.03 (0.09)	-0.12 (0.13)	0.02 (0.12)	-0.07 (0.25)
GDP per capita	0.04 (0.07)	0.10 (0.09)	-0.07 (0.11)	0.25 (0.21)
Europe	0.43*** (0.16)	0.37** (0.15)	0.50** (0.20)	0.32 (0.26)
Number of obs.	126	55	73	28
Number of studies	37	14	24	8
Var (study random effect)	0.13	0.00	0.12	0.00
Var (product random eff.)	0.01	0.05	0.00	0.00
AIC	229.37	92.09	153.37	71.29
BIC	266.24	118.19	183.15	87.28
Log Likelihood	-101.69	-33.05	-63.69	-23.64

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

Table A.22: 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.

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 two 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. Alternatively, consumers can navigate to the Climate Pledge Friendly page, choose a carbon-neutral certification and then filter all products labeled as such. Figure B.1 illustrates an example of a product certified as carbon neutral by Climate Partner on Amazon.com.

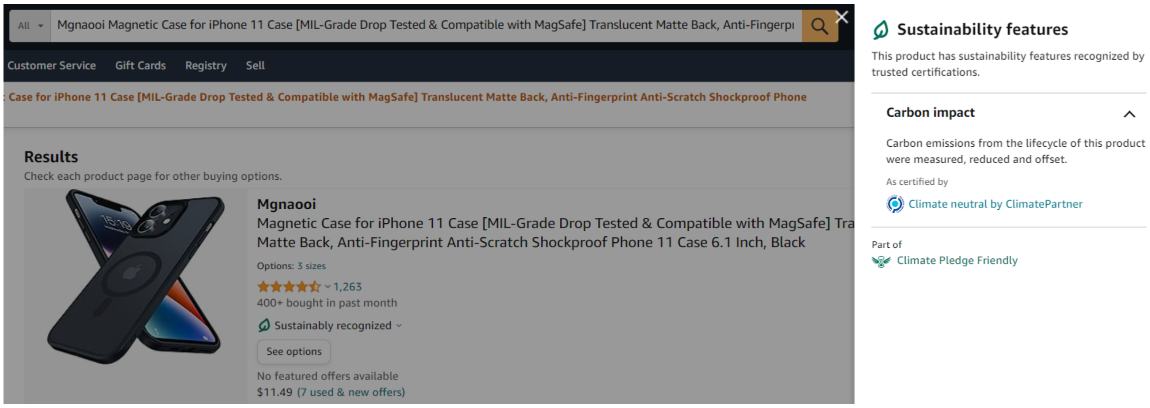


Figure B.1: A product certified carbon neutral by Climate Partner on Amazon.com

Amazon uses the term “Climate Pledge Friendly labels” to refer to various aspects of sustainability, not just those related to carbon neutrality.[6] These other sustainability labels cover various aspects, including energy efficiency, recycling, organic certification, fair trade, animal welfare, and CO_2 reduction.[7] We focus on carbon-neutral labels.

[6]For the purpose of our study, we focused only on carbon-neutral labels to estimate the effect, while we categorized the “Reducing CO_2” label among other “Climate Pledge Friendly” labels.

[7]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: Compact by Design, Pre-owned Certified, BIFMA LEVEL, Blue Angel, Bluesign, Certified Animal Welfare Approved, 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, Rainforest Alliance, Organic Content Standard Blended, Recycled Claim Standard 100, Recycled Claim Standard Blended, Regenerative Organic Certified, Responsible Wool Standard, U.S. EPA Safer Choice, Soil Association, STANDARD 100 by OEKO-TEX, TCO Certified, USDA Organic, WaterSense, and Reducing CO_2.

B.2 Treatment and control products

This section presents Table B.1, summarizing the restrictions used to identify changes in treatment status and the corresponding control products, as explained in Section 2.2 of the main body of text.

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 series.
	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 changes in treatment status and the products that received a carbon-neutral label, along with their corresponding control products, for each category across the three marketplaces. We successfully scraped data for the United States from March 2023 until December 2024, from May 2024 for Germany and the United Kingdom.

Tables B.5, B.6, and B.7 provide detailed information on the changes of treatment status, including ASINs,[8] product categories (as provided by Amazon), the dates the products were first identified as carbon-neutral during our scraping, and the product prices at the start of the panel.

[8] 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	302
Cell Phones & Accessories	53	2882
Electronics	91	1710
Grocery & Gourmet Food	1	219
Health & Household	14	926
Musical Instruments	1	37
Office Products	1	357
Safety & Security	2	25
Tools & Home Improvement	9	42
Toys & Games	3	49
Video Games	21	711
Total	208	7260

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	680
Arts & Crafts	1	279
Cooking & Dining	1	291
Gardening	2	76
Head/Earphones & Accessories	4	846
Hi-Fi & Home Audio	1	488
Microphones	2	95
Mobile Phones & Communication	29	2701
Sports	2	424
Wearable Technology	8	360
Unknown	0	9
Other	0	9
Total	52	6258

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. 'Other' and 'Unknown' categories refer to control products that were matched with experiments at a lower-level category but differ in their higher-level category or lack a higher-level category name, respectively.

Category	Treatment	Control
Computer & Accessories	47	3749
Electronics & Photo	36	2071
Games	5	491
Health & Personal Care	2	425
Stationery & Office Supplies	1	90
Toys	1	99
Unknown	0	10
Total	92	6935

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

This table presents the number of treated products (products receiving carbon-netural labels) and control products (without a label) by first-level category for the German market. 'Unknown' category refers to control products that were matched with experiments at a lower-level category but lack a higher-level category name respectively.

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

Table B.5: Timing of the changes in treatment status (United States)

Product ASIN	Category	First Treated	Price in Mar 2023 (USD)	Price in Nov 2024 (USD)
B07RQRMGKB	Electronics	24 Jul 2023	11.32	9.74
B085ZXC2HS	Cell Phones & Accessories	24 Jul 2023	15.99	14.99
B08GJ3F11N	Beauty & Personal Care	24 Jul 2023	11.99	9.99
B08L3WX26S	Electronics	24 Jul 2023	24.99	19.94
B09FDJFJ6Z	Electronics	24 Jul 2023	7.99	6.40
B09YFH1C8X	Beauty & Personal Care	24 Jul 2023	15.09	16.99
B086JBZW48	Health & Household	31 Jul 2023	12.97	14.99
B089LDX88M	Cell Phones & Accessories	31 Jul 2023	15.03	11.99
B08P27Y27M	Health & Household	31 Jul 2023	12.99	10.79
B08PHY1PJF	Health & Household	31 Jul 2023	12.99	8.66
B09L9RKN7W	Health & Household	31 Jul 2023	10.99	9.99
B0BGHM8SY4	Electronics	14 Aug 2023	11.90	8.88
B0BLK79BZ2	Electronics	14 Aug 2023	28.95	23.99
B086QW23YD	Electronics	28 Aug 2023	12.99	11.98
B08BR4V18G	Electronics	28 Aug 2023	14.99	14.99
B09HKX6HRB	Electronics	28 Aug 2023	10.99	8.52
B0BBSP2JNQ	Beauty & Personal Care	28 Aug 2023	19.92	21.75
B074KV9TT4	Electronics	04 Sep 2023	37.32	27.39
B088RHCSG3	Electronics	04 Sep 2023	14.99	12.96
B093T7GQWB	Electronics	04 Sep 2023	18.79	9.95
B09J1DFTTV	Electronics	04 Sep 2023	19.91	17.99
B09J1FYF9V	Electronics	04 Sep 2023	20.95	21.95
B0BGHRM5DV	Electronics	04 Sep 2023	18.99	15.99
B0BLTDYG2B	Cell Phones & Accessories	11 Sep 2023	14.99	14.71
B07Y9G18V7	Electronics	18 Sep 2023	36.32	29.99
B0831BF1FH	Cell Phones & Accessories	18 Sep 2023	28.49	23.99
B08883JK8Y	Electronics	18 Sep 2023	33.99	29.86
B08GG42WXY	Tools & Home Improvement	18 Sep 2023	11.19	8.79
B08K8S4ZDW	Electronics	18 Sep 2023	45.99	41.49
B08RDF9B3F	Cell Phones & Accessories	18 Sep 2023	12.38	16.99
B08XQQ5XTZ	Cell Phones & Accessories	18 Sep 2023	27.66	16.99
B095GJDXNG	Electronics	18 Sep 2023	31.99	27.32

Table B.5: Timing of the changes in treatment status (United States)

Product ASIN	Category	First Treated	Price in Mar 2023 (USD)	Price in Nov 2024 (USD)
B09PR1BTM7	Tools & Home Improvement	18 Sep 2023	15.99	13.66
B09PV827TS	Electronics	18 Sep 2023	31.99	27.99
B0BC21JFYH	Cell Phones & Accessories	18 Sep 2023	10.99	8.62
B0BGN9R72N	Tools & Home Improvement	18 Sep 2023	10.99	8.09
B0BHH7M4YJ	Cell Phones & Accessories	18 Sep 2023	9.99	8.62
B0BHHVN541	Cell Phones & Accessories	18 Sep 2023	9.99	8.62
B0BK99PT9K	Electronics	18 Sep 2023	32.99	28.49
B0BM4QL882	Cell Phones & Accessories	18 Sep 2023	9.99	8.99
B0BM4LPT4Y	Cell Phones & Accessories	25 Sep 2023	9.99	8.99
B08K8DNVB4	Cell Phones & Accessories	02 Oct 2023	43.88	36.25
B0B66RHD7B	Video Games	16 Oct 2023	28.49	27.99
B0B96PKNVL	Video Games	16 Oct 2023	20.32	18.66
B01M11FLUJ	Office Products	30 Oct 2023	14.17	9.97
B016XTADG2	Electronics	06 Nov 2023	25.99	25.99
B01MTB55WH	Electronics	06 Nov 2023	36.66	33.99
B07Z4RF1D3	Electronics	06 Nov 2023	16.73	16.15
B08ZXYNR34	Video Games	06 Nov 2023	179.50	117.23
B087LRK3H4	Electronics	13 Nov 2023	17.99	12.99
B093C2B4K3	Electronics	13 Nov 2023	19.32	16.99
B096BCMK8N	Electronics	13 Nov 2023	27.32	16.39
B0B1MCHS14	Electronics	13 Nov 2023	26.99	15.49
B01BT02Q88	Beauty & Personal Care	20 Nov 2023	14.99	14.99
B07J4TNYV8	Electronics	20 Nov 2023	139.99	128.32
B07JR1XZ78	Electronics	20 Nov 2023	84.99	71.66
B082Y6YDZZ	Electronics	20 Nov 2023	64.98	58.45
B0B2BSQQL7	Electronics	20 Nov 2023	89.89	79.99
B0BLBQ9G2C	Cell Phones & Accessories	20 Nov 2023	26.99	26.99
B0BP7HG18T	Electronics	20 Nov 2023	64.99	61.72
B0BQB8JNFB	Cell Phones & Accessories	20 Nov 2023	23.99	24.69
B0BRC415HH	Cell Phones & Accessories	20 Nov 2023	21.99	20.99
B0BTRTFK4S	Cell Phones & Accessories	20 Nov 2023	26.99	26.99
B07QXV6N1B	Cell Phones & Accessories	27 Nov 2023	21.99	22.32

Table B.5: Timing of the changes in treatment status (United States)

Product ASIN	Category	First Treated	Price in Mar 2023 (USD)	Price in Nov 2024 (USD)
B0874M3KW4	Electronics	27 Nov 2023	69.99	46.99
B0BJZ5VMD6	Cell Phones & Accessories	27 Nov 2023	26.99	26.99
B07ZCRWPPV	Electronics	04 Dec 2023	66.99	62.52
B08SJDXF73	Electronics	11 Dec 2023	10.99	9.97
B0BRKVSXG4	Electronics	18 Dec 2023	109.99	106.36
B07CSBYNWG	Beauty & Personal Care	25 Dec 2023	19.99	16.95
B0B7DP9CGN	Health & Household	25 Dec 2023	24.69	24.30
B09P37WCS4	Electronics	22 Jan 2024	15.99	15.79
B09P5BBPVY	Video Games	29 Jan 2024	29.99	27.22
B09X9JCLR7	Video Games	29 Jan 2024	29.99	26.46
B09WDH6K1T	Toys & Games	05 Feb 2024	40.32	46.66
B09YR1J35N	Electronics	05 Feb 2024	27.99	26.99
B0BHZ6MWC1	Cell Phones & Accessories	05 Feb 2024	68.40	59.20
B0BHZ84Z9C	Cell Phones & Accessories	05 Feb 2024	68.40	59.20
B0BJ2D5X2R	Cell Phones & Accessories	05 Feb 2024	74.10	59.20
B0BN1P1KKL	Cell Phones & Accessories	05 Feb 2024	68.40	53.65
B0BQ2L5KJJ	Cell Phones & Accessories	05 Feb 2024	94.73	56.86
B0BQ35Q43S	Cell Phones & Accessories	05 Feb 2024	74.10	49.60
B0BRY2FPKM	Cell Phones & Accessories	05 Feb 2024	74.10	59.20
B088NGVY4C	Electronics	12 Feb 2024	12.78	11.19
B08FTDWPTX	Electronics	12 Feb 2024	11.99	11.69
B0BRXY8RH7	Cell Phones & Accessories	12 Feb 2024	64.60	54.57
B01NAI2TXC	Video Games	19 Feb 2024	55.79	55.36
B07HC4NBQ8	Video Games	19 Feb 2024	30.89	29.52
B089PYQQSQ	Electronics	19 Feb 2024	17.97	17.07
B08SJ5Z8JL	Video Games	19 Feb 2024	19.99	18.32
B09ZQQPNXD	Beauty & Personal Care	19 Feb 2024	11.99	11.54
B0BHSVQXHG	Cell Phones & Accessories	19 Feb 2024	59.93	62.00
B0BQ2QJCQQ	Cell Phones & Accessories	26 Feb 2024	77.90	50.45
B07VCS8QTK	Electronics	04 Mar 2024	17.99	12.83
B09BN32Y86	Electronics	04 Mar 2024	11.32	7.89
B0B9SK4WD3	Cell Phones & Accessories	04 Mar 2024	10.98	16.98

Table B.5: Timing of the changes in treatment status (United States)

Product ASIN	Category	First Treated	Price in Mar 2023 (USD)	Price in Nov 2024 (USD)
B084FSYC1B	Toys & Games	11 Mar 2024	19.99	29.99
B08YNKKB7M	Electronics	11 Mar 2024	18.79	9.95
B09J4RQFK7	Electronics	11 Mar 2024	25.99	24.17
B09JBBPC9K	Electronics	11 Mar 2024	17.95	15.79
B09JLLD5QH	Electronics	11 Mar 2024	15.95	9.61
B09KXSJZ6K	Electronics	11 Mar 2024	21.99	20.66
B09KZFH1JP	Electronics	11 Mar 2024	22.99	21.99
B09R6JP7K5	Electronics	11 Mar 2024	18.99	15.99
B0B3R73C5F	Electronics	11 Mar 2024	19.99	15.99
B0BGH6L5B6	Electronics	11 Mar 2024	18.99	14.99
B0BJV4888V	Electronics	11 Mar 2024	14.99	10.49
B082ZYNMC8	Health & Household	18 Mar 2024	9.49	9.66
B08FFFGHJF	Toys & Games	18 Mar 2024	22.24	27.99
B07H8TJMX7	Electronics	03 Jun 2024	10.40	9.98
B07L2LS9SK	Electronics	03 Jun 2024	33.96	32.26
B07P7MB88J	Electronics	03 Jun 2024	35.14	34.19
B07PMBCTSY	Electronics	03 Jun 2024	66.66	55.32
B07SQP1GHC	Electronics	03 Jun 2024	35.99	35.99
B07TS6R1SF	Electronics	03 Jun 2024	30.79	32.66
B08R5CCRFD	Electronics	03 Jun 2024	43.98	37.99
B08VVWRFLS	Electronics	03 Jun 2024	46.99	47.48
B0921JJMZT	Electronics	03 Jun 2024	15.99	13.06
B093L2Y8KQ	Electronics	03 Jun 2024	9.95	7.74
B095VLRB2J	Electronics	03 Jun 2024	32.99	27.99
B09BN47YHV	Electronics	03 Jun 2024	22.99	35.64
B09BYJLZ16	Electronics	03 Jun 2024	32.66	24.99
B09HQFYY88	Tools & Home Improvement	03 Jun 2024	11.32	10.83
B09MHFSSFB	Tools & Home Improvement	03 Jun 2024	11.67	10.99
B09SW6L7H8	Cell Phones & Accessories	03 Jun 2024	15.99	12.24
B09TDHLXMZ	Electronics	03 Jun 2024	28.49	27.99
B09VPBF8NY	Video Games	03 Jun 2024	19.99	19.99
B09YRVDWCP	Tools & Home Improvement	03 Jun 2024	15.99	13.49

Table B.5: Timing of the changes in treatment status (United States)

Product ASIN	Category	First Treated	Price in Mar 2023 (USD)	Price in Nov 2024 (USD)
B09YRVVFVK	Tools & Home Improvement	03 Jun 2024	15.99	12.99
B09ZPCC1J3	Tools & Home Improvement	03 Jun 2024	15.99	12.24
B09ZPDMMRW	Tools & Home Improvement	03 Jun 2024	15.99	12.24
B09ZTXVNVD	Cell Phones & Accessories	03 Jun 2024	28.99	16.19
B0B2K2SMH7	Cell Phones & Accessories	03 Jun 2024	13.99	14.91
B0B63LNZBW	Electronics	03 Jun 2024	29.99	13.99
B0B73JCBRZ	Electronics	03 Jun 2024	19.99	20.99
B0B8X44B4Y	Cell Phones & Accessories	03 Jun 2024	15.99	13.29
B0B9SP1CZ2	Cell Phones & Accessories	03 Jun 2024	11.98	16.98
B0BBG5RRXF	Electronics	03 Jun 2024	28.49	27.35
B0BJ7GST13	Cell Phones & Accessories	03 Jun 2024	13.98	16.98
B0BK1T5PF4	Cell Phones & Accessories	03 Jun 2024	16.98	17.98
B0BMLFV2DJ	Electronics	03 Jun 2024	25.99	24.26
B0BPYJWMP7	Cell Phones & Accessories	03 Jun 2024	16.98	17.98
B01H6GUCCQ	Video Games	17 Jun 2024	25.99	21.91
B081JP3MJK	Video Games	17 Jun 2024	33.99	28.86
B09Q7LTBTR	Beauty & Personal Care	17 Jun 2024	34.18	27.55
B0B16VD9RQ	Beauty & Personal Care	17 Jun 2024	19.99	19.98
B0BG21S94B	Electronics	24 Jun 2024	52.49	48.66
B0BNPBTJDP	Video Games	24 Jun 2024	42.99	37.85
B07KCRTN9Q	Video Games	08 Jul 2024	44.99	37.96
B098S48QWM	Electronics	22 Jul 2024	10.58	9.98
B01MTVC775	Electronics	29 Jul 2024	56.99	49.10
B0BPCHQBS7	Electronics	29 Jul 2024	119.99	99.99
B076Q6442Z	Beauty & Personal Care	05 Aug 2024	7.98	6.99
B07GBXVX7W	Cell Phones & Accessories	12 Aug 2024	15.99	16.99
B07L793HPW	Cell Phones & Accessories	12 Aug 2024	17.99	13.29
B07THZ6MVP	Cell Phones & Accessories	12 Aug 2024	16.99	11.42
B0811RH5MF	Cell Phones & Accessories	12 Aug 2024	16.99	13.19
B0811RYZ2J	Cell Phones & Accessories	12 Aug 2024	17.99	15.99
B08F79BQD3	Cell Phones & Accessories	12 Aug 2024	16.99	15.74
B08M636GG3	Cell Phones & Accessories	12 Aug 2024	16.42	16.99

Table B.5: Timing of the changes in treatment status (United States)

Product ASIN	Category	First Treated	Price in Mar 2023 (USD)	Price in Nov 2024 (USD)
B09D941CFQ	Cell Phones & Accessories	12 Aug 2024	16.99	16.64
B09D952JQQ	Cell Phones & Accessories	12 Aug 2024	17.99	18.24
B0BBKW53L3	Cell Phones & Accessories	12 Aug 2024	22.99	8.99
B0BCJ8Q1QN	Cell Phones & Accessories	12 Aug 2024	18.99	17.99
B01K2UMMI0	Beauty & Personal Care	19 Aug 2024	24.99	22.39
B081S71B77	Health & Household	19 Aug 2024	19.97	23.95
B08L3K9LC6	Health & Household	19 Aug 2024	19.99	32.80
B07R1R1MKW	Health & Household	26 Aug 2024	17.97	23.39
B07XVCP7F5	Video Games	26 Aug 2024	66.99	55.59
B08JCV3J5P	Video Games	26 Aug 2024	79.99	75.97
B0932BCM2T	Musical Instruments	26 Aug 2024	31.30	30.75
B08FDPW8KR	Electronics	09 Sep 2024	35.32	35.99
B0B979GR4Z	Electronics	16 Sep 2024	31.32	27.49
B00N1YTJRC	Health & Household	23 Sep 2024	38.37	41.74
B0B6BVHS4W	Safety & Security	07 Oct 2024	9.99	8.99
B0B6BW56FF	Safety & Security	07 Oct 2024	8.99	8.35

Table B.5: Timing of the changes in treatment status (United States)

Product ASIN	Category	First Treated	Price in May 2024 (GBP)	Price in Nov 2024 (GBP)
B0773F8S74	Mobile Phones & Communication	18 Jun 2024	15.99	15.99
B0BGNCY746	Cooking & Dining	18 Jun 2024	60.92	50.05
B09BW1QVVT	Head/Earphones & Accessories	16 Jul 2024	79.95	119.71
B09BW1T7X2	Head/Earphones & Accessories	16 Jul 2024	79.95	119.71
B0C3C8M5X6	Accessories	16 Jul 2024	9.99	9.99
B0CD226VG1	Arts & Crafts	30 Jul 2024	6.29	6.73
B07D6N526S	Hi-Fi & Home Audio	06 Aug 2024	10.99	19.99
B07GBXVX7W	Mobile Phones & Communication	06 Aug 2024	12.99	13.24
B07TFD7KR3	Mobile Phones & Communication	06 Aug 2024	13.99	12.99
B07Z1CVWD2	Mobile Phones & Communication	06 Aug 2024	19.99	19.99
B081H1N3PJ	Mobile Phones & Communication	06 Aug 2024	13.99	13.29
B08DHT9KJZ	Wearable Technology	06 Aug 2024	7.99	6.80
B08F7Q8Y5W	Mobile Phones & Communication	06 Aug 2024	13.99	13.08
B08R78YY9M	Mobile Phones & Communication	06 Aug 2024	13.99	13.99
B099968ZQK	Mobile Phones & Communication	06 Aug 2024	13.99	13.21
B09996WC24	Mobile Phones & Communication	06 Aug 2024	13.99	13.46
B09D94T83V	Mobile Phones & Communication	06 Aug 2024	14.99	14.43
B09D952JQQ	Mobile Phones & Communication	06 Aug 2024	11.89	14.96
B0BCHZFSFD	Mobile Phones & Communication	06 Aug 2024	13.99	10.92
B0BCJ4KZWG	Mobile Phones & Communication	06 Aug 2024	12.99	12.99
B0BN54PK3X	Mobile Phones & Communication	06 Aug 2024	13.99	11.24
B0BN5HTP3K	Mobile Phones & Communication	06 Aug 2024	15.99	15.19
B0BZCMKWGV	Mobile Phones & Communication	06 Aug 2024	12.99	12.50
B0BZH6ZF7M	Sports	06 Aug 2024	15.99	16.99
B0C8N8D6GF	Sports	06 Aug 2024	17.99	16.14
B0CB5XH9J5	Mobile Phones & Communication	06 Aug 2024	23.99	24.53
B0CHRFQPCC	Mobile Phones & Communication	06 Aug 2024	13.59	15.99

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

Product ASIN	Category	First Treated	Price in MaY 2024 (GBP)	Price in Nov 2024 (GBP)
B0CNVGVM3R	Head/Earphones & Accessories	06 Aug 2024	32.99	43.86
B0CNVHKVVL	Head/Earphones & Accessories	06 Aug 2024	29.99	47.49
B08ZXQLJN9	Accessories	13 Aug 2024	19.99	21.49
B09L4GBWDV	Wearable Technology	13 Aug 2024	7.99	6.80
B0BHYKBQLP	Gardening	13 Aug 2024	28.22	28.94
B0C8N7MKF6	Mobile Phones & Communication	13 Aug 2024	12.99	12.99
B0CCN9Q27D	Gardening	13 Aug 2024	65.13	32.28
B0CHLXSBND	Mobile Phones & Communication	13 Aug 2024	29.40	21.16
B09B3LJVFJ	Microphones	27 Aug 2024	36.99	35.60
B0BK84XP9K	Microphones	27 Aug 2024	49.99	46.24
B0CHNSY4S8	Mobile Phones & Communication	17 Sep 2024	43.99	37.49
B0CHYKQQ6S	Mobile Phones & Communication	17 Sep 2024	43.99	41.79
B0CHYL54H8	Mobile Phones & Communication	17 Sep 2024	33.43	41.79
B08GCNLQT6	Wearable Technology	24 Sep 2024	6.49	7.58
B09H2JD8F8	Wearable Technology	24 Sep 2024	6.49	7.58
B09KN7CNRZ	Wearable Technology	24 Sep 2024	6.49	7.58
B0BDFDRCKV	Wearable Technology	24 Sep 2024	6.58	7.29
B0BPNT6XYY	Wearable Technology	24 Sep 2024	6.49	7.62
B0BPNYZ8NN	Wearable Technology	24 Sep 2024	6.49	7.62
B0CHRQF8VX	Mobile Phones & Communication	08 Oct 2024	46.99	19.69
B082SNXJ4G	Mobile Phones & Communication	15 Oct 2024	21.99	20.89
B0915H9JD8	Mobile Phones & Communication	15 Oct 2024	19.99	19.17
B0C273FR2T	Mobile Phones & Communication	15 Oct 2024	17.99	17.84
B0CB1C69BY	Mobile Phones & Communication	15 Oct 2024	16.98	17.73
B0CHYBKQPM	Mobile Phones & Communication	15 Oct 2024	16.99	16.34

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

Product ASIN	Category	First Treated	Price in May 2024 (EUR)	Price in Nov 2024 (EUR)
B096FX9226	Electronics & Photo	19 Jun 2024	21.99	20.52
B09KLYT52T	Electronics & Photo	19 Jun 2024	9.99	9.99
B0BG21S94B	Computer & Accessories	19 Jun 2024	72.33	31.50
B0CDFMW94G	Computer & Accessories	19 Jun 2024	43.95	30.75
B09VB3WXQS	Computer & Accessories	26 Jun 2024	13.99	12.73
B09X1FZQPX	Computer & Accessories	26 Jun 2024	23.99	24.99
B09X1H9VNZ	Computer & Accessories	26 Jun 2024	15.99	15.99
B0B31FVQPQ	Computer & Accessories	26 Jun 2024	16.99	15.52
B0BVLX7BXW	Computer & Accessories	26 Jun 2024	16.09	14.72
B0BVLY3JNJ	Computer & Accessories	26 Jun 2024	17.99	15.99
B0BW95FDB6	Computer & Accessories	26 Jun 2024	19.99	18.97
B0C3LB86PN	Computer & Accessories	26 Jun 2024	54.99	44.99
B0C68N2BH1	Computer & Accessories	26 Jun 2024	16.99	15.91
B0C6KF5HKT	Computer & Accessories	26 Jun 2024	16.59	14.79
B0C748DZRH	Electronics & Photo	26 Jun 2024	22.99	32.99
B0C7Q55ZM5	Computer & Accessories	26 Jun 2024	26.99	19.44
B0C9DJK1QX	Computer & Accessories	26 Jun 2024	14.09	13.50
B0C9ZVN154	Computer & Accessories	26 Jun 2024	49.99	45.96
B0CD7LYR4C	Computer & Accessories	26 Jun 2024	24.64	26.99
B0CMCGLT21	Computer & Accessories	26 Jun 2024	39.67	45.99
B0CTQ2346R	Computer & Accessories	26 Jun 2024	30.99	26.05
B0CTQ94TV3	Computer & Accessories	26 Jun 2024	39.99	35.09
B0CTQBG9YP	Computer & Accessories	26 Jun 2024	28.99	25.54
B0CC1CS6J4	Electronics & Photo	10 Jul 2024	31.99	40.99
B0CC1DW8G8	Electronics & Photo	10 Jul 2024	31.99	49.99
B0CC1G218B	Electronics & Photo	10 Jul 2024	31.99	29.49
B0CC1GP8SR	Electronics & Photo	10 Jul 2024	31.99	43.99
B0CC1MM35H	Electronics & Photo	10 Jul 2024	42.99	59.99
B0CGZVDMKG	Computer & Accessories	10 Jul 2024	55.99	46.63
B075V27G2R	Computer & Accessories	17 Jul 2024	11.19	12.59

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

Product ASIN	Category	First Treated	Price in May 2024 (EUR)	Price in Nov 2024 (EUR)
B07F2YJRN2	Computer & Accessories	17 Jul 2024	55.38	43.63
B0BM5XSKDR	Computer & Accessories	17 Jul 2024	9.99	25.77
B08M5PSFWF	Computer & Accessories	24 Jul 2024	7.89	9.46
B0C3L93F2Q	Office Supplies & Stationery	24 Jul 2024	25.49	27.74
B0CSYMR7GZ	Electronics & Photo	24 Jul 2024	32.38	37.80
B07GBXVX7W	Electronics & Photo	07 Aug 2024	13.95	13.45
B07JNJGM1G	Electronics & Photo	07 Aug 2024	13.98	12.50
B09996WC24	Electronics & Photo	07 Aug 2024	13.56	15.95
B0BR5JG23N	Games	07 Aug 2024	19.99	19.99
B0CH346J32	Games	07 Aug 2024	23.98	19.99
B0CH7VQJKH	Games	07 Aug 2024	23.95	19.32
B0CN8GG24V	Games	07 Aug 2024	39.99	37.19
B0CN8LRLLH	Games	07 Aug 2024	39.99	39.99
B08ZXQLJN9	Computer & Accessories	14 Aug 2024	29.99	29.99
B0CL6LL5SF	Electronics & Photo	14 Aug 2024	12.74	14.99
B0CPDZT72H	Electronics & Photo	14 Aug 2024	12.74	13.87
B01MY4L8BV	Drugstore & Personal Care	21 Aug 2024	9.95	9.95
B0BLND9W1C	Electronics & Photo	04 Sep 2024	17.68	14.09
B073RY7XD7	Computer & Accessories	02 Oct 2024	14.99	19.49
B07D5QDZTY	Computer & Accessories	02 Oct 2024	15.99	21.74
B0873358VL	Computer & Accessories	02 Oct 2024	15.99	20.47
B09XR315M4	Computer & Accessories	02 Oct 2024	59.01	42.59
B0CGHF5G95	Computer & Accessories	02 Oct 2024	47.97	61.49
B0CGHRZD4Q	Computer & Accessories	02 Oct 2024	45.96	48.52
B0CGLXNPHL	Computer & Accessories	02 Oct 2024	47.99	58.13
B0CGM1DJZ8	Computer & Accessories	02 Oct 2024	36.97	43.24
B0CGR7H7BT	Computer & Accessories	02 Oct 2024	41.62	55.89
B0CN8G45K1	Electronics & Photo	02 Oct 2024	59.99	55.93
B0CPPDCGBT	Computer & Accessories	02 Oct 2024	47.95	62.78
B08V4Z8224	Electronics & Photo	16 Oct 2024	18.93	18.66
B08V8NPY3Y	Electronics & Photo	16 Oct 2024	16.99	16.99
B0B3MKD39C	Electronics & Photo	16 Oct 2024	23.99	24.19

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

Product ASIN	Category	First Treated	Price in May 2024 (EUR)	Price in Nov 2024 (EUR)
B0C273FR2T	Electronics & Photo	16 Oct 2024	19.99	17.99
B0C3C8CWYQ	Computer & Accessories	16 Oct 2024	10.99	12.99
B0C3C9GCGY	Computer & Accessories	16 Oct 2024	10.99	12.99
B0CB1C69BY	Electronics & Photo	16 Oct 2024	19.99	18.99
B0CB3DRLCT	Electronics & Photo	16 Oct 2024	15.99	15.93
B08NSJR3TN	Computer & Accessories	23 Oct 2024	55.91	60.57
B0BV6NT6CH	Computer & Accessories	23 Oct 2024	10.99	25.95
B09GG64C6G	Toys	30 Oct 2024	17.99	17.09
B0CL94BQ56	Electronics & Photo	30 Oct 2024	17.97	11.64
B0749MNW3N	Drugstore & Personal Care	06 Nov 2024	8.49	9.99
B09F3P3DQD	Electronics & Photo	06 Nov 2024	6.95	6.84
B09F3RCJJR	Electronics & Photo	06 Nov 2024	6.95	6.69
B09FYBKN69	Computer & Accessories	06 Nov 2024	9.89	9.31
B09FYCQDTK	Computer & Accessories	06 Nov 2024	9.89	9.11
B09QT5H713	Computer & Accessories	06 Nov 2024	9.89	9.23
B09QT6M1WS	Computer & Accessories	06 Nov 2024	9.89	8.99
B09VH599VG	Electronics & Photo	06 Nov 2024	6.89	6.69
B09X768KKV	Electronics & Photo	06 Nov 2024	6.89	6.95
B09X777HXL	Electronics & Photo	06 Nov 2024	6.89	6.68
B09ZYJB6RB	Electronics & Photo	06 Nov 2024	6.89	6.95
B0BD5D5JHQ	Electronics & Photo	06 Nov 2024	6.89	6.69
B0BD5J9M98	Electronics & Photo	06 Nov 2024	6.95	6.68
B0BMQPWBK6	Electronics & Photo	06 Nov 2024	6.89	6.43
B0BVRD97MT	Electronics & Photo	06 Nov 2024	6.95	6.43
B0BVVN31X8	Computer & Accessories	06 Nov 2024	10.95	8.99
B0C4LRY247	Electronics & Photo	06 Nov 2024	6.95	6.95
B0C4LTQZ62	Electronics & Photo	06 Nov 2024	6.89	6.95
B0C84Q8TFV	Computer & Accessories	06 Nov 2024	17.95	17.95
B0CG1R72SM	Computer & Accessories	06 Nov 2024	17.99	15.99
B0CJMJS3DS	Electronics & Photo	06 Nov 2024	6.89	6.67

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

B.4 Difference in differences analysis

This section presents the output of the difference in differences model (Callaway and Sant'Anna, 2021b) described in Section 3.2 of the main body of the paper. Tables B.8, B.10, and B.12 present the dynamic effects for the United States, United Kingdom, and Germany, respectively, while Tables B.9, B.11, and B.13 display the corresponding calendar effects.

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	-5.27	2.95	1	-0.90	-2.92	1.12
-17	-4.80	-24.09	14.49	2	0.43	-1.92	2.78
-16	-1.15	-3.84	1.54	3	-0.26	-2.62	2.11
-15	0.09	-1.52	1.70	4	-0.67	-3.58	2.23
-14	-0.53	-3.15	2.09	5	-1.77	-4.90	1.35
-13	0.45	-1.63	2.52	6	-2.86	-7.08	1.36
-12	-0.08	-1.87	1.71	7	-2.36	-6.81	2.09
-11	0.25	-1.27	1.78	8	-1.98	-6.45	2.48
-10	0.28	-1.01	1.56	9	-3.20	-7.64	1.24
-9	-0.98	-2.68	0.71	10	-3.54	-9.13	2.05
-8	1.64*	0.04	3.24	11	-3.42	-9.13	2.30
-7	-1.00	-3.16	1.17	12	-2.25	-8.36	3.86
-6	1.94	-0.13	4.02	13	-2.46	-8.31	3.39
-5	-0.37	-2.05	1.30	14	-4.58	-10.85	1.69
-4	-0.50	-1.86	0.85	15	-5.34	-13.54	2.86
-3	-0.33	-1.63	0.97	16	-4.28	-14.21	5.66
-2	-0.10	-1.63	1.43	17	-5.35	-19.10	8.41
-1	-1.12	-2.65	0.42	18	-6.67	-31.93	18.59
0	0.15	-1.27	1.56	19	10.94	-13.82	35.69

Table B.8: Dynamic effects (US)

This table presents the effect of carbon-neutral label 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	-3.16	9.49
May 2023	-0.55	-4.18	3.09
June 2023	0.89	-2.36	4.14
July 2023	-0.90	-3.79	1.99
August 2023	-1.75	-5.78	2.28
September 2023	-0.57	-3.87	2.73
October 2023	-0.72	-4.68	3.23
November 2023	-0.76	-5.18	3.66
December 2023	0.10	-4.04	4.24
January 2024	-2.05	-6.21	2.11
February 2024	-1.27	-5.04	2.50
March 2024	-2.47	-6.25	1.31
April 2024	-2.07	-6.13	2.00
May 2024	-2.62	-6.78	1.54
June 2024	-1.52	-4.44	1.40
July 2024	-1.05	-3.95	1.85
August 2024	-1.11	-3.99	1.77
September 2024	-2.35	-5.22	0.52
October 2024	-2.16	-5.45	1.14
November 2024	-4.53*	-7.86	-1.19

Table B.9: Calendar Effects (US)

This table presents the effect of carbon-neutral label 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.

Month	Estimate (%)	Lower 95% CI	Upper 95% CI
-4	-0.46	-7.19	6.28
-3	5.40	-2.32	13.11
-2	-2.73	-6.11	0.65
-1	1.13	-2.80	5.06
0	2.95	-3.80	9.69
1	0.29	-8.13	8.71
2	1.75	-7.63	11.13
3	5.78	-5.08	16.65
4	-4.56	-26.35	17.24
5	1.89	-13.91	17.69

Table B.10: Dynamic Effects (UK)

This table presents the effect of carbon-neutral label on product price changes, expressed in percentages, relative to the product's price in May 2024 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.

Time	Estimate (%)	Lower 95% CI	Upper 95% CI
June 2024	21.66	-17.02	60.34
July 2024	3.38	-13.38	20.13
August 2024	3.23	-5.27	11.73
September 2024	2.46	-6.49	11.40
October 2024	1.03	-6.53	8.59
November 2024	1.72	-5.54	8.98

Table B.11: Calendar Effects (UK)

This table presents the effect of carbon-neutral label on product price changes, expressed in percentages, relative to the product's price in May 2024 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.

Time	Estimate (%)	Lower 95% CI	Upper 95% CI
-5	-4.25	-8.95	0.45
-4	-0.94	-6.09	4.20
-3	-4.34	-9.74	1.07
-2	0.20	-3.43	3.82
-1	2.47	-1.02	5.96
0	-0.08	-4.94	4.79
1	-7.13	-30.99	16.74
2	-47.29	-199.30	104.72
3	-24.80	-82.64	33.04
4	-8.36	-27.85	11.12
5	-18.42*	-28.83	-8.01

Table B.12: Dynamic Effects (Germany)

This table presents the effect of carbon-neutral label on product price changes, expressed in percentages, relative to the product's price in May 2024 on Amazon's German 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
June 2024	-4.33*	-8.61	-0.06
July 2024	-12.60*	-20.34	-4.87
August 2024	-21.44	-67.68	24.81
September 2024	-58.60	-227.51	110.31
October 2024	-4.33	-14.98	6.32
November 2024	-0.71	-9.72	8.29

Table B.13: Calendar Effects (Germany)

This table presents the effect of carbon-neutral label on product price changes, expressed in percentages, relative to the product's price in May 2024 on Amazon's Germany 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.5 Robustness Tests

This section presents a list of robustness tests for the main dynamic effect estimation using data from Amazon's three marketplaces.

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. Next, Figure B.3, B.4, and B.5 show the estimation results using unbalanced data for the United States, United Kingdom, and Germany, respectively. Figure B.6 shows the results excluding products with Climate Pledge Friendly or Small Business labels introduced after March 2023 for the United States.

Additionally, Figures B.7, B.8, and B.9 present the results when the requirement of having at least 10 control products per treated product is relaxed. Finally, Figures B.10, B.11, and B.12 show the results using absolute price level as the outcome variable for the United States, United Kingdom, and Germany, respectively.

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

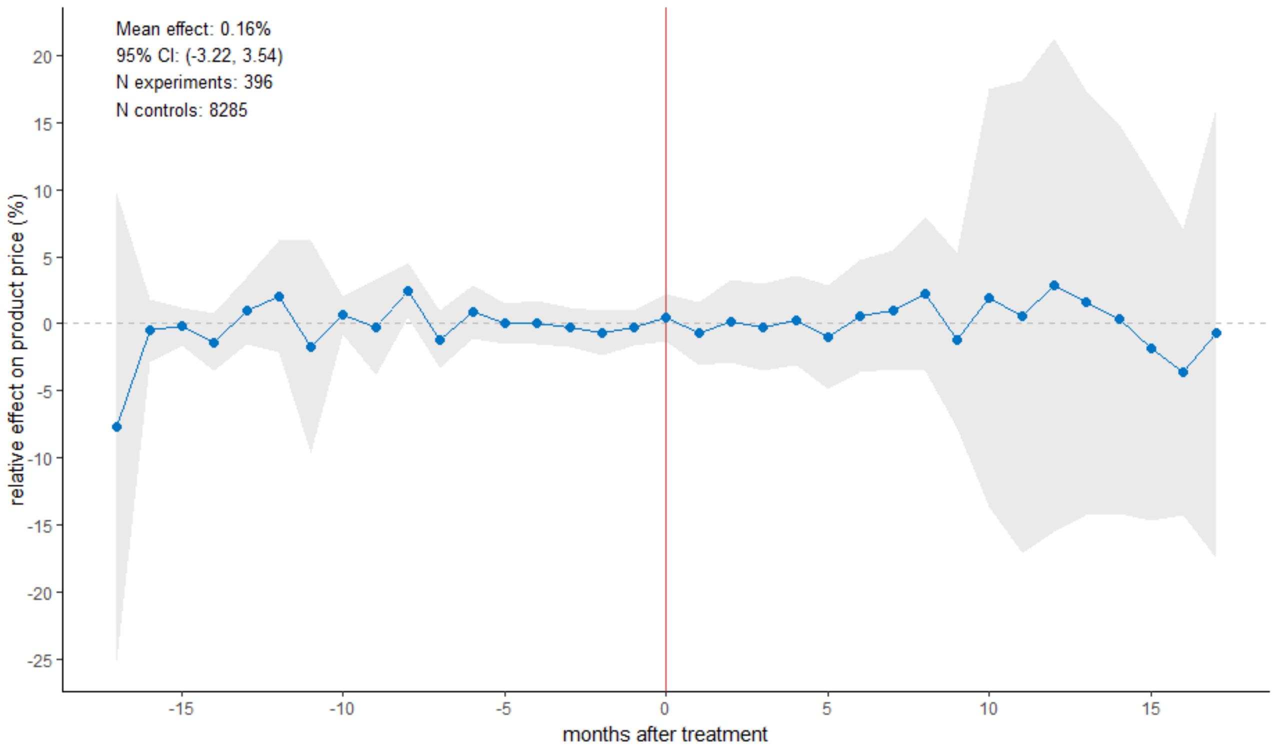


Figure B.2: Effect of carbon-neutral label when label consistency constraint is removed (United States)

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.

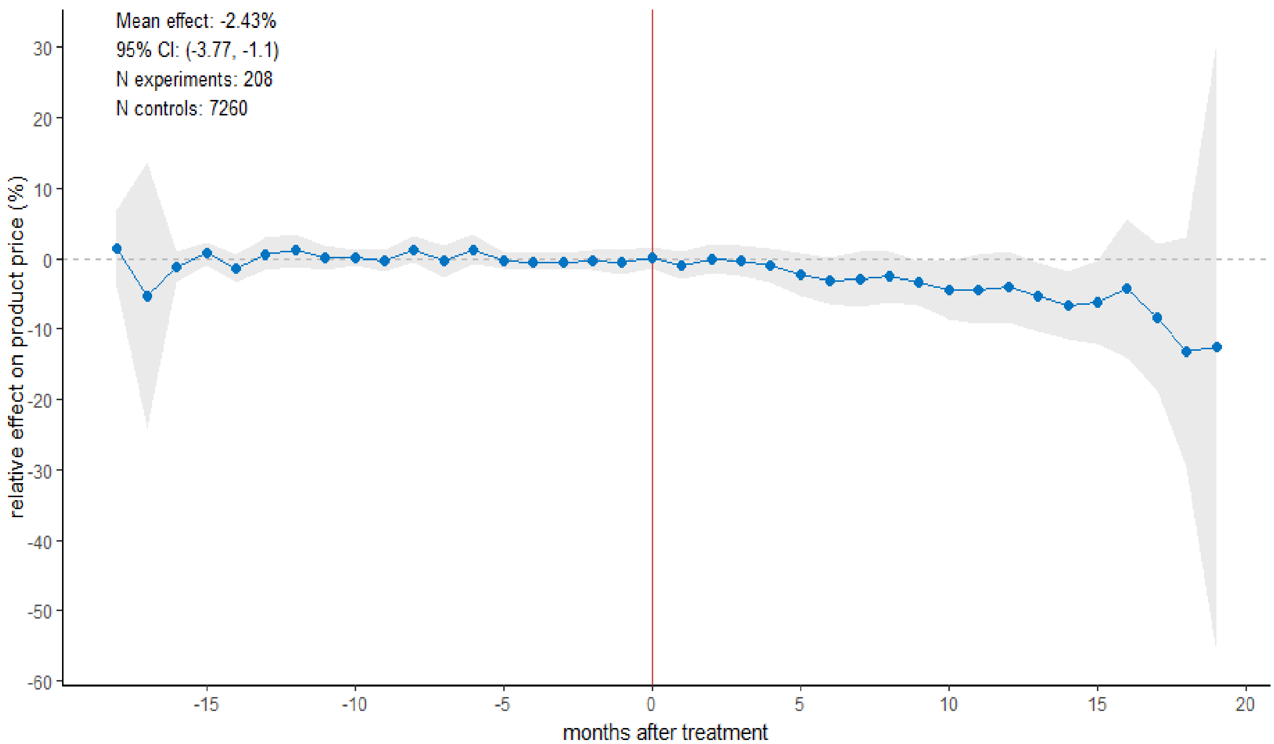


Figure B.3: Effect of carbon-neutral label using unbalanced data option for estimation (United States)

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.

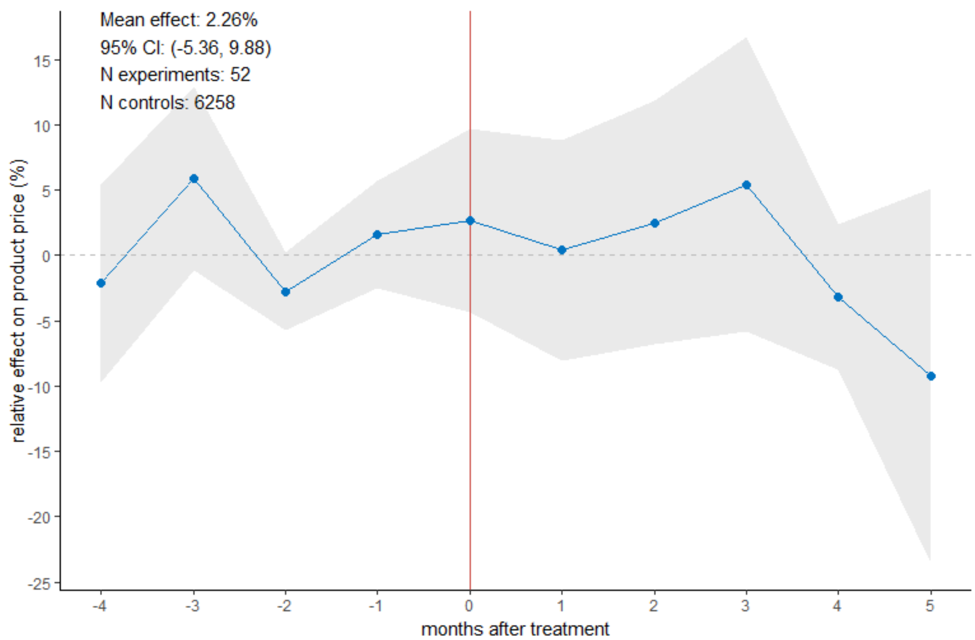


Figure B.4: Effect of carbon-neutral label using unbalanced data option for estimation (United Kingdom)

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.

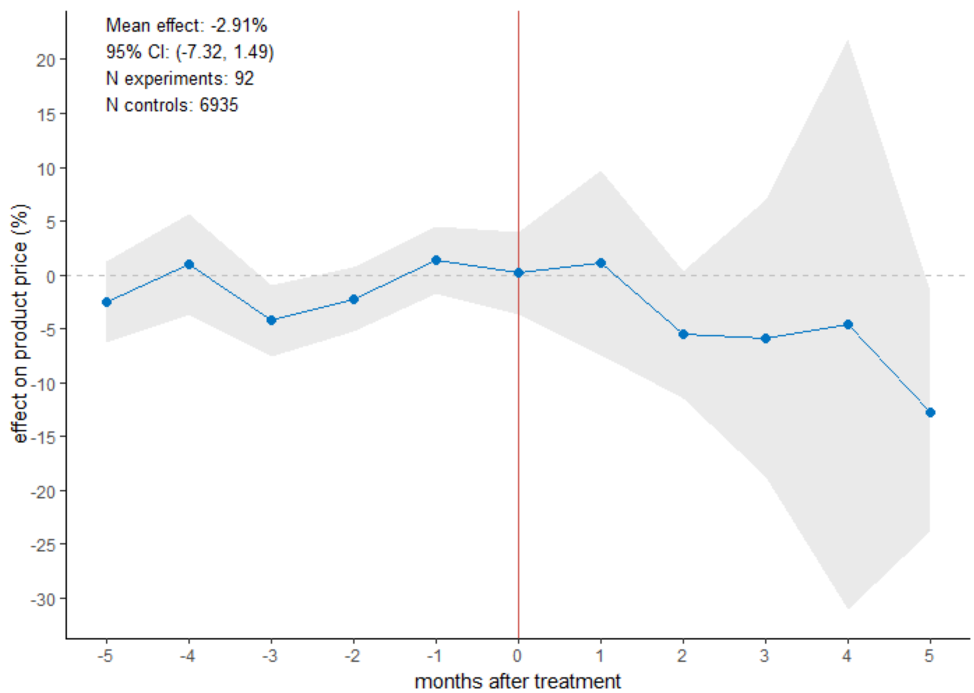


Figure B.5: Effect of carbon-neutral label using unbalanced data option for estimation (Germany)

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.

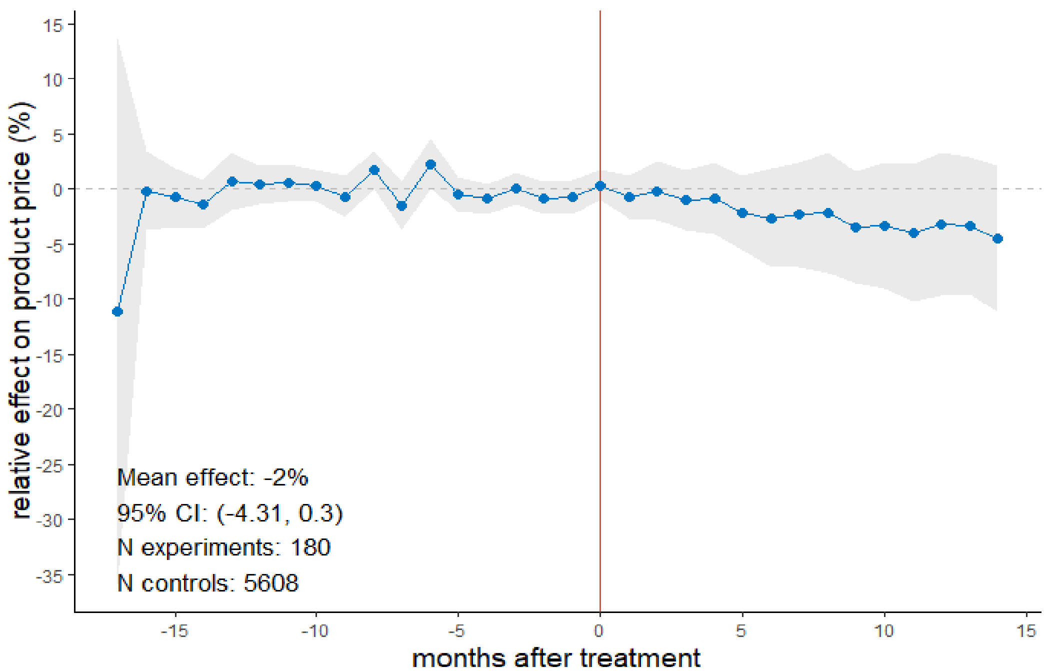


Figure B.6: Effect of carbon-neutral label excluding new Climate Pledge Friendly labels and Small Business labels (United States)

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.

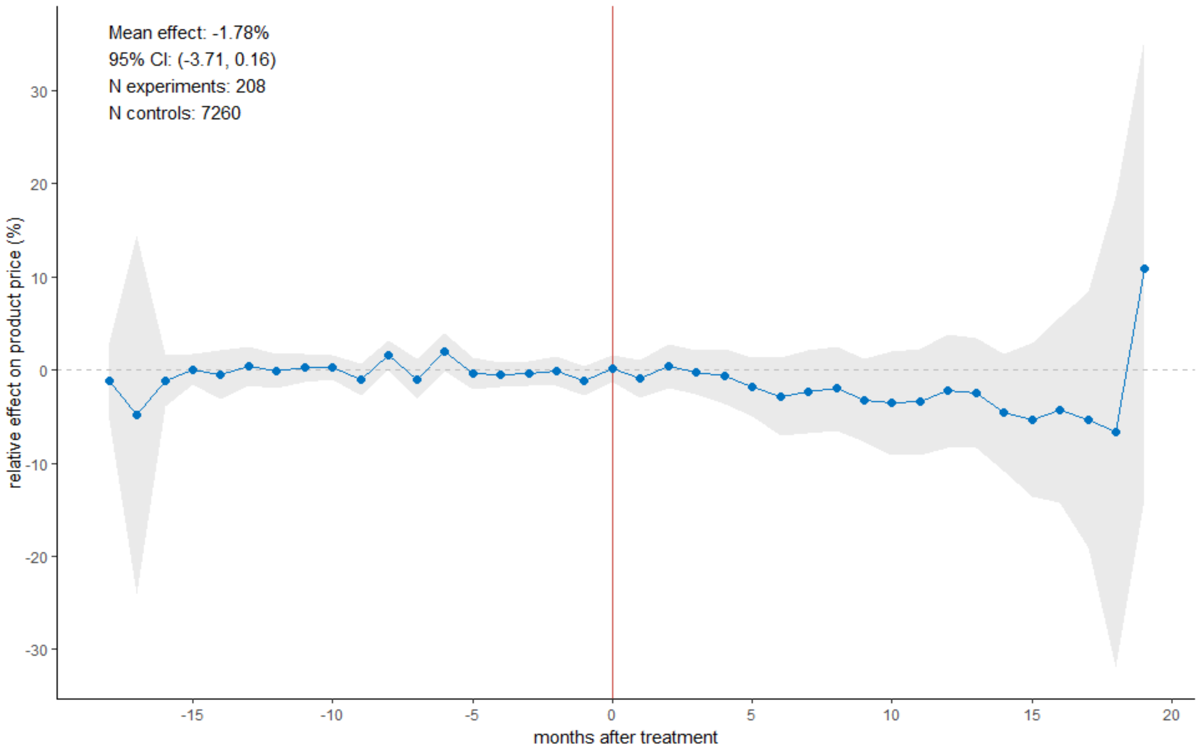


Figure B.7: Effect of carbon-neutral label without restriction on minimum number of control products per experiment (United States)

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.

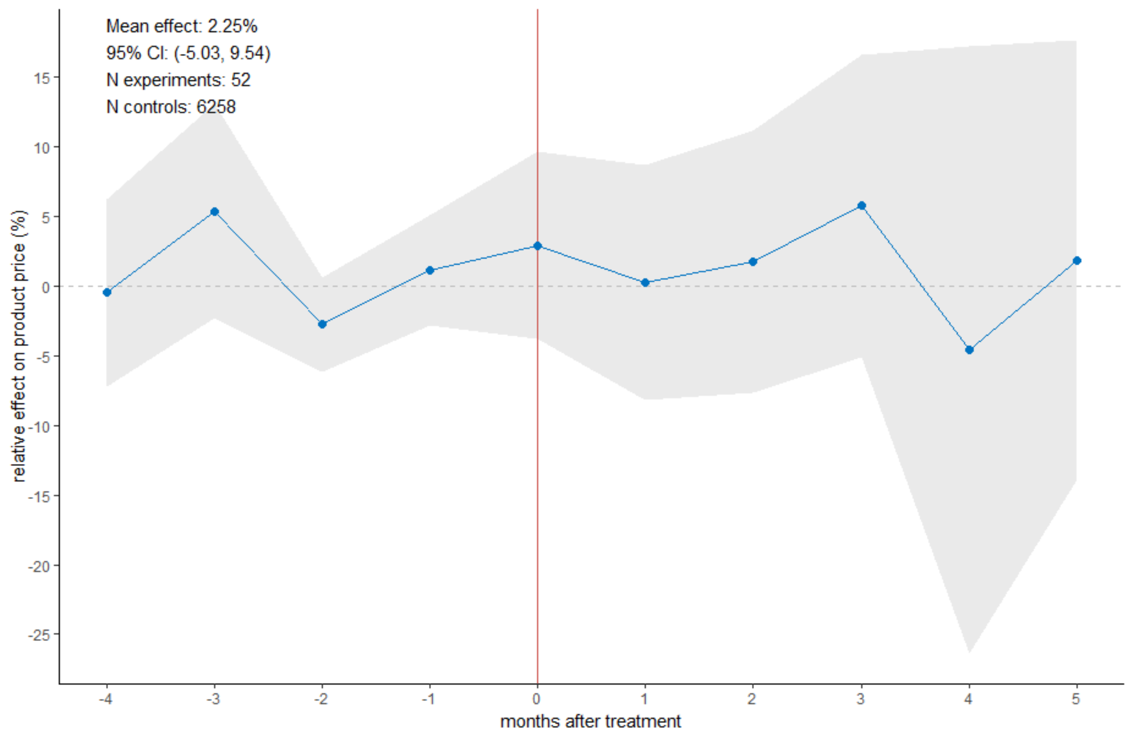


Figure B.8: Effect of carbon-neutral label without restriction on minimum number of control products per experiment (United Kingdom)

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.

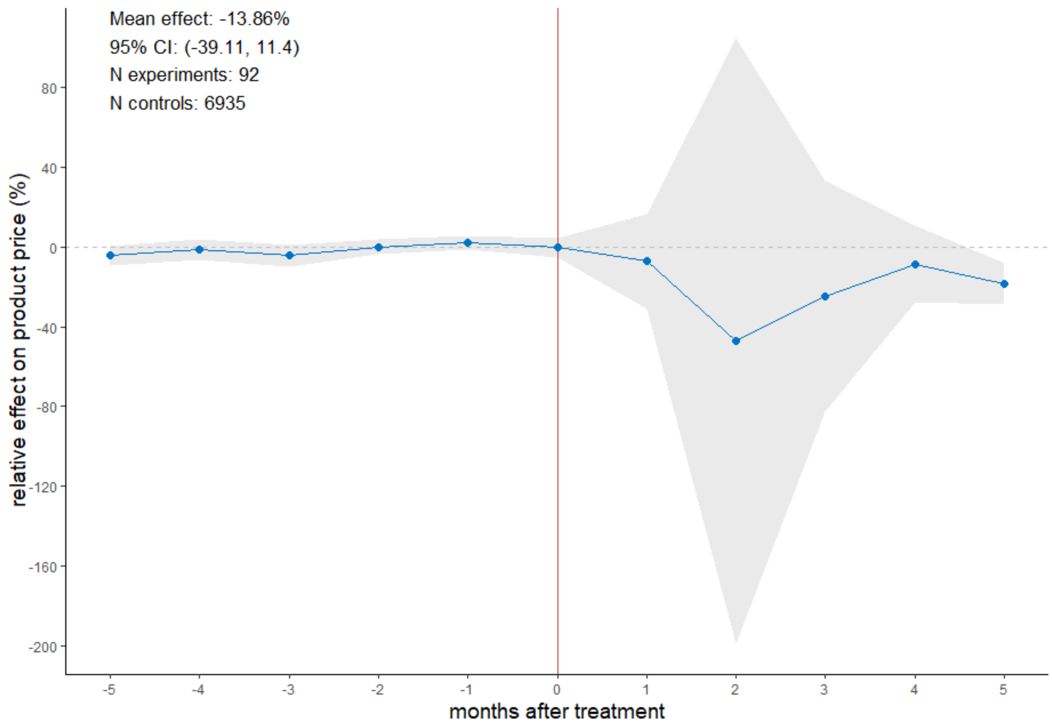


Figure B.9: Effect of carbon-neutral label without restriction on minimum number of control products per experiment (Germany)

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.

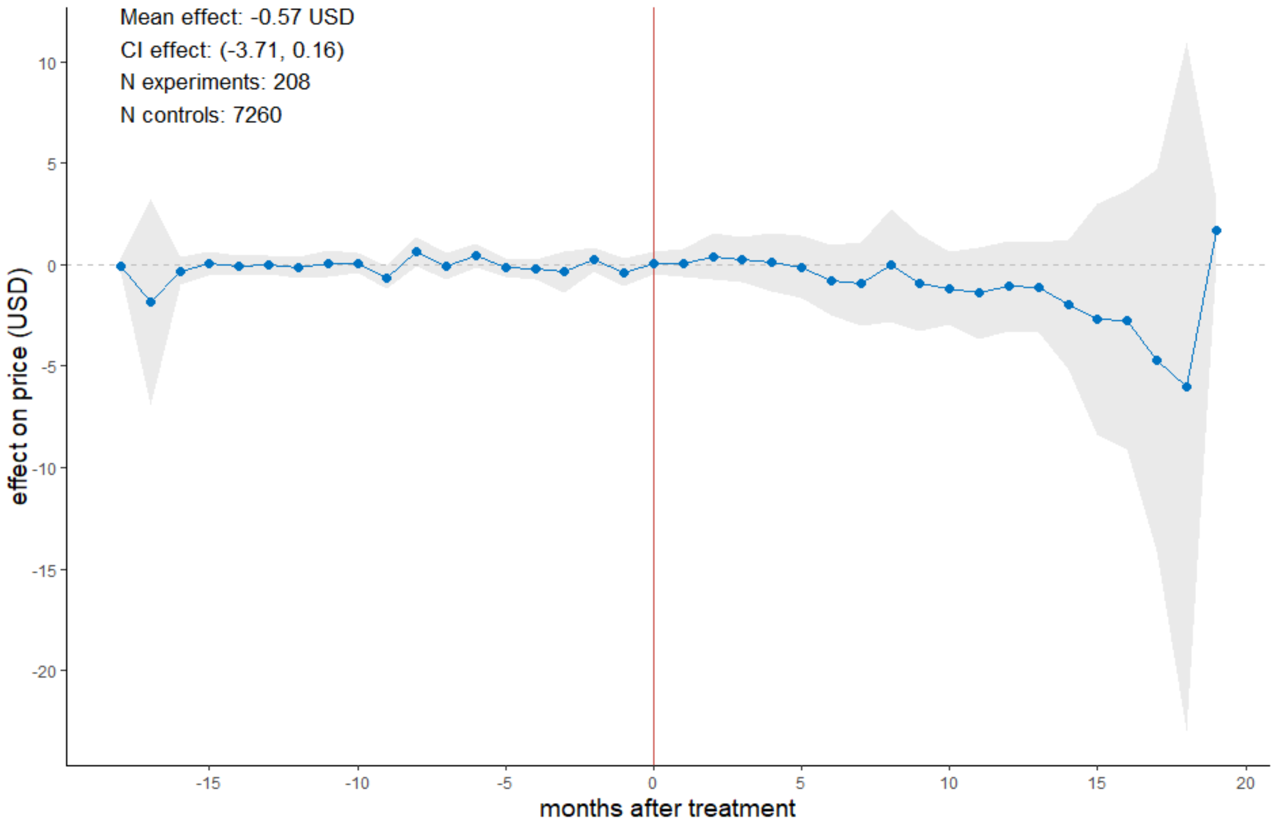


Figure B.10: Effect of carbon-neutral label using absolute price level as outcome variable (US)

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.

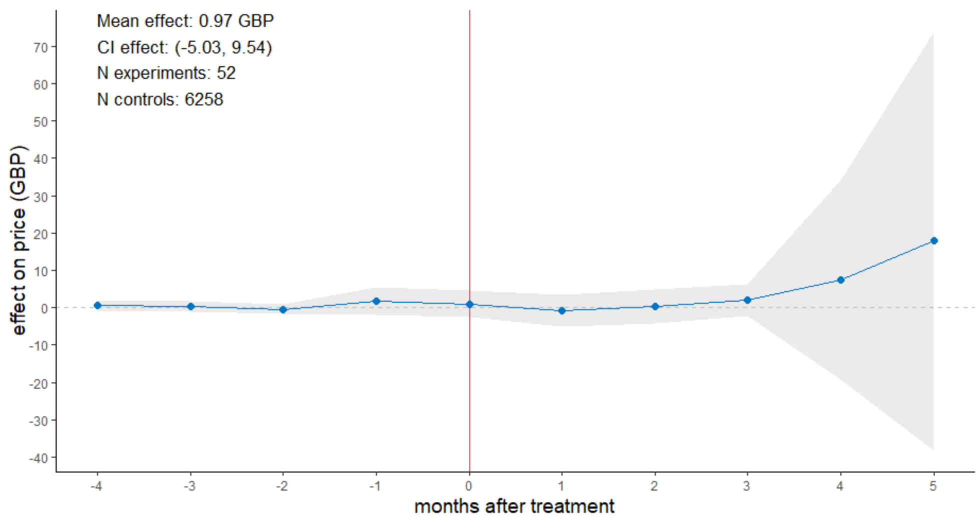


Figure B.11: Effect of carbon-neutral label using absolute price level as outcome variable (UK)

This plot shows the dynamic treatment effect in GBP. 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.

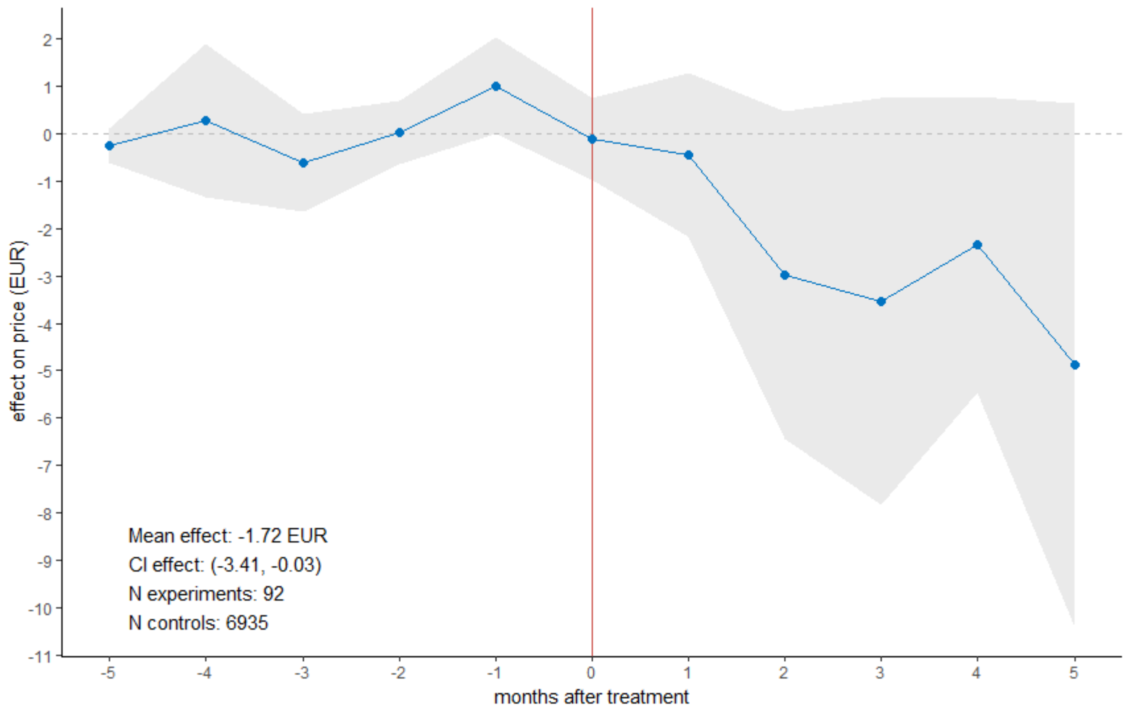


Figure B.12: Effect of carbon-neutral label using absolute price level as outcome variable (Germany)

This plot shows the dynamic treatment effect in EUR. 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.

B.6 Additional Estimations

This section presents the estimations using the number of product ratings as the outcome variable. Table B.13, B.14, and B.15 show the results for the United States, United Kingdom, and Germany. The control variables include product categories. Further discussion of results are provided in Section 3.2.

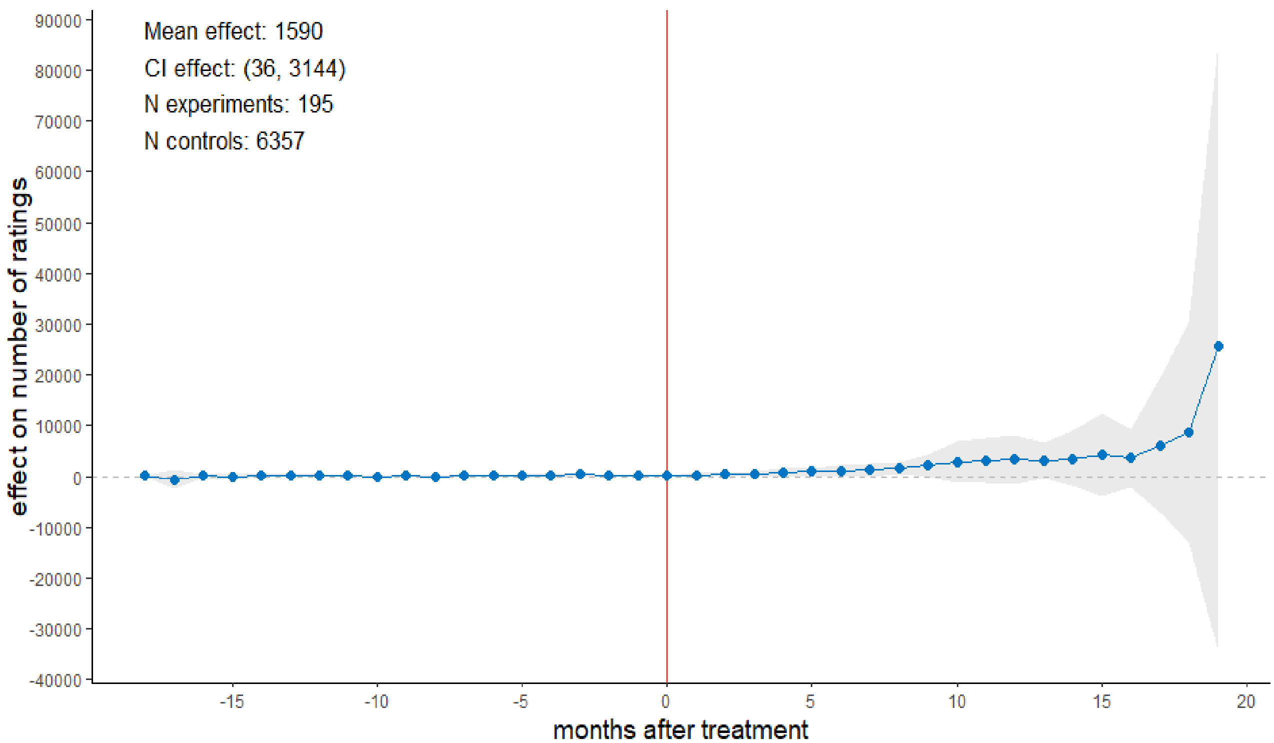


Figure B.13: Effect of carbon-neutral label using the number of ratings as the outcome variable (US)

This plot shows the dynamic treatment effect of carbon-neutral label on the rating count 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.

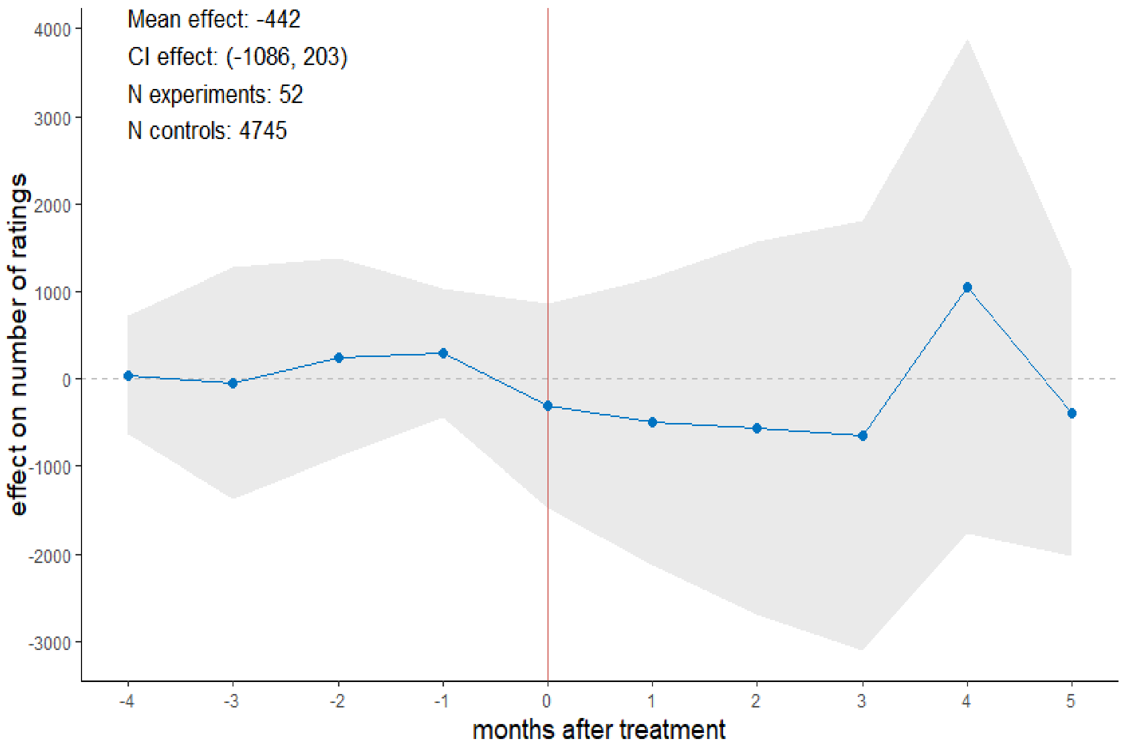


Figure B.14: Effect of carbon-neutral label using the number of ratings as the outcome variable (UK)

This plot shows the dynamic treatment effect of carbon-neutral label on the rating count 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.

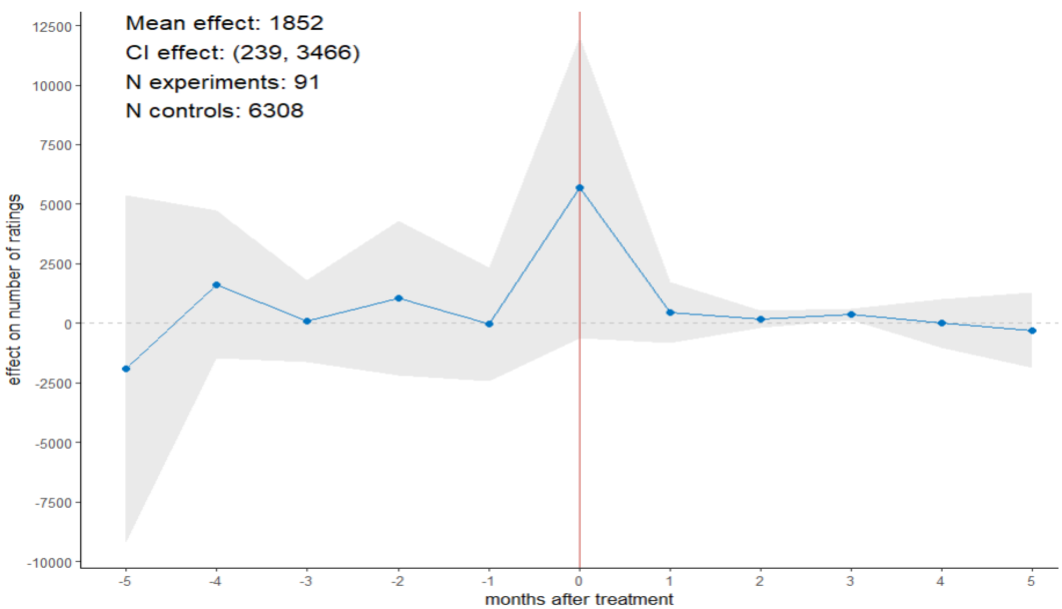


Figure B.15: Effect of carbon-neutral label using the number of ratings as the outcome variable (Germany)

This plot shows the dynamic treatment effect of carbon-neutral label on the rating count 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.