

Combined carbon and health taxes outperform single-purpose information or fiscal measures in designing sustainable food policies

Article

Accepted Version

Faccioli, M., Law, C. ORCID: <https://orcid.org/0000-0003-0686-1998>, Caine, C. A., Berger, N., Yan, X., Weninger, F., Guell, C., Smith, R. D. and Bateman, I. J. (2022) Combined carbon and health taxes outperform single-purpose information or fiscal measures in designing sustainable food policies. *Nature Food*, 3. pp. 331-340. ISSN 2662-1355 doi: 10.1038/s43016-022-00482-2 Available at <https://centaur.reading.ac.uk/105301/>

It is advisable to refer to the publisher's version if you intend to cite from the work. See [Guidance on citing](#).

To link to this article DOI: <http://dx.doi.org/10.1038/s43016-022-00482-2>

Publisher: Nature

All outputs in CentAUR are protected by Intellectual Property Rights law, including copyright law. Copyright and IPR is retained by the creators or other copyright holders. Terms and conditions for use of this material are defined in

the [End User Agreement](#).

www.reading.ac.uk/centaur

CentAUR

Central Archive at the University of Reading

Reading's research outputs online

This version of the article has been accepted for publication, after peer review (when applicable) but is not the Version of Record and does not reflect post-acceptance improvements, or any corrections. The Version of Record is available online at: <http://dx.doi.org/10.1038/s43016-022-00482-2>. Use of this Accepted Version is subject to the publisher's Accepted Manuscript terms of use <https://www.springernature.com/gp/open-research/policies/acceptedmanuscript-terms>

Combined carbon and health taxes outperform single-purpose information or fiscal measures in designing sustainable food policies

*Michela Faccioli^{*1}, Cherry Law², Catherine A. Caine³, Nicolas Berger⁴, Xiaoyu Yan⁵, Federico Weninger⁶, Cornelia Guell⁷, Brett Day⁸, Richard D. Smith⁹, Ian J. Bateman¹⁰*

Editor's summary

The extent to which policy-induced changes in food demand patterns help address environmental and health challenges remains poorly understood. Based on a randomised-controlled survey of almost 6,000 respondents from the United Kingdom, this study assesses the impacts on food purchases, greenhouse gas emissions and dietary health of applying carbon and/or health taxes, information provision, and a combination of both tax and information strategies.

Abstract

The food system is a major source of both environmental and health challenges. Yet, the extent to which policy-induced changes in the patterns of food demand address these challenges remains poorly understood. Using a randomised-controlled survey of 5,912 respondents from the United Kingdom (UK), we evaluate the potential impact of carbon and/or health taxes, information and combined tax and information strategies on food purchase patterns and their resulting impact on greenhouse gas emissions and dietary health. Our results show that while information on the carbon and/or health characteristics of food is not irrelevant, it is the imposition of taxes which exerts the most substantial effects on food purchasing decisions. Furthermore, while carbon or health taxes are best at separately targeting emissions and health challenges respectively, a combined carbon and health tax policy maximises benefits both in terms of environmental and health outcomes. We show that such a combined policy could contribute to around one third of the residual emission reductions required to achieve the UK's 2050 net zero commitments, while discouraging the purchase of unhealthy snacks, sugary drinks and alcohol and increasing the purchase of fruit and vegetables.

Main

The Paris Climate Agreement and United Nations' Sustainable Development Goals together challenge governments across the world to both tackle climate change and improve people's health.^{1,2} These apparently different priorities have one point of very clear intersection; food systems. Current food

production, processing, transport, packaging and consumption patterns generate more than one-third of global greenhouse gas (GHG) emissions, contributing substantially to climate change,³ while unhealthy diets account for nearly one in five deaths globally.⁴ Integrated food policies which tackle both the climate and health aspects of the food system are a clear and urgent priority.^{5,6}

Supply-side initiatives to promote environmentally friendly agricultural practices, such as the 2021-2027 Common Agricultural Policy (CAP) in Europe, are potentially important to reducing GHG emissions from food production. However, the scale and speed of transformation^{7,8,9} needed to deliver net-zero commitments^{10,11} and achieve public health targets require that we also consider the potential contribution that demand-side shifts in food consumption¹² might play in reaching those targets. This paper contributes to that demand-side analysis.

Policies to influence food demand have ranged from education, information or nudging, which are often considered ‘soft-policy’ initiatives, to ‘hard measures’, such as regulation or taxation.^{13,14} Information provision, typically through food labelling, can encourage consumers towards healthier,^{15,16} more environmentally sustainable^{17,18} food purchases. A related body of literature has also found that consumers tend to react differently to different labels that certify foods with higher environmental or health standards^{19,20}. While politically challenging, some food taxes have also been successfully applied in recent years, mostly with the objective of introducing changes in consumption (i.e. reduction of salt, fat and sugar intake^{21,22}) to improve people’s health. Similarly, simulation studies and experiments have also shown how the application of carbon taxes could result in a reduction of GHG emissions²³.

Despite this growing body of literature, however, previous studies have typically limited their focus to specific food products and single policy instruments, targeting **either** improvements in health **or** the environment. While some research^{24,25} has discussed the opportunities and trade-offs of implementing a broad range of policies, very few empirical applications exist which have recently appraised the combined impact of different mechanisms^{16,26}. Moreover, only a few studies^{27,28,29} have

looked at both the environmental and health impacts of food. This latter body of research has relied on simulations of food taxation or dietary change scenarios starting from ‘historic’ data on consumption. Such an approach, though, implicitly assumes that past behaviour is a good predictor of behaviour in the face of new policies. This is not necessarily a realistic assumption,³⁰ especially when future policies are anticipated to generate significant changes in behaviour. In addition, ‘historic’ data are not suitable to explore the role of “soft” measures not implemented before. In this paper, we thus empirically explore consumers’ food purchase intentions in the face of future “soft” and “hard” policies to achieve broad dietary transformations and we systematically assess and compare the resulting environmental and health expected impacts. This represents a critical, but previously missing, piece of information that can guide policy-makers in the choice of the most appropriate policy instrument, while considering the potential for synergies as well as the trade-offs associated with the adoption of different measures. For example, encouraging a shift towards more plant-based foods is generally associated with positive health outcomes and relatively low GHG emissions, but not all low emission foods are also good for health (e.g. sugary drinks and confectioneries).^{31,32}

The present study has addressed this gap through the analysis of the potential impacts on carbon emissions *and* dietary health from changes in household food purchase behaviour prompted by a range of information policies and taxes reflecting a True Cost Accounting approach.³³ In line with this, to internalise the externalities associated with food-related GHG emissions, we applied carbon taxes that change food prices proportionally to the food carbon content to reflect the social cost of carbon, while to account for the externalities arising from consuming unhealthy food, we applied taxes that increase the price of food proportionally to a score which measures the healthiness of food (i.e. nutritional content). Given that data is currently unavailable to address our research question, we designed a survey-based, randomised-controlled experiment and applied it to a nationally representative sample of N=5,912 UK citizens. Our survey design consistently assessed and compared the effects of different policies (see Figure 1 for an overview), and it was guided by data on household observed purchase behaviour from the Kantar Fast-Moving Consumer Goods (FMCG) panel,³⁴ carbon

footprint information based on a review of Life Cycle Assessment literature, as well as nutritional evidence based on the Nutrient Profiling model and Nutri-Score data.³⁵

Overview of the survey design

In our survey-based, randomised-controlled experiment, respondents were randomly allocated to one of three *policy streams* (as specified in Figure 1) within which study participants were presented with a Baseline scenario followed by two *policy instruments* defined by different combinations of new *information* and/or *taxes*. In the Baseline scenario, common across all three policy streams, respondents were asked to report their typical food and beverage purchases for home consumption, starting from a list of commonly purchased food products (see Methods). Respondents were then asked to imagine that a new policy instrument was introduced. They were presented again with the list of food products - this time including additional product information and/or increased prices, depending on the policy instrument - and they were asked to adjust their food product choices in response to the policy introduced. The policy instruments presented in the Carbon Information and Tax (CIT) policy stream were: Carbon Information (CI) - detailing the carbon emissions associated with each food – followed by Carbon Tax (CT) – adding a carbon tax to the baseline food prices and the carbon information as presented in CI (note that variation in tax rates was systematically introduced across respondents). Similarly, the policy instruments presented in the Health Information and Tax (HIT) policy stream, included: Health Information (HI) – presenting details about the healthiness of each food – followed by Health Tax (HT) – adding a health tax to the baseline food prices and the health information presented in HI. Both policy instruments considered in the Unlabelled Tax/Carbon + Health Tax (UT/CHT) policy stream involved the application to food prices of the combined tax rates presented in CT and HT. However, while in the case of the Unlabelled Tax (UT), presented as the first policy instrument, respondents were not informed of the reason behind this price increase, in the case of the Carbon + Health Tax (CHT), presented as second policy instrument, respondents were

additionally informed about the level of emissions and healthiness of each food (as in the previous policy streams) and were told that these were the drivers of the price increase.

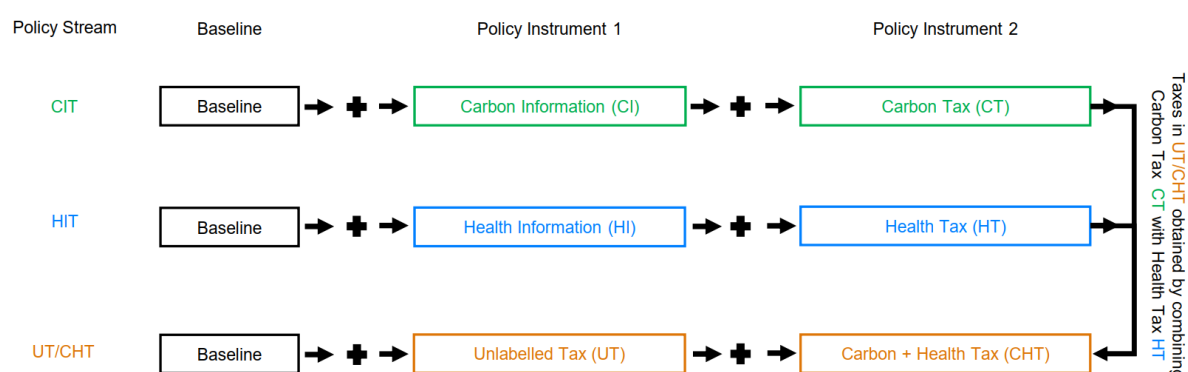


Figure 1. Overview of the design of the randomised-controlled trial. This figure summarises the sequence of information presented to respondents (i.e. a Baseline scenario followed by Policy Instrument 1 and Policy Instrument 2) in each of the three policy streams (i.e. CIT in green, HIT in blue and UT/CHT in orange).

The randomised-controlled design specified in Figure 1 allowed us to separate out the effects of information, taxation, or combined policies on the carbon emissions and dietary health of consumers' food choices. Further information on the survey design is provided in the Methods section.

Results

Food purchase patterns and GHG emissions

For our study, we collected data from N=5,912 respondents in total. No significant differences were detected in participants' socio-economic or demographic characteristics, or baseline patterns of food purchases, between the three policy streams, or compared against census and Kantar food purchase data for the overall UK population (see Supplementary Tables 1-3). As reported in Supplementary Table 3, the main food and beverage products, by volume, that the average survey respondent reported to purchase at baseline were fruit and vegetables, followed by dairy products and eggs (especially milk), beverages (especially non-sugary drinks and alcohol), meat (especially poultry, pork and unprocessed beef), and carbohydrates (especially bread, pasta, rice, flour and cereals). In monetary terms, the average survey respondent reported to spend the highest share of their monthly

baseline food expenditure on meat (about 26%), beverages (19%), fruit and vegetables (17%), dairy products and eggs (12%) and snacks (11%).

Based on our findings, these baseline food purchase patterns would result in an average of roughly 3,200 kgCO₂e of GHG emissions per person per year; equivalent to the emissions from driving a regular petrol car across the USA almost three times (13,000km). As reported in Supplementary Table 4, most of these emissions are linked to meat purchases: based on our survey responses, unprocessed beef alone would contribute to about 32% of our respondents' total food basket GHG emissions, followed by processed beef, lamb, pork and poultry, which together would contribute to another 26% of the total food basket emissions. This is not surprising given that meat products – especially beef – are associated with the highest levels of emissions per kilogram of food. Some lower emission products (such as milk and yoghurt, fruit and vegetables), however, would also contribute a significant share of total emissions (about 15%), given the high volume of purchase in these food groups. These results were consistent across all baselines in the three policy streams (see tests reported in Supplementary Table 4).

Figure 2 illustrates the average change in food-related GHG emissions per person per month for the CIT (panel (a)) and UT/CHT (panel (b)) policy streams across different food groups (further information is reported in Supplementary Tables 5 and 6 and in Extended Data Figure 1 for the HIT policy stream). A general finding of our study is that tax instruments, with or without information, would deliver greater impacts than reliance upon information alone. In addition, based on our results, the most significant reductions in the average levels of GHG emissions would be achieved by decreasing the volume of unprocessed beef purchased, which - depending on the policy mechanism considered - would lead to reductions of between 17 to 31 kgCO₂e per person per month, compared to the Baseline.

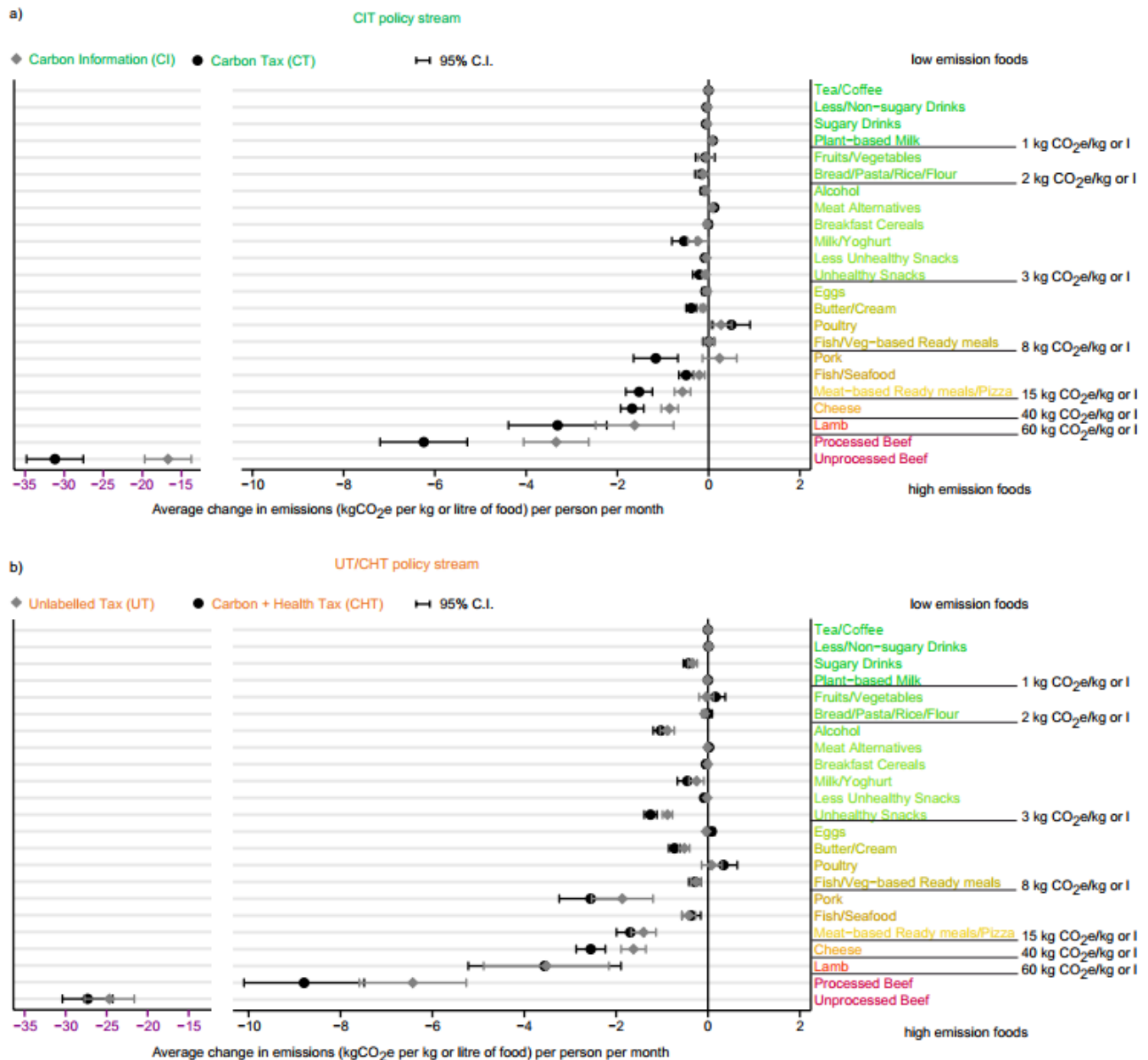


Figure 2. Average change (from the baseline) in per person monthly emissions (ppme) by food group across the different policy streams and policy instruments. Food groups are ordered from low emissions per kg (or litre) to high emissions per kg (or litre). Panel (a) refers to the average changes in ppme across respondents in the CIT policy stream. ◆ and ● indicate the average changes in ppme with the application of the Carbon Information (CI) and Carbon (Information and) Tax (CT) instruments, respectively. Panel (b) refers to the average changes in ppme across respondents in the UT/CHT policy stream. ◆ and ● indicate the average changes in ppme with the application of the Unlabelled Tax (UT) and Carbon + Health (Information and) Tax (CHT) instruments, respectively. — shows the 95% Confidence Interval (C.I.), based on normality assumptions. Note: in each scenario where taxes are applied, responses from all tax rate groups in that scenario are pooled. Figure 4 discusses the impact of varying tax rates.

In our results, more modest GHG emission reductions would be achieved through changing the purchase level of other meat products. Despite having high carbon content per kilogram of product,

both processed beef and lamb only represent a small share of the total amount of meat purchase reported in our survey (approximately 4% and 6%, respectively). Consequently, any reduction in the level of purchase of these types of meat that would be achieved through the food policies explored has little influence on total emissions (while varying across policy instruments, the average reductions are around 6 and 2 kgCO₂e per person per month for processed beef and lamb, respectively). Smaller emission reductions would also be achieved through a decrease in the purchase of other relatively carbon-intensive food products, such as: cheese (around 2 kgCO₂e reduction per person per month), pork (around 1 kgCO₂e reduction per person per month), and meat-based ready meals and pizza (1 to 2 kgCO₂e reduction per person per month). Emission levels associated with all other food groups are relatively less sensitive to the application of the different policy instruments. More details about the average change in per person monthly emissions for each food group across the different policy instruments are available in Supplementary Table 6.

Figure 3 summarises the mean per person per annum GHG emission reductions that would be achieved across the different policy streams and instruments for all food purchases. Considering first the CIT policy stream we found that the Carbon Information (CI) policy instrument would reduce emissions by on average 282 kgCO₂e per person per year; a significant reduction given the relatively low cost of such a policy. However, this reduction would almost be doubled to 558 kgCO₂e per person per year through the addition of a Carbon Tax (CT). When moving to the HIT policy stream, it is possible to note the GHG emission reduction co-benefits arising from the sequential introduction of health information and taxes. The fact that both the HI and HT policy instruments would reduce emissions shows the correlation between dietary improvement and reduced emissions, primarily because of the lower meat and dairy content of healthier diets. Clearly the potential exists for health policies to generate environmental co-benefits.

The CIT and HIT policy streams show the substantial impact which both carbon and health policies targeting food demand can have upon GHG emissions. However, the UT/CHT policy stream suggests

potential limits to the impact of combined policies on emissions reduction. Here the Unlabelled Tax (UT) policy instrument shows the expected implications on emissions of imposing a food tax (combining the tax levels used in CT and HT) when consumers are not informed of the reason for this price increase. In contrast, the CHT policy instrument applies the same combined tax level but now informs consumers of the GHG and health motivations for that tax. While the average reduction in emissions is significantly greater under the CHT than UT instrument, the reduction in emissions produced by the CHT instrument is not statistically different from that achieved by the CT instrument alone. These conclusions are based on the results of t-tests on mean equality reported in Supplementary Table 7.

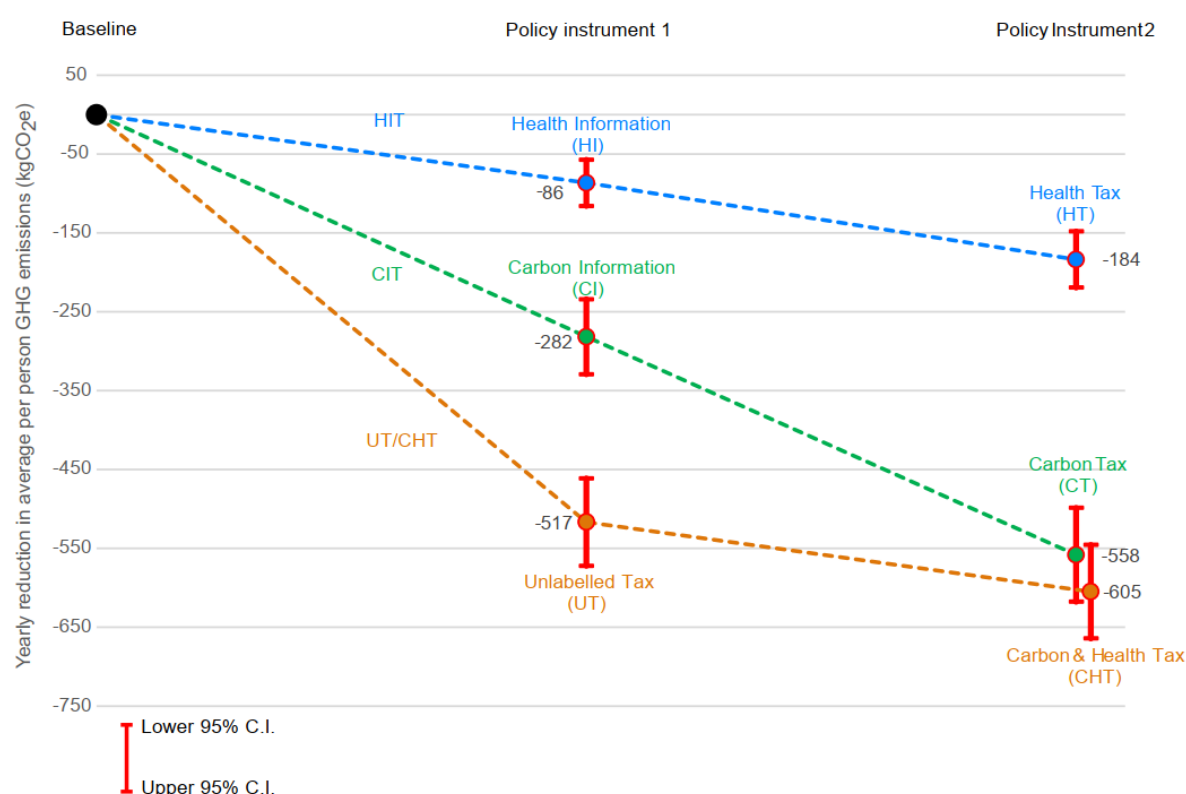


Figure 3. Yearly reductions in average per person GHG emissions (kgCO₂e) from food consumption across all policy streams and policy instruments. Green dots indicate the yearly reduction in average per person food basket emissions from the baseline for respondents in the Carbon Information and Tax (CIT) policy stream. Blue dots indicate the yearly reduction in average per person food basket emissions from the baseline for respondents in the Health Information and Tax (HIT) policy stream. Orange dots indicate the yearly reduction in average per person food basket emissions from the baseline for respondents in the Unlabelled Tax / Carbon + Health Tax (UT/CHT) policy stream. I gives the 95% Confidence Interval (C.I.), based on normality assumptions. Note: in each scenario where taxes are applied, responses from all different tax rate groups in that scenario are pooled. Figure 4 discusses the impact of varying tax rates. Supplementary Table 7 provides test results for the statistical significance of the difference in mean emission reductions across the policy instruments.

Figure 4 analyses the effectiveness of tax instruments in greater detail by examining how different rates of tax impact upon emissions (see Supplementary Table 8 for more details). These relationships are illustrated in Panel (a) for the Carbon Tax (CT) policy instrument and in Panel (b) for the Carbon + Health Tax (CHT) policy instrument, with both panels showing similar patterns (see Extended Data Figure 2 for the corresponding graph for the UT policy instrument). While the initial introduction of these tax instruments delivers highly significant reductions in carbon emissions relative to the Baseline, ongoing increases in tax eventually fail to yield significantly greater emission reductions, indicating non-linearities in the responses to tax rate increases. In economic terms the initial relatively 'elastic' response to higher prices becomes more 'inelastic' as consumption falls to levels where individuals are more resistant to further reductions; a common observation across many goods.³⁶ These findings suggest that applying an intermediate tax rate may be preferable, as it would enable emission reductions very close to those obtained with the highest tax rate, but with a lower increase in food prices, which could potentially boost the social (political) acceptability of the intervention.

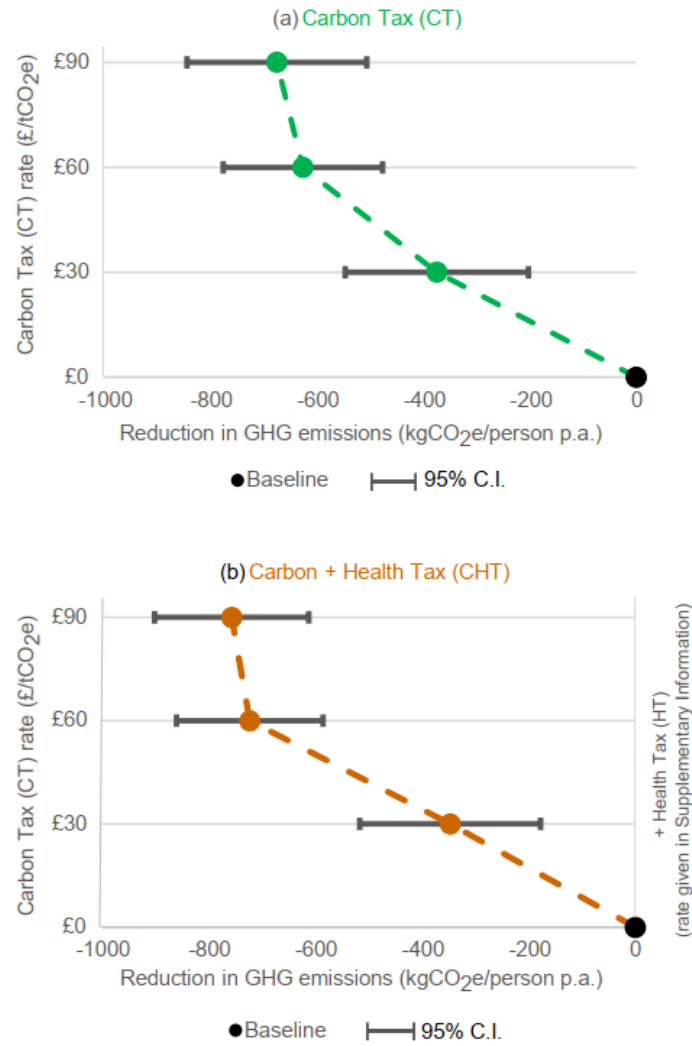


Figure 4. Effects of different food tax rates on GHG emission reductions. Panel (a) reports the relationship between different levels of Carbon Tax (CT) derived using True Cost Accounting principles, and food emission reductions per person per annum (p.a.). Panel (b) adds a Health Tax (HT) linked to the Nutri-Score rating of each food category (see Methods and Supplementary Table 8). As there is no perfect correlation between carbon emissions and health the vertical axis in Panel (b) lists the CT amount to which the HT amount is added. Therefore, the two vertical axes are not identical in absolute terms and full details are presented in Supplementary Table 8. However, both graphs reveal the diminishing sensitivity to tax increases exhibited by both CT and CHT. — indicates the 95% Confidence Interval (C.I.), calculated based on normality distribution assumptions.

In order to understand the emission reduction potential at national scale from the application of food policies such as these, we aggregated the values reported in Figure 3 to the UK level (as explained in more details in Supplementary Note 1). Table 1 reports these findings with the second column (from left to right) detailing the aggregate emission reductions that would be achieved, on average, under each food demand policy instrument. The remaining columns report these findings as a percentage of the overall reduction required to reach the 2050 net zero commitment (detailed in Supplementary

Note 1) either in the absence (third column) or after the implementation (fourth column) of planned emission reduction measures. While such food policies are obviously not a panacea on their own, our findings show that food demand policies which include carbon taxes could address around one-third of the net zero GHG removal gap currently predicted for 2050 (i.e. after planned decarbonisation policies are implemented).⁷ These values exceed the levels of emission reductions that the UK Government predicts to achieve via societal dietary changes; the 2019 report by the Committee on Climate Change⁷ predicts that only up to 14.9 MtCO₂e of emissions could be reduced in the UK by 2050 through dietary changes involving 50% lower consumption of beef, lamb and dairy. We show that much more could be achieved via appropriate food demand policies.

Table 1. Contribution of each policy instrument to the achievement of UK net zero targets by 2050. Note: in this table, in each scenario where taxes are applied, all responses from the different tax rate groups are considered (as per Figure 3). Figure 4 presents the impact of varying tax rates.

Food demand policy instrument	Aggregate average GHG emission reductions at UK scale under each policy instrument	Emission reduction potential for each policy as a share of the emission reductions required for net zero by 2050:	
		(a) in the absence of other emission reduction policies (-503 MtCO ₂ e)	(b) after implementing all planned emission reduction policies (-102.4 MtCO ₂ e)
Carbon information (CI)	-18.4 MtCO ₂ e	3.7%	18.0%
Carbon tax (CT)	-36.4 MtCO ₂ e	7.2%	35.6%
Health information (HI)	-5.7 MtCO ₂ e	1.1%	5.5%
Health tax (HT)	-12.0 MtCO ₂ e	2.4%	11.7%
Unlabelled tax (UT)	-33.7 MtCO ₂ e	6.7%	32.9%
Carbon + health tax (CHT)	-39.5 MtCO ₂ e	7.9%	38.6%

Dietary health implications

Just as the carbon focussed CIT policy stream was more effective at reducing GHG emissions than the health focused HIT policy stream, when viewed from a perspective of optimising the healthiness of diets so this pattern is, as might be expected, reversed (see Extended Data Figure 3 compared to Figure 5). Panel (a) of Figure 5 shows that the HIT policy stream performs particularly well in terms of reducing

the reported purchase of unhealthy snacks, sugary drinks and alcohol and increasing the reported purchase of fruit and vegetables. As before, the tax instrument (HT), combined with information, outperforms the provision of information alone (HI). While the UT/CHT policy stream seems to provide comparable benefits in terms of improved healthiness of diets compared to HIT (see Supplementary Table 9 for more details on the average change in the volume of purchased food groups across the different policy streams and instruments), we have shown that the expected reductions in emissions would be significantly larger in UT/CHT. The overall message is therefore clear; single policy objectives are best addressed through focussed policies; however combined policies can contribute significant benefits across multiple objectives.

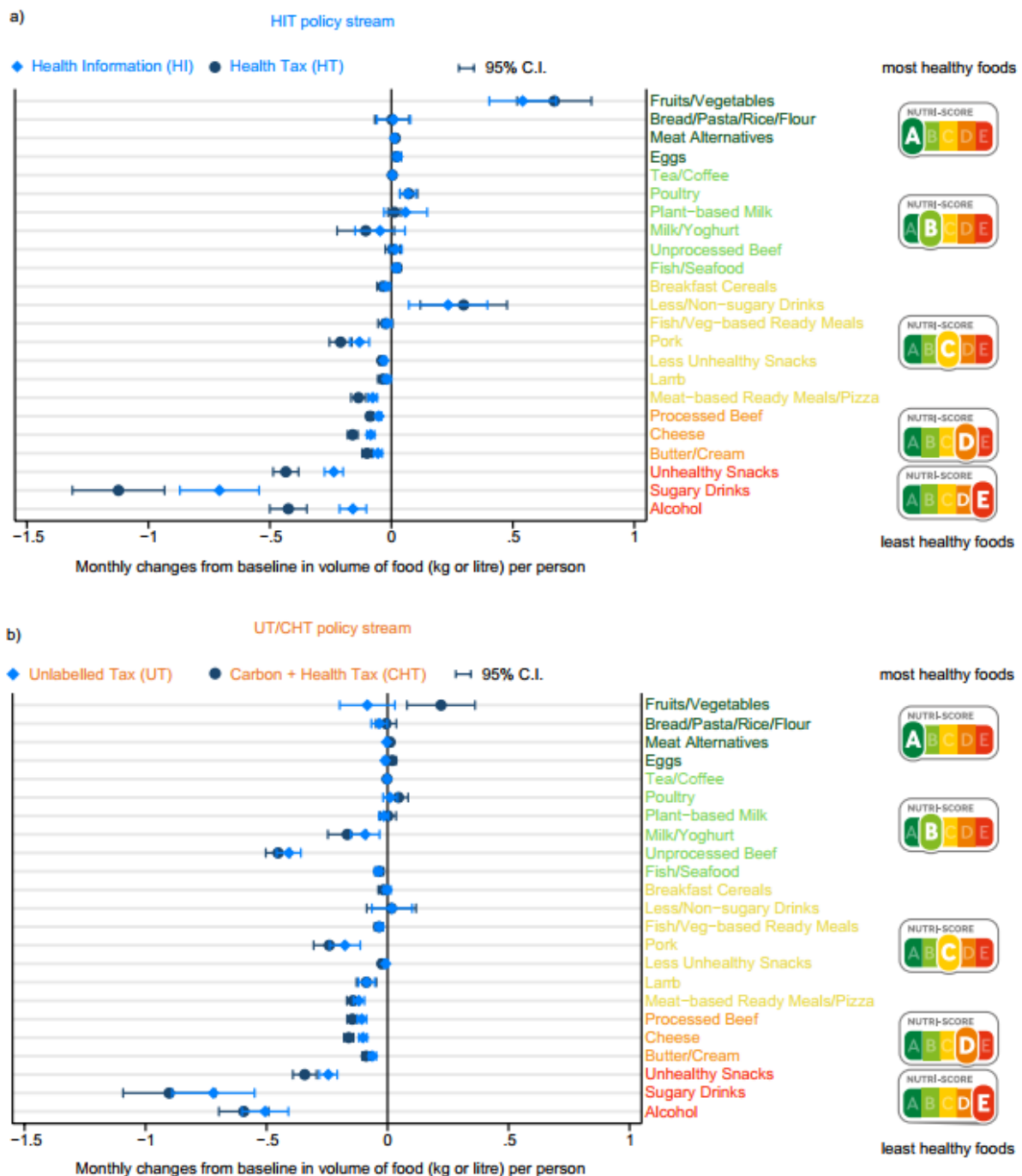


Figure 5. Average change (from the baseline) in per person monthly volume of purchases (ppmvp) by food group across the different policy streams and policy instruments. Food groups are ordered based on their Nutri-Scores from A (Most healthy) to E (Least Healthy). Panel (a) refers to the average changes in ppmvp across the respondents in the Health Information and Tax (HIT) policy stream. Light blue diamond and dark blue dot symbols indicate the average changes in ppmvp with the application of the Health Information (HI) and Health (Information and) Tax (HT) instruments, respectively. Panel (b) refers to the average changes in ppmvp across the respondents in the Unlabelled Tax / Carbon + Health Tax (UT/CHT) policy stream. Light blue diamond and dark blue dot symbols indicate the average changes in ppmvp with the application of the Unlabelled Tax (UT) and Carbon + Health (Information and) Tax (CHT) instruments, respectively. — shows the 95% Confidence Interval (C.I.), based on normality assumptions.

Conclusions

Creating a food system which reduces its negative impacts upon both the environment and health is a major policy challenge facing governments globally. While supply side, technological and other advancements in the production of food are important, as has been demonstrated in product reformulation to reduce sugar content for people's health,³⁷ consumer demand is a major, but complex, driver requiring greater policy coherence. Our analysis, a large-scale randomised-controlled trial evaluating the anticipated environmental and dietary health impact of information and/or fiscal measures across the food basket, clearly demonstrates the power of demand-side policy interventions.

Our results suggest a significant impact, compared to baseline control purchasing, of fiscal measures and/or information provision, with primacy of fiscal measures over information provision alone. The potential magnitude of benefits arising from these policies is clear. To date Governments around the world have been reticent, and at best hesitant, to implement food taxes, with the focus of such tax incentives being mostly to deter consumption of unhealthy foods, in order to improve personal health and reduce pressures upon health services.²¹ Using demand side fiscal measures can however also offer the prospect of highly substantial environmental benefits. Specifically, based on our study, carbon taxes applied to food purchases could address around one third of the net zero gap predicted to require GHG removal by 2050 in the UK.

Some limitations must, however, also be acknowledged. First, our study only focuses on a single, high-income country, so more work is needed to test the generalisability of our results to other (particularly low- and middle-income) countries. Second, while our findings support the employment of taxation to achieve both environmental and dietary health improvements, more research is required to spell out the distributional implications of the different policy instruments explored.³⁸ The potential for carbon taxes to fall disproportionately on the poorer has been highlighted.³⁹ Our analysis points to the possibility of using intermediate levels of tax rates to achieve emission reductions very close to those

obtained with higher tax rates, but with a lower increase in food prices, potentially boosting the social (political) acceptability of the intervention and possibly reducing the regressive effects. Much less is known regarding the distributional effects of health taxes,⁴⁰ which remains an area for future work. Third, while improving both the environment and dietary health is a key concern for policy-makers, the political challenges of targeting multiple benefits through a combination of policies should not be underestimated.⁴¹ Policy-makers often operate by tackling different problems separately. However, as shown in our study, while the achievement of single objectives might best be reached through specific, single-purpose measures, the achievement of multiple objectives are best targeted through multiple, integrated measures. Research focusing on multiple dimensions might address each in less detail than single-focus studies. Yet, if the systems concerned are complex and multi-dimensional, then single-focus analyses may actually be a misleading guide for policy and decision making. The food system is both multi-dimensional and involves many, inter-dependent actors, whose role we do not explicitly study in our research. For instance, it is likely that shifts in consumers' behaviour will also affect (and be affected by) the decisions of all other actors involved in the food supply and distribution chain and, in turn, that all these interlinked choices are influenced by wider shifts in social, demographic and environmental systems. An analysis of the broader cascading effects of the different policy mechanisms on the various components of the wider food system and the connected socio-ecological networks is beyond the scope of this study, but it represents an interesting question for future work. Such an analysis of the dynamics and feedback loops that might arise with the application of different food policies could represent valuable information to better guide policy-making.

Methods

This study was based on a randomised-controlled trial survey which elicits respondents' behaviour in the current baseline food purchase situation (as a control) and in the face of a range of hypothetical policy instruments that reflect: the provision of information on food products' carbon emissions, dietary health or both; and/or taxation of food based on its carbon emissions, healthiness or both. In the absence of alternative data available, the survey represents an appropriate method to measure the expected effect of specific food policies that will be implemented in the future, what these would mean in terms of consumers' food choices and the resulting implications for the environment and dietary health. The survey also offered a controlled environment to consistently and systematically identify the effect of the different food policies of interest, which wouldn't have been possible in non-experimental settings. This is particularly important when one of the aims is to evaluate consumers' response to the provision of new carbon and health information, which is not reflected in historic consumption/purchase data and hence can only be derived from stated preferences. The survey is also unique in the way in which it replicated an online supermarket where realistic prices and information about the food products were displayed to respondents. In order to achieve the above, we designed the survey using: data from the Kantar FMCG panel, accurate GHG emissions which were calculated using the Life Cycle Assessment (LCA) method, and indicators of the healthiness of food products which were inferred from the aggregated nutritional value based on the Nutri-Score labelling system.

Survey Design

Our survey-based randomised-controlled trial was designed to elicit UK respondents' food purchase behaviour for three policy streams. In each *policy stream*, respondents were first asked about their food purchase choices in the current baseline situation (as a control), namely they were required to report information about their typical purchases of food and beverage to consume at home in normal settings (e.g. excluding out-of-home food purchases, unusual circumstances like the Covid-19

pandemic or special occasions such as Christmas). In this baseline scenario, the same for all policy streams, a list of food and beverage categories was displayed to mimic an online supermarket platform and each category was presented with its name, a picture and price information (a copy of the food list can be made available upon request from the authors). Respondents were then asked to indicate the amount they buy and the frequency of purchase (each week, each two weeks or each month) for each category listed.

Once respondents had worked through the baseline scenario, they were then presented with two hypothetical policy instruments, varying depending on the policy stream that the participant was randomly allocated to (see Figure 1 for an overview of each policy stream and the policy instruments contained within). Our study participants could either be confronted with: (i) the provision of Carbon Information (CI) and the additional application of a Carbon Tax (CT) in the Carbon Information and Tax (CIT) policy stream; or with (ii) the provision of Health Information (HI) and the additional application of a Health Tax (HT) in the Health Information and Tax (HIT) policy stream; or with (iii) the application of an unlabelled food tax (UT) and the additional provision of environmental and dietary health information regarding the reasons of the price increase (CHT) in the policy stream called Unlabelled Tax / Carbon + Health Tax (UT/CHT). These policy instruments, though hypothetical, reflect current policy discussions.^{42,43,44,45,46,47,48,49,50} We grouped the different instruments in such a way that the second policy instrument presented in each policy stream displayed some additional elements compared to the first policy instrument in the same policy stream. Our survey design, relying on both within- and between-sample approaches, allowed us to ensure the identification of each separate policy effect – namely the role of information provision (on the food categories' carbon emissions, dietary health or both), in addition to or as opposed to the role of taxation (based on the food carbon emissions, on dietary health or both) – whilst avoiding respondent fatigue. Further details on each policy intervention are outlined later in the Methods section. After being introduced to each policy instrument, respondents were again shown the list of food categories presented in the baseline, revised as appropriate to include additional food labels or modified prices depending on the policy

instrument considered. Study participants were then asked if they wanted to revise any of their food purchase choices and, to simplify this task, the amount and frequency of purchase of each food category were each time pre-populated with the choices made by the respondent in the immediately preceding scenario. This way, the responses provided in the baseline were used to pre-populate choices in CI, HI and UT and the responses in CI, HI, UT were used to pre-populate the choices in CT, HT and CHT, respectively.

Kantar FMCG panel

In order to ensure that the survey presented respondents with a realistic set of foods that are commonly purchased in Great Britain, along with a set of realistic prices for each food category, we used disaggregated data on households' actual purchases from the Kantar FMCG panel.³⁴ We obtained volume, expenditure and nutritional information for 37,650,088 food and beverage purchases made for consumption at home by 31,725 British households in 2017.⁵¹ This dataset covers a wide range of places of purchase, which include supermarkets, convenience stores, newsagents and specialist stores such as butchers, greengrocers, and therefore provides an accurate picture of British households' current food purchase behaviour.

This dataset was used primarily to identify the main food categories (in terms of volume of purchases) to include in the survey. We defined a final list of 72 food categories which were identified as homogeneous with respect to their nutritional content and carbon footprint, and which were representative of British food purchase patterns. The selected food categories accounted for 72.8% of all products reported in the Kantar FMCG dataset and for 81.1% of the take-home expenditure made on food and beverage in Great Britain. A summary of the food categories displayed in the survey, along with their volume of purchase according to the 2017 Kantar FMCG data, is provided in Supplementary Table 10.

The Kantar FMCG dataset was also used to provide accurate information on the price ranges for each food category to be used in the survey. To identify the 'typical' prices for each food category, the full

price distribution from the Kantar FMCG data was truncated between the 25th and 75th percentiles to exclude extreme values. The resulting truncated distribution of prices (reported in Supplementary Table 10) was subsequently simulated in Matlab to obtain individual-specific levels for each food category, such that each respondent was displayed with different baseline prices. Prices were also adjusted to April 2020 values to account for inflation since 2017.

GHG Emissions of Food

Information on the GHG emissions for each food category was presented to respondents in the survey using a colour-coded indicator displayed under the price of each food category. Extended Data Figure 4 provides an example of the GHG emission indicator that we designed and used for our study. For each food category, the level of this indicator was informed by a desk-based review of studies reporting the ‘farm to fork’ GHG emissions associated with the whole supply chain. The reviewed studies rely on the well-established LCA method, which represents the most comprehensive approach available to accurately calculate the GHG emissions associated with food.⁵² For most food categories, the GHG emission estimates relied on the meta-analysis study provided by Poore and Nemecek,⁵³ which summarises the most up-to-date information in the published literature regarding the environmental impacts of food. When information from the Poore and Nemecek study was not available for specific food categories, alternative published sources were used. A summary of the reviewed LCA papers used in our study is reported in Supplementary Table 11. Where possible, we relied on information on the median (else the mean) GHG emissions for each food category.

Healthiness of Food

Information on the healthiness of food categories was communicated to participants (where applicable) using a Nutri-Score label. This is a letter-based, colour-coded indicator that is increasingly used in many countries to convey information of the nutrient value of a given food. Despite some concerns around its capacity to reduce calories intake,⁵⁴ the Nutri-Score is one of the clearest and simplest food labelling approaches to signal the nutritional quality and healthiness of food products

^{55,56,57} and one of the most effective labelling tools to encourage healthy purchases.⁵⁸ Food and beverage products marked with a dark or light green letter A or B are generally recommended for a healthy diet, while products with an orange D or red E should be consumed in small quantities and less often as they are unhealthy (see Extended Data Figure 5 for an overview of the different Nutri-Score letters). To represent the healthiness of each food category in the survey, we calculated the Nutri-Score of each product purchased in the Kantar FMCG dataset and identified the most frequent Nutri-Score in each food category (see Supplementary Table 12 for an overview of the Nutri-Score assigned to each food category). To calculate the Nutri-Score, positive points were assigned to products that are high in unfavourable (less healthy) nutrients that should be avoided such as calories, sugars, sodium and saturated fats, and negative points were attributed to favourable (healthier) nutrients such as fibre, protein, fruit, vegetables and nuts, rapeseed oil, walnut oil and olive oil.³⁵ The positive points were subtracted from the negative points to obtain a final score, which allows to classify each given food product into Nutri-Score categories A to E.

Carbon Tax

As governments are well aware, food taxes have the potential to be highly contentious. Given this, rather than taxing every food based on its carbon content, in an approach which presaged the recently published UK National Food Strategy Plan (2021),⁵⁹ we relied on a simple approach which taxes the most carbon-intensive foods only. This is a more feasible approach than a universally applied tax and it also proved generally acceptable in our pre-test investigations. Given this, and following previous studies,^{27,28} for those food categories with higher-than-average GHG emissions per kilogram or litre (i.e. above 8.75 kgCO₂e as explained in Supplementary Table 11), we simulated a carbon tax by increasing the baseline prices proportionally to the level of carbon emissions of the food. For each food category, the price increase was derived by multiplying the level of GHG emissions per unit of food (summarised in Supplementary Table 11) by the price of carbon. We followed the UK Government's recommendations to use the short term non-traded carbon prices.⁶⁰ Different values

exist, however, and there is uncertainty regarding which one would be most appropriate: £60 per tonne of CO₂e represents the central value estimate for 2020, but additionally lower bound estimates (£30 per tonne of CO₂e) and upper bound estimates (£90 per tonne of CO₂e) are also available. In the CIT and UT/CHT policy streams, where carbon taxes were applied, we therefore randomly assigned the respondents to one of three possible groups, each using a different short-term non-traded carbon price for 2020. The consideration of multiple carbon prices allows to test for: i) the sensitivity of the results to uncertainties regarding the carbon prices and ii) the presence of non-linearities in behavioural responses to the application of the tax instrument.

Health Tax

Where health taxes were applied in our survey, respondents were presented with a price increase for those food categories classified as having a Nutri-Score D or E. The tax on unhealthy food (added to the price displayed in the baseline) was designed to reflect the structure of most existing taxes on food around the world.⁶¹ For each unhealthy food category subject to taxation, the price increase per volume was calculated as a given percentage of the average price of that food. To account for the uncertainties associated with this approach, we considered different possible percentage increases – generally higher for foods with a Nutri-Score E compared to a Nutri-Score D, given that E products are unhealthier and therefore should be taxed proportionally more.^{62,63} Respondents were randomly allocated to one of three possible tax rate groups, each associated with a different percentage increase, depending on the Nutri-Score classification of the food category of reference:

- for food categories with a Nutri-Score D, a price increase of either 5%, 15% or 25% was used;
- for food categories with a Nutri-Score E, a price increase of either 25%, 35% or 45% was used.

These tax rates were informed by food tax examples in the real world and the literature. Food tax rates are rarely lower than 5% and generally fall within the price increase of 20%.⁶¹ However, existing studies have found that low tax rates, which only lead to minor price changes, also only result in minor demand variations.^{16,64} Therefore, in our study we also considered higher tax rates of up to 45%.

Data collection, preparation and validation

Different survey versions for each policy stream were distributed online using a market research company (for an overview of the survey versions see Supplementary Table 13 and for the detailed information provided to respondents in each survey version see Supplementary Note 2). When collecting data, we followed a randomised quota-based sampling approach to ensure that the sample is representative of the UK population in terms of dietary profile, age, gender, geographical region of residence and socio-economic status. The survey could only be completed by those members of the household who are frequently in charge of the food shopping. The main data collection campaign took place in autumn 2020. The final survey was informed by the results of in-depth individual interviews (to qualitatively explore the general public's understanding of the food system and its impacts and discuss framings for experimental food choice tasks), and pre-testing and piloting (to guide the drafting and to refine the survey design) over spring and summer 2020. A set of criteria (Supplementary Note 3) was used by the market research company to identify unreasonable responses, which were screened out at the sampling stage and replaced with new respondents with similar demographics. Overall 5,912 completed surveys were collected from 1,979 respondents in the CIT policy stream, 1,958 in the HIT policy stream and 1,975 in the UT/CHT policy stream.

For the purpose of data analysis, we aggregated the 72 food categories displayed in the survey into 23 food groups (see Supplementary Table 14) based on their product similarity, healthiness and GHG emission levels. This way, we could focus on the key purchase changes across food groups and enhance the interpretability of our results.

We validated the survey data in three ways. First, we checked the socio-demographic characteristics of the respondents in the final dataset to ensure that these were similar across the policy streams, and also that they were representative of the UK population. We found that in the three policy streams respondents do not display significantly different socio-demographic characteristics, which reflect the patterns in the UK population (Supplementary Table 1). Second, to ensure credibility of the data from the questionnaire, we cross-validated the survey responses in the baseline scenarios with real-

purchase data from the Kantar FMCG panel using Wilcoxon rank-sum tests.⁶⁵ We calculated the average per person monthly volume of purchase for each of the 23 food groups using the Kantar FMCG data⁵¹ and compared this information with the corresponding volume data in the survey baseline instruments. For each policy stream, the patterns of baseline food purchase (reported in Supplementary Table 2) are not significantly different from the Kantar data or from each other, suggesting a high degree of face validity. Third, we assessed the equivalence of the baseline emissions across all policy streams to make sure that they originate from identical population distributions. To do that, we ran Kruskal-Wallis tests.⁶⁶ The test results (reported in Supplementary Table 4) suggested that the baseline emissions are equivalent (and can be compared without further adjustments) at both food group and food basket levels.

Performance of the different policy instruments

To evaluate the performance of the different policies in reducing GHG emissions, we first calculated the level of monthly per person GHG emissions (kgCO₂e) for each food group under each policy instrument and then averaged across all respondents in that policy stream. We then computed the average changes in emissions from the baseline for each food group and compared variations in these changes across the different policy instruments. To evaluate the extent of the environmental impact, we also looked at the significance of the differences in total emissions from the food basket across the different policy instruments, using two-sample or pairwise two-sided t-tests of mean equality, as appropriate. We also looked at the relationship between the tax rate applied and level of emission reductions achieved under the policy instruments where taxes were presented to respondents. In those scenarios where a carbon tax is considered, we employed different carbon prices to reflect different tax rates. We assumed that: (i) a lower bound carbon price of £30 per tonne of CO₂e represents a low tax rate; (ii) a central estimate of carbon price of £60 per tonne of CO₂e represents a medium tax rate; and (iii) an upper bound carbon price of £90 per tonne of CO₂e constitutes a high tax rate. In the policy stream where a health tax is additionally considered (i.e. UT/CHT), the tax rate

also depended on the application of a health tax. Considering the ranges of price increases employed in our survey to design the health tax, we assumed that: (i) a 5% increase in price for food categories with Nutri-Score D (25% if Nutri-Score E) represents a low tax rate on unhealthy food; (ii) a 15% increase in the price of Nutri-Score D food categories (35% if Nutri-Score E) constitutes a medium tax rate; and (iii) a 25% price increase for food categories with Nutri-Score D (45% if Nutri-Score E) represents a high tax rate. The tax rates applied in the different tax scenarios are summarized in Supplementary Table 8, alongside information on the average per person total emission reductions (at food basket level) achieved under each policy instrument.

To draw conclusions on the potential impacts on dietary health of applying the different policies, we similarly computed the per person monthly volume purchased (in kg or litre) for each food group in each policy instrument and averaged across all the respondents in that policy stream. We then assessed the changes in average volume purchased across policy instruments for each food group by analysing the distribution of changes in purchases in relation to the average Nutri-Score of the different food groups. This was done to evaluate the effectiveness of each policy in terms of encouraging the purchase of healthy versus unhealthy food.

Data availability:

Survey data collected as part of this study can be made available to interested readers upon reasonable request to the corresponding author. Kantar FMCG data are available from Kantar Worldpanel (www.kantarworldpanel.com/en). Any other data used to design the survey is reported in the Supplementary Information file that accompanies this manuscript.

References:

1. Semba, R. D. *et al.* Adoption of the 'planetary health diet' has different impacts on countries' greenhouse gas emissions. *Nat. Food* **1**, 481–484 (2020).
2. Chand, A. Paris Agreement needs food system change. *Nat. Food* **1**, 772–772 (2020).
3. Crippa, M. *et al.* Food systems are responsible for a third of global anthropogenic GHG emissions. *Nat. Food* **2**, 198–209 (2021).

4. Gakidou, E. *et al.* Global, regional, and national comparative risk assessment of 84 behavioural, environmental and occupational, and metabolic risks or clusters of risks, 1990–2016: a systematic analysis for the Global Burden of Disease Study 2016. *The Lancet* **390**, 1345–1422 (2017).
5. Scheelbeek, P. F. D. *et al.* United Kingdom's fruit and vegetable supply is increasingly dependent on imports from climate-vulnerable producing countries. *Nat. Food* **1**, 705–712 (2020).
6. Mullen, A. Dietary guidelines for people and planet. *Nat. Food* **1**, 462 (2020).
7. *Net Zero – Technical Report* (Climate Change Committee, 2019)
<https://www.theccc.org.uk/publication/net-zero-technical-report/>.
8. *Land use: Policies for a Net Zero UK* (Climate Change Committee, 2020)
<https://www.theccc.org.uk/publication/land-use-policies-for-a-net-zero-uk/>.
9. *Greenhouse gas removal* (Royal Society & Royal Academy of Engineering, 2018)
<https://www.raeng.org.uk/publications/reports/greenhouse-gas-removal>.
10. *The Climate Change Act 2008 (2050 Target Amendment) Order 2019* (legislation.gov.uk, 2019).
<https://www.legislation.gov.uk/ukxi/2019/1056/contents/made>.
11. *Net zero in the UK* (Hirst, D., Bolton, P. & Priestley, S, 2021)
<https://commonslibrary.parliament.uk/research-briefings/cbp-8590/>.
12. *IPCC Special Report on Climate Change and Land: Chapter 5 Food Security* (Mbow, C. & Rosenzweig, C., 2019) https://www.ipcc.ch/site/assets/uploads/sites/4/2021/02/08_Chapter-5_3.pdf.
13. Messer, K. D., Costanigro, M. & Kaiser, H. M. Labeling Food Processes: The Good, the Bad and the Ugly. *Applied Economic Perspectives and Policy* **39**, 407–427 (2017).
14. Carattini, S., Carvalho, M. & Fankhauser, S. Overcoming public resistance to carbon taxes. *WIREs Climate Change* **9**, e531 (2018).
15. Kaur, A., Scarborough, P. & Rayner, M. Modelling the dietary impact of health-related claims on food labels in the UK. *Proceedings of the Nutrition Society* **79**, e326 (2020).
16. Cornelsen, L., Quaife, M., Lagarde, M. & Smith, R. D. Framing and signalling effects of taxes on sugary drinks: A discrete choice experiment among households in Great Britain. *Health Economics* **29**, 1132–1147 (2020).
17. Gadema, Z. & Oglethorpe, D. The use and usefulness of carbon labelling food: A policy perspective from a survey of UK supermarket shoppers. *Food Policy* **36**, 815–822 (2011).
18. Shewmake, S., Okrent, A., Thabrew, L. & Vandenberg, M. Predicting consumer demand responses to carbon labels. *Ecological Economics* **119**, 168–180 (2015).
19. Fischer, C. & Lyon, T.P. Competing Environmental Labels. *Journal of Economics & Management Strategy* **23** (3), 692–716 (2014).
20. Yi, L. Competing Eco-Labels and Product Market Competition. *Resource and Energy Economics* **60**, 101149 (2020).
21. Cornelsen, L., Mazzocchi, M. & Smith, R. D. Fat tax or thin subsidy? How price increases and decreases affect the energy and nutrient content of food and beverage purchases in Great Britain. *Soc Sci Med* **230**, 318–327 (2019).
22. Scarborough, P. *et al.* Impact of the announcement and implementation of the UK Soft Drinks Industry Levy on sugar content, price, product size and number of available soft drinks in the UK, 2015–19: A controlled interrupted time series analysis. *PLOS Medicine* **17**, e1003025 (2020).
23. Säll, S. & Gren, I. Effects of an environmental tax on meat and dairy consumption in Sweden. *Food Policy* **55**, 41–53 (2015).
24. Mozaffarian, D., Rogoff Kenneth, S., & Ludwig, D. S. The Real Cost of Food – Can Taxes and Subsidies Improve Public Health? *JAMA* **312**(9), 889–890 (2014)

25. Mozaffarian, D. *et al.* Role of government policy in nutrition – barriers to and opportunities for healthier eating. *BMJ* **361**, k2426 (2018).
26. Panzone, L. A., Ulph, A., Zizzo, D. J., Hilton, D. & Clear, A. The impact of environmental recall and carbon taxation on the carbon footprint of supermarket shopping. *Journal of Environmental Economics and Management* 102137 (2018).
27. Revoredo-Giha, C., Chalmers, N. & Akaichi, F. Simulating the Impact of Carbon Taxes on Greenhouse Gas Emission and Nutrition in the UK. *Sustainability* **10**, 134 (2018).
28. Briggs, A.D.M. *et al.* Simulating the impact on health of internalising the cost of carbon in food prices combined with a tax on sugar-sweetened beverages. *BMC Public Health* **16**,107 (2016).
29. Springmann, M. *et al.* Health and nutritional aspects of sustainable diet strategies and their association with environmental impacts: a global modelling analysis with country-level detail. *Lancet Planetary Health* **2**, e451-61 (2018).
30. Malter, M.S. *et al.* The past, present, and future of consumer research. *Marketing Letters* **31**, 137-149 (2020).
31. Drewnowski, A. *et al.* Energy and nutrient density of foods in relation to their carbon footprint. *The American Journal of Clinical Nutrition* **101**, 184–191 (2015).
32. Clark, M. A., Springmann, M., Hill, J. & Tilman, D. Multiple health and environmental impacts of foods. *PNAS* **116**, 23357–23362 (2019).
33. The true cost of food. *Nature Food* **1**, 185–185 (2020).
34. *Consumer Goods Panel* (Kantar Group and Affiliates, 2021)
<https://www.kantar.com/expertise/consumer-shopper-retail/consumer-panels/consumer-goods-panel>.
35. *Nutri-Score* (Hercberg, S., 2021) <https://www.santepubliquefrance.fr/en/nutri-score>.
36. Mankiw, N.G. *Principles of Microeconomics*, 7th Edition (South-Western College Pub, Cincinnati, USA, 2014).
37. Pell, D. *et al.* Changes in soft drinks purchased by British households associated with the UK soft drinks industry levy: controlled interrupted time series analysis. *BMJ* **372**, n254 (2021).
38. Whitfield, S. *et al.* A framework for examining justice in food system transformations research. *Nat. Food*. **2**, 383-385 (2021).
39. Caillavet, F., Fadhuile, A., Nichèle, V. Assessing the distributional effects of carbon taxes on food: Inequalities and nutritional insights in France. *Ecological Economics* **163**, 20-31 (2019).
40. Jain, V. *et al.* Distributional equity as a consideration in economic and modelling evaluations of health taxes: A systematic review. *Health Policy* **24(9)**, 919-931 (2020).
41. Sterner, T. *et al.* Policy design for the Anthropocene. *Nat. Sust.* **2**, 14-21 (2019).
42. *Should your supermarket receipt count calories?* (Ramaswamy, C., 2017)
<http://www.theguardian.com/business/shortcuts/2017/jul/10/should-your-supermarket-receipt-count-calories>.
43. *'Fat tax' on unhealthy food must raise prices by 20% to have effect, says study* (Campbell, D, 2012)
<http://www.theguardian.com/society/2012/may/16/fat-tax-unhealthy-food-effect>.
44. *Doctors call on government to tax junk food, meat and dairy products* (Diabetes.co.uk, 2012)
<https://www.diabetes.co.uk/news/2020/june/doctors-call-on-government-to-tax-junk-food-meat-and-dairy-products.html>.
45. *EU urged to adopt meat tax to tackle climate emergency* (Carrington, D, 2020)
<http://www.theguardian.com/environment/2020/feb/04/eu-meat-tax-climate-emergency>.

46. *Low-emission cows: farming responds to climate warning* (Watts, J., 2018)
<http://www.theguardian.com/environment/2018/oct/12/low-emission-cows-farming-responds-to-climate-warning>.
47. *A Carbon Tax on Meat?* (Heikkinen, N., 2016)
<https://www.scientificamerican.com/article/a-carbon-tax-on-meat/>.
48. *The Livestock Levy: Are Regulators Considering Meat Taxes?* (FAIRR, 2017)
<https://www.fairr.org/article/livestock-levy-regulators-considering-meat-taxes/>.
49. *Traffic-light system of 'eco-scores' to be piloted on British food labels* (Iqbal, N, 2021)
https://www.theguardian.com/business/2021/jun/27/traffic-light-system-of-eco-scores-to-be-piloted-on-british-food-labels?CMP=Share_iOSApp_Other.
50. *Thursday briefing: 'Fix UK diet for health and climate'* (Murray, M, 2021)
https://www.theguardian.com/world/2021/jul/15/thursday-briefing-fix-uk-diet-for-health-and-climate?CMP=Share_iOSApp_Other.
51. Berger, N., Cummins, S., Smith, R. D. & Cornelsen, L. Recent trends in energy and nutrient content of take-home food and beverage purchases in Great Britain: an analysis of 225 million food and beverage purchases over 6 years. *BMJ Nutrition, Prevention & Health* 1–9 (2019).
52. Bjørn, A., Owsianiak, M., Molin, C. & Hauschild, M. Z. LCA History. in *Life Cycle Assessment: Theory and Practice* (eds. Hauschild, M. Z., Rosenbaum, R. K. & Olsen, S. I.) 17–30 (Springer International Publishing, 2018).
53. Poore, J. & Nemecek, T. Reducing food's environmental impacts through producers and consumers. *Science* **360**, 987–992 (2018).
54. Finkelstein, E. A. *et al.* A Randomized Controlled Trial Evaluating the Relative Effectiveness of the Multiple Traffic Light and Nutri-Score Front of Package Nutrition Labels. *Nutrients* **11**(9), 2236 (2019).
55. Egnell, M. *et al.* Compared to other front-of-pack nutrition labels, the Nutri-Score emerged as the most efficient to inform Swiss consumers on the nutritional quality of food products. *PLOS ONE* **15**, e0228179 (2020).
56. Egnell, M. *et al.* Consumers' Responses to Front-of-Pack Nutrition Labelling: Results from a Sample from The Netherlands. *Nutrients* **11**, 1817 (2019).
57. Medina-Molina, C. & Pérez-González, B. Nutritional labelling and purchase intention interaction of interpretative food labels with consumers' beliefs and decisions. *British Food Journal* **123**, 754–770 (2020).
58. Durcot, P. Impact of Different Front-of-Pack Nutrition Labels on Consumer Purchasing Intentions. *American Journal of Preventive Medicine* **50**(5), 627-636 (2016).
59. *National Food Strategy* (Dimbleby, H. 2021) <https://www.nationalfoodstrategy.org/the-report/>.
60. *Carbon valuation in UK policy appraisal: a revised approach* (Department of Energy & Climate Change, 2009) <https://www.gov.uk/government/publications/carbon-valuation-in-uk-policy-appraisal-a-revised-approach>.
61. *Health related taxes on food and beverages* (Cornelsen, L, Carriedo, A., 2015)
<https://foodresearch.org.uk/publications/health-related-taxes-on-food-and-beverages/>.
62. *Fiscal policies for diet and prevention of noncommunicable diseases: technical meeting report* (Waqanivalu, T., Nederveen, L., & World Health Organization., 2015)
<https://www.who.int/dietphysicalactivity/publications/fiscal-policies-diet-prevention/en/>.
63. *Taxes on Sugar-Sweetened Beverages*. (World Bank, 2020)
<https://openknowledge.worldbank.org/handle/10986/33969>.

64. Waterlander, W. E. *et al.* The effect of food price changes on consumer purchases: a randomised experiment. *The Lancet Public Health* **4**, e394–e405 (2019).
65. Wilcoxon, F. Individual Comparisons by Ranking Methods. *Biometrics Bulletin* **1**, 80–83 (1945).
66. Kruskal, W. H. & Wallis, W. A. Use of Ranks in One-Criterion Variance Analysis. *Journal of the American Statistical Association* **47**, 583–621 (1952).

Acknowledgements

M.F., C.L., C.A.C., N.B., X.Y., C.G. and I.J.B. gratefully acknowledge the funding provided for this research by the CUHK-Exeter Joint Centre for Environmental Sustainability and Resilience (ENSURE) Partnership (grant number 111240) and M.F. and I.J.B. are thankful for the support provided by the NERC-funded program SWEEP (grant number NE/P011217/1).

Author information

Affiliations

¹ Dr. Michela Faccioli (*corresponding author): Land, Environment, Economics and Policy Institute (LEEP), Department of Economics, University of Exeter Business School (UEBS), Xfi Building, Rennes Drive, Exeter, EX4 4PU, United Kingdom. Email: m.faccioli@exeter.ac.uk; ORCID: <https://orcid.org/0000-0002-8092-9105>

² Dr. Cherry Law: Population Health Innovation Lab, Department of Public Health, Environments and Society, London School of Hygiene and Tropical Medicine, Keppel St, London WC1E 7HT, United Kingdom. Email: cherry.law@lshtm.ac.uk; ORCID: <https://orcid.org/0000-0003-0686-1998>

³ Dr. Catherine A. Caine: Exeter University Law School, College of Social Sciences and International Studies, Amory Building, Exeter University, Rennes Drive, Exeter, EX4 4RJ, United Kingdom. Email: C.Caine@exeter.ac.uk ORCID: <https://orcid.org/0000-0001-6833-1007>

⁴ Dr. Nicolas Berger: Population Health Innovation Lab, Department of Public Health, Environments and Society, London School of Hygiene and Tropical Medicine, Keppel St, London WC1E 7HT, United Kingdom. Email: nicolas.berger@lshtm.ac.uk. Secondary affiliation: Department of Epidemiology and Public Health, Sciensano (Belgian Scientific Institute of Public Health), Rue Juliette Wytsman 14, 1050 Brussels, Belgium. Email: nicolas.berger@sciensano.be. ORCID: <http://orcid.org/0000-0002-4213-6040>

⁵ Dr. Xiaoyu Yan: University of Exeter, Environment and Sustainability Institute, Penryn, TR10 9FE, United Kingdom. Email: Xiaoyu.Yan@exeter.ac.uk ORCID: <https://orcid.org/0000-0003-3165-5870>

⁶ Federico Weninger: Boxergy Ltd, EI Incubation Centre, Appleton Tower, 11 Crichton Street, Edinburgh, EH8 9LE. Email: wenifede@gmail.com. ORCID: <https://orcid.org/0000-0002-7638-6187>

⁷ Dr. Cornelia Guell: European Centre for Environment and Human Health, University of Exeter Medical School, Knowledge Spa, Royal Cornwall Hospital, Truro, TR1 3HD, United Kingdom. Email: C.Guell@exeter.ac.uk. ORCID: <https://orcid.org/0000-0003-0105-410X>

⁸ Prof. Brett Day: Land, Environment, Economics and Policy Institute (LEEP), Department of Economics, University of Exeter Business School (UEBS), Xfi Building, Rennes Drive, Exeter, EX4 4PU, United Kingdom. Email: Brett.day@exeter.ac.uk. ORCID: <https://orcid.org/0000-0001-7519-5672>

⁹ Prof. Richard D. Smith: Executive Suite, University of Exeter Medical School, St Luke's Campus University of Exeter, Exeter, EX1 2LU, United Kingdom. Email: Rich.Smith@Exeter.ac.uk ORCID: <https://orcid.org/0000-0003-3837-6559>. Secondary affiliation: Faculty of Public Health and Policy, London School of Hygiene and Tropical Medicine, 15-17 Tavistock Place, London, WC1H 9SH, United Kingdom. Email: Richard.smith@lshtm.ac.uk

¹⁰ Prof. Ian J. Bateman: Land, Environment, Economics and Policy Institute (LEEP), Department of Economics, University of Exeter Business School (UEBS), Xfi Building, Rennes Drive, Exeter, EX4 4PU, United Kingdom. Email: I.Bateman@exeter.ac.uk. ORCID: <https://orcid.org/0000-0002-2791-6137>

Contributions

M.F., I.J.B., C.A.C., R.D.S., conceptualised the overarching research goals and aims; M.F., I.J.B., B.D., R.D.S., C.A.C., C.L., N.B., F.W., X.Y. conceptualised and developed the overall methodology for the research; M.F., C.A.C., C.G. and I.J.B. designed the survey, with support from C.L., N.B., F.W., X.Y., and R.D.S.; M.F., C.A.C., F.W. tested the survey; C.L., M.F., N.B. analysed the data; C.L., N.B., M.F., I.J.B. curated data visualisation; M.F. and C.A.C. coordinated and managed the project; I.J.B. and R.D.S. provided supervisory support; I.J.B., C.G. and C.A.C. secured the funding; M.F. wrote the first draft of the paper and C.A.C., I.J.B., R.D.S., C.L., N.B., X.Y., C.G., F.W., contributed with edits and revisions. All authors have approved the submitted version of the manuscript.

Corresponding author

Michela Faccioli | e-mail: m.faccioli@exeter.ac.uk

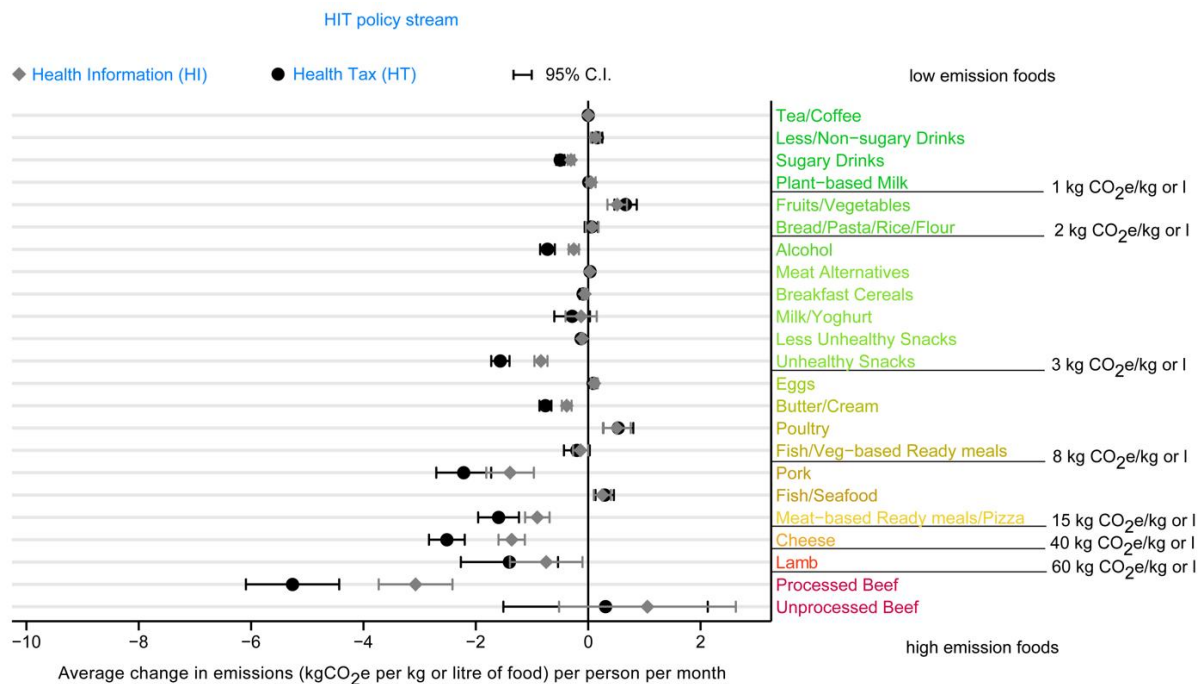
Ethics declaration

Competing Interests: We declare that none of the authors have competing financial or non-financial interests as defined by Nature Research.

Ethics approval:

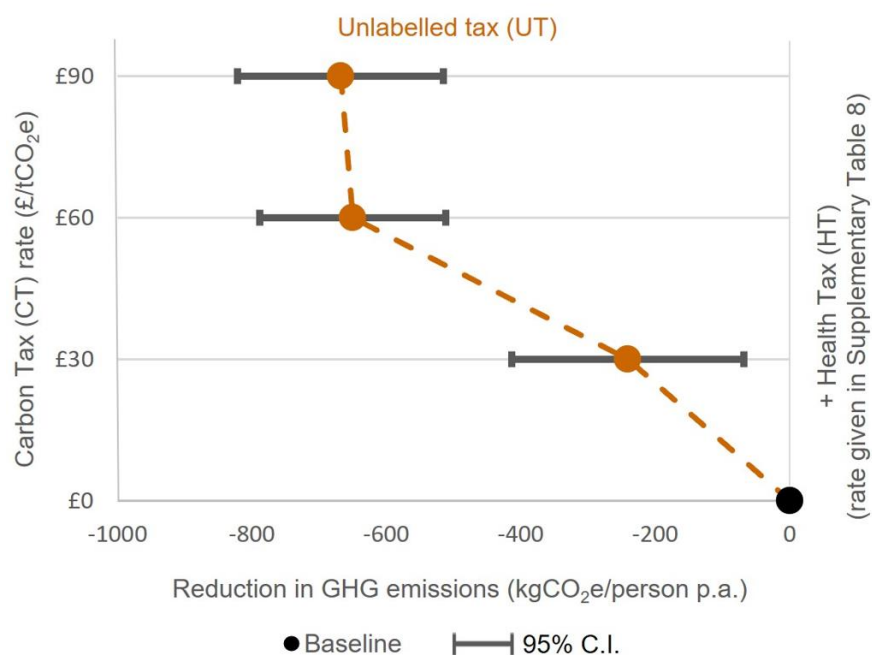
This project received approval from the University of Exeter Business School Research Ethics Committee, UK (reference number eUEBS002059 v6.0). We have obtained informed consent from all the participants in the research.

Extended Data Figure 1. Average change in per person monthly emissions (from the baseline) by food group in the Health Information and Tax (HIT) policy stream



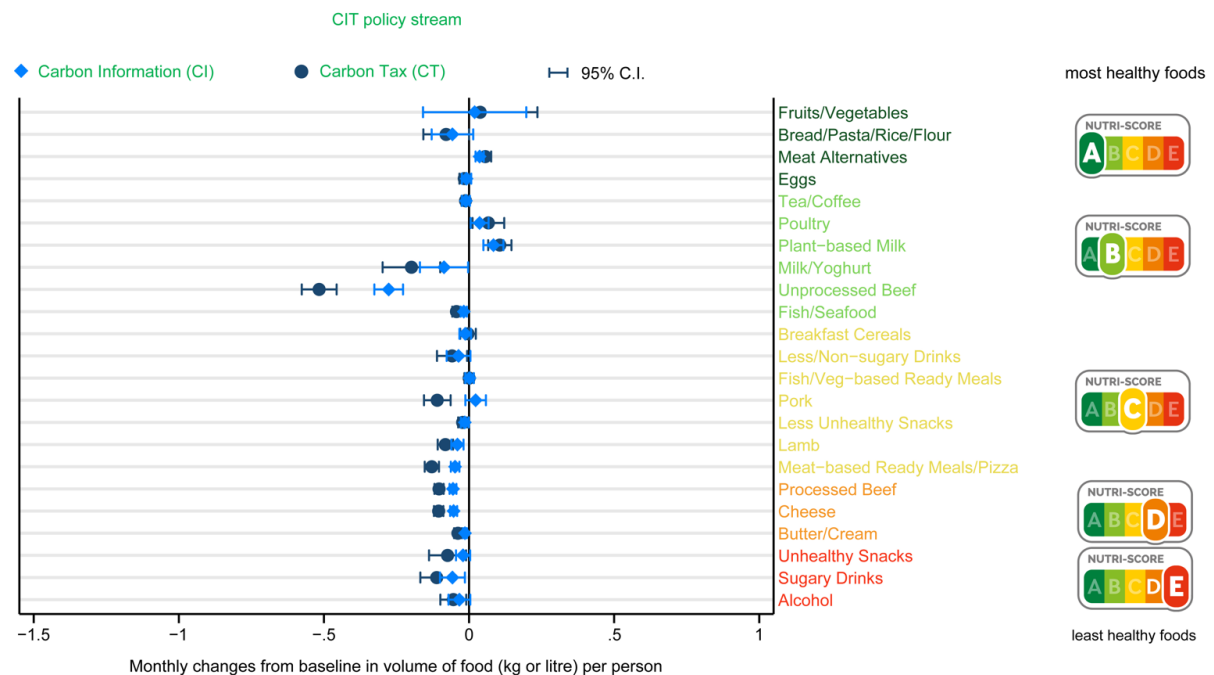
This figure refers to the average changes in per person monthly emissions (from the baseline) across respondents in the HIT policy stream. Food groups are ordered from low emission per kg or litre to high emission level per kg or litre. ◆ and ● indicate the average changes in per person monthly emissions (from the baseline) under the Health Information (HI) instrument and Health (Information and) Tax (HT) instrument, respectively. — shows the corresponding 95% confidence interval (C.I.), based on normality assumptions.

Extended Data Figure 2. Effects of different food tax rates on greenhouse gas emission reductions with the application of the Unlabelled Tax (UT) policy instrument



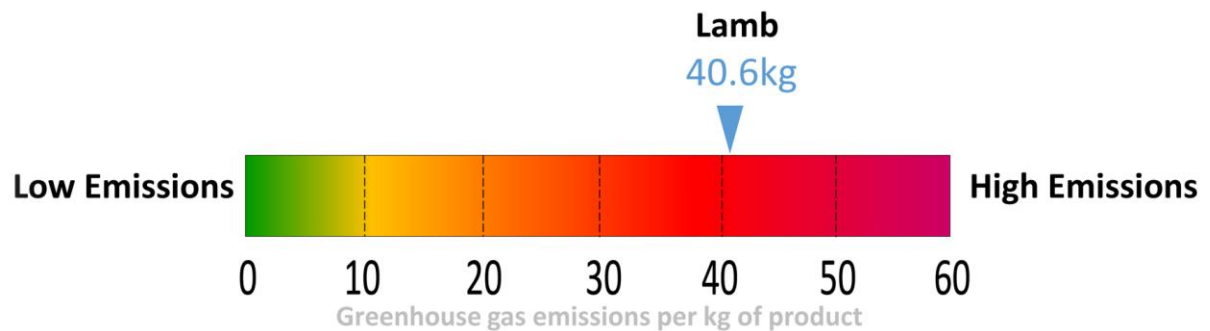
This figure shows the relationship between different tax rates and the resulting average reduction in greenhouse gas emissions with the application of the Unlabelled Tax (UT) policy instrument. ● indicates the baseline. Orange dots give the average reduction in emissions that would be achieved depending on the different tax rates used. For more information on the values employed for each tax rate, see Methods and footnote to Supplementary Table 8. — indicates the 95% Confidence Interval (C.I.), based on normality assumptions.

Extended Data Figure 3. Average change in the reported per person monthly volume (from the baseline) of the different food groups in the Carbon Information and Tax (CIT) policy stream



This figure refers to the average change in per person monthly volume purchases from the baseline by food groups for the Carbon Information and Tax (CIT) policy stream. Food groups are ordered based on their Nutri-Scores from A (Most Healthy) to E (Least Healthy). Light blue diamond and dark blue dot symbols indicate the average changes (from the baseline) in per person monthly volume of purchases with the application of the Carbon Information (CI) instrument and Carbon (Information and) Tax (CT) instrument, respectively. ┊ shows the corresponding 95% confidence interval (C.I.), based on normality assumptions.

Extended Data Figure 4. Example of the colour-coded indicator used in the survey to illustrate the level of greenhouse gas emissions associated with each food category



To illustrate the level of greenhouse gases associated with the production of each type of food we designed and used this colour-coded indicator. This is an example for lamb. The blue arrow shows that the production of 1kg of lamb generates 40.6kg of greenhouse gas emissions. The closer the blue arrow is to the right hand (red) end of the scale the higher the emissions. The closer the blue arrow is to the left hand (green) end of the scale the lower the emissions.

Extended Data Figure 5. Overview of the Nutri-Score possible categories



The following 'traffic light' indicator (called the "Nutri-Score") is a simple way to show the level of healthiness of different food categories, which we have used in the survey. Foods shown with a Green A or B are those generally recommended for a healthy diet. Foods labelled with an Orange D or Red E are those that should be eaten less often and in small amounts in order to have a healthy diet.