Essays on the Impact of Climate Change and Related Policies

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Introduction

The concentration of greenhouse gases in the atmosphere, as a result of the use on a large scale of fossil fuels, has been steadily increasing since the first industrial revolution (IPCC, 2021): as a direct consequence, temperatures are becoming warmer. At the global level, the average temperature between 2011 and 2020 has been more than 1°C higher than the pre-industrial level (IPCC, 2021). The year 2023 has set a new record for global temperatures[1] and 2024 is on track to follow suit as the summer has been the hottest on record[2]. The resulting impacts, both expected and already taking place, are manifold and they contribute to alter the equilibria of natural ecosystems, resulting in widespread deterioration (IPCC, 2022a). In addition to the impacts on natural systems, global warming is going to increasingly affect human societies and economies, in ways that are predominantly negative. The economic literature has devoted considerable effort in order to understand the magnitude of these impacts. At the macro level, results broadly point towards an inverted-U relationship between economic output and temperatures (e.g., Acevedo et al., 2020; Burke & Emerick, 2016; Burke et al., 2015; Dell et al., 2012), such that countries in cooler climates might benefit to some extent from warmer temperatures, but many other, mostly developing economies, will suffer. These findings have a parallel at the micro level. From a biologic perspective, heat is a source of stress for the human body: on the one hand, it affects health, through morbidity and mortality (Barreca et al., 2016; Carleton & Hsiang, 2016), and on the other, it affects labour productivity through impaired cognitive ability and absenteeism (Chen et al., 2018; Graff Zivin & Neidell, 2014; Zhao et al., 2021), especially in heat-exposed industries where activity takes places mainly outdoor or in facilities that are difficult to climate control. Evidence about the negative impact of temperatures is found also at the firm level (Pankratz et al., 2023; Pankratz & Schiller, 2024; Somanathan et al., 2021; Zhang et al., 2018), regardless of the sector. In agriculture, extreme temperatures are known to be damaging for crops (Gammans et al., 2017; Schauberger et al., 2017; Schlenker & Roberts, 2009), as well as for livestock (IPCC, 2022a). Importantly, future impacts are projected to be increasingly severe in the temperature anomaly. Therefore, the Paris Agreement advocates to keep the temperature increase "well below" 2°C while aiming for a 1.5°C target in order to "significantly reduce the risks and impacts of climate change."

In this context, the strategy to limit the impending damages from climate change develops along two dimensions: mitigation and adaptation. Mitigation refers to the set of initiatives aimed at limiting the temperature increase, by reducing future emissions of greenhouse gases (IPCC, 2012). Adaptation consists of the set of efforts aimed at reducing the vulnerability of human systems to the consequences

[1] https://climate.copernicus.eu/copernicus-2023-hottest-year-record

[2] https://climate.copernicus.eu/copernicus-summer-2024-hottest-record-globally-and-europe

of climate change (IPCC, 2022a). Given that mitigation goals begin with the intention to limit the temperature anomaly, adaptation becomes necessary to cope with unavoidable adverse impacts; at the same time, adaptation cannot completely offset the impacts of climate change. Mitigation and adaptation are thus two complementary aspects in the management of climate change. In order to ensure an effective transition to a low carbon economy, policy-makers need to implement the appropriate policy mix that is sustainable also from the social point of view.

This thesis has been developed within this framework. It takes the form of a collection of papers, some of which have arisen from the opportunities of working with more senior researchers that I have encountered during my career as a Ph.D. student. Each chapter discusses in a different setting the issue of climate change and how it affects the behaviour of firms and consumers, specifically through the perspective of adaptation efforts and mitigation policies.

The first chapter is titled "Climate change impacts and investments in adaptation in agricultural firms" and it has been the result of a joint work with Carlo Fezzi (University of Trento). The exposure of agriculture to climate change is well-known, as it has been extensively studied by economists (Dell et al., 2014). On the other hand, the extent to which farmers have been adapting, and the efficacy of these efforts, remain debated (Carter et al., 2018), due in part also to the lack of appropriate data. In this work, we focus on Italian farms as an interesting case study, since the country is expected to be particularly exposed to damages from increasing temperatures (Bozzola et al., 2018; Van Passel et al., 2017). Methodologically, our contribution to the literature is to propose an indirect approach in estimating the mediation between higher temperatures and crop yields resulting from the adaptation process. We study how investments are affected by an occurrence of heat that is abnormal with respect to the local historical climate distribution. Our approach stems from the observation that beliefs about climate change are affected by salience, under which striking events, such as extreme weather, are more likely to lead to a process of belief updating (e.g., Deryugina, 2013; Dessaint & Matray, 2017; Hoffmann et al., 2022). In order to understand if these investments are linked with he acquisition of technologies that help farmers to cope with higher temperatures, we look at how the uptake of irrigation systems changes after such events. Finally, we analyse how past exposure to heat shocks interacts with vulnerability to temperatures in the subsequent years, in order to quantify the increase in resilience of the production process due to implicit adaptation.

The second chapter shifts the focus to a different setting, namely the borrowing of firms on international financial markets. The work is titled "Corporate cost of debt in the low-carbon transition: The effect of climate policies on firm financing and investment through the banking channel" and it has been part of a joint project with Mauro Pisu (OECD Economics Department), Tobias Kruse (OECD Economics Department), and Filippo Maria D'Arcangelo (OECD Economics Department). This paper was developed during the period where I worked as an external consultant for the OECD Economics Department. In this article, we investigate to what extent investors in the syndicated loan market price transition risk, i.e., the loss in profitability that might affect more carbon intensive firms, for example due to changes in demand or competition from greener technologies (Giglio et al., 2021), as climate policies become increasingly stringent. The syndicated loan market is a setting of interest for different reasons: lenders are sophisticated investors that expend substantial resources in monitoring their clients (Gustafson et al., 2021) and therefore they are likely to be more sensitive to the presence of transition risk, while borrowers are large companies that have substantial environmental footprint, as well as the ability to reduce it. While climate policies provide the framework for the green transition, the allocation of the capitals needed for the adoption of greener technologies takes place in the financial markets. Hence, it is important to understand if investors, by pricing in the interest rates of loans the transition risk, provide the financial incentive for more polluting firms to decarbonize. In contrast to previous works that have focused on environmental performance (e.g., Bolton & Kacperczyk, 2021; Delis et al., 2019; Ehlers et al., 2022), we do not only measure the exposure to transition risk through the environmental performance of firms, but include the level of climate policy stringency in order to understand the interaction between policy framework and sustainability. Using the market-pull and technology-push framework (Jaffe et al., 2005), we consider emission pricing green technology support subsidies as channels of the effect of mitigation policy. In addition, we do not resort to a single indicator of environmental performance, but include two dimensions: emission intensity and patenting in mitigation technologies. Furthermore, we also investigate the role of ESG scores: they are commonly used by investors to assess the environmental sustainability of firms but often found to be inadequate (Boffo & Patalano, 2020).

The third and last chapter similarly investigates mitigation policies, while returning to the food sector. This work is coauthored with Michela Faccioli (University of Trento), Carlo Fezzi (University of Trento), and Ian J. Bateman (University of Exeter). The chapter is titled "The impact of carbon taxation and carbon labelling on greenhouse gas emissions and welfare in food demand." Food production and consumption have been estimated to account for more than a third of global greenhouse gas emissions (Crippa et al., 2021), but this sector has received so far less attention from policy-makers. From the demand side, it offers a large mitigation potential through changes in socio-cultural factors (IPCC, 2022b). To ensure this transition, different policy instruments are needed, ranging from 'hard' policies, such as taxation and regulation, to 'softer' ones, such as informational campaigns and information provision (European Commission, 2023; Willett et al., 2019). However, the optimal policy mix that can both deliver emission reduction and limit welfare loss from increased prices remains uncertain. In this work, we investigate the impact that demand management policies have on the carbon footprint of at-home food consumption of UK households. More specifically, we look at the introduction of a carbon tax and carbon labelling, both alone and combined. The advantage of carbon labelling is that it increases the salience of carbon content in food products, thus correcting misperceptions (Camilleri et al., 2019) and allowing consumers to make informed choices aligned with their preferences (Edenbrandt & Nordström, 2023). On the other hand, their effect in reducing the carbon footprint might be limited in magnitude (Taufique et al., 2022). Carbon pricing is a theoretically desirable intervention, since it allows consumers to internalize the cost of GHG emissions linked to their consumption (Baranzini et al., 2017), but it is difficult to introduce (Carattini et al., 2018) and possibly regressive (Klenert et al., 2023). The combination of the two instruments can thus alleviate the limitations of each, while preserving their benefits. Importantly, since these policies have not been yet been applied, we are able to study them through data that were collected in a survey-based randomized controlled experiment, where these policies were introduced as treatments (Faccioli et al., 2022).

Ultimately, this thesis aims to be a small contribution to our understanding of the interaction between climate change and the economy in a way that can help the design of policies to tackle the current climate crisis. In this perspective, the first chapter looks at direct damages and efforts to adapt to new climatological conditions in order to understand the extent of the vulnerability of firms in the agricultural sector, and in turn the need for policy-makers to intervene in this sector. The second chapter investigates the indirect effects of climate policies that can accelerate the green transition, by considering the role of the syndicated loan market in aligning economic incentives for firms to decarbonize through the pricing of their transition risk in the lending conditions. The third chapter concludes this thesis and it focuses on the design of a policy mix that addresses the carbon content of food consumption in order to reduce the footprint of the sector while limiting the welfare impact for consumers.

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Climate change impacts and investments in adaptation in agricultural firms

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Abstract

The exposure of agriculture to climate change is well-known, but the extent to which farmers have been adapting to it remains debated. In order to investigate this aspect, we study a panel of Italian farms between 2011 and 2021 using granular information about their balance sheets matched with local weather realizations. First, we find that heat during the growing season has a significant adverse effect on output. Then, we investigate if exposure to unexpected weather shocks induces investments, which is consistent with a process of belief updating and adaptation to extreme temperatures. We find that investment in tangible assets, both on the extensive and the intensive margin, increases after a temperature shock. Furthermore, we find an increase in the adoption of irrigation systems following such shocks. Finally, we find that farmers exposed to past shocks are less vulnerable to higher temperatures, with a reduction in the adverse impact that we estimate to be about 60%. We interpret these results as evidence that farmers are responding to growing temperature by updating their beliefs about climate change, and, accordingly, investing in adaptation technologies such as irrigation.

1 Introduction

Weather variables, such as temperature and rainfall, play a fundamental role in determining plant health and growth, thus affecting crop yields. For this reason, the impact of climate change on the agricultural sector has been the focus of extensive attention in the economic literature: the global increase in temperatures, both in global averages and extreme phenomena, is projected to cause substantial losses in crop yields (Auffhammer, 2018; Carter et al., 2018; Gammans et al., 2017; IPCC, 2022; Schauberger et al., 2017; Schlenker & Roberts, 2009; Wing et al., 2021). At the same time, the net impact of global warming on agriculture depends also on adaptation efforts, which can counterbalance the decrease in productivity, to an extent that remains debated: the study of adaptation has been approached from different perspectives, which have yielded different conclusions about its effectiveness (Carter et al., 2018). In the Ricardian approach (Mendelsohn et al., 1994), farms are taken to be perfectly adapted to the climate specific to their location and therefore the estimated temperature-land value relationship is already accounting for the optimal response by farmers (Auffhammer, 2018; Mendelsohn et al., 1994). Reviewing studies that use this approach, Mendelsohn and Massetti (2017) report that a 2°C warming scenario would entail a reduction between 8 and 12% in net farm revenues, at the global level. However, this approach has been criticized as vulnerable to omitted variable bias, since it is inherently cross-sectional (Deschênes & Greenstone, 2007). This concern has spurred the panel approach, which is able to control for time-invariant determinants of output by considering within-unit variation (Carter et al., 2018). However, its strength has been also argued to be its main drawback: by relying on yearly variation, the estimated relationship is short-term in nature and thus not able to consider longer-term adaptation (Fisher et al., 2012). As a response, the panel approach has led to long differences (Burke & Emerick, 2016), by which the relationship between weather and crop yields is allowed to vary over decades. Results from this approach do not suggest a very large extent of adaptation (Burke & Emerick, 2016; Wing et al., 2021). More recent approaches attempt to account for adaptation in panel data through parametric solutions, such as decomposing the variation in the weather between yearly shocks and climate (Mérel & Gammans, 2021; Quddoos et al., 2022; Zeilinger et al., 2022), comparing different fixed effects structures (Huang & Sim, 2021), or correcting for selection bias (Asmare et al., 2022). Another strand of the literature looks explicitly at adaptation efforts, obtained for instance through surveys (Aragón et al., 2021; Di Falco et al., 2011).

A second question that follows the efficacy of adaptation is the determinants of the willingness to uptake this set of measures. Recent work has shown that salient climate events may lead individuals to change their beliefs about climate change (e.g., Deryugina, 2013; Dessaint & Matray, 2017; Hoffmann et al., 2022). Benincasa et al. (2024) find that extreme weather increases the probability for firms to invest in climate-friendly measures, which they explain as a consequence of heightened environmental awareness. Pankratz and Schiller (2024) report that climate shocks to supplier firms that exceed customers' expectations make more likely for the supply-chain relationship to terminate. Similar results have been found for farmers, who take their business decisions, such as acreage and crop choices, taking into account recent salient shocks (Ji & Cobourn, 2021; Wilke & Morton, 2017). Other kinds of adaptation include crop choice, which depends on weather expectations that are in turn affected by weather patterns (Ji & Cobourn, 2021; Ramsey et al., 2021), and adjustments in variable inputs, such as fertilizers (Wimmer et al., 2024). In addition, firms can innovate, for example by patenting new technologies or introducing new varieties, in response to weather variability (Auci et al., 2021) or exposure to damaging temperatures (Moscona & Sastry, 2023), or choose different forms of irrigation systems (Fabri et al., 2024).

The purpose of this article is to investigate if Italian farmers are investing in adaptation measures, and to what extent these efforts have been effective in moderating the impact of higher temperatures on output. Among European countries, Italy is predicted to be among those more exposed to damages from increasing temperatures (Van Passel et al., 2017), especially in Southern regions (Bozzola et al., 2018). Our work stems from the panel approach in agricultural economics (Auffhammer, 2018), since we investigate behaviour directly at the farm level over time. We extend this model by allowing farmers to adapt to a changing environment: in this way, we provide evidence to bridge the gap from short-term vulnerability to long-term adaptation. In order to do so, we proceed in the following way. First, we look at the temperature-output relationship: our results, in line with the literature, indicate that higher temperatures during the growing season decrease firm revenues. In turn, this finding suggests that expectations about a warming climate might prompt farmers to invest in adaptation. Therefore, we look at the role of temperature shocks that are abnormal relatively to the farms' local climate distribution as computed from historical data. We find that unexpectedly large shocks significantly increase investments in tangible assets, both on the extensive and the intensive margin. By considering a particular form of adaptation, i.e., the adoption of irrigation systems, we find that farmers are more likely to be install this type of equipment after a shock. Finally, we provide an estimation of the effectiveness of adaptation. First, by estimating a reduced form model where we proxy investments with past exposure to temperature shocks we find a substantial reduction in the impact of high temperatures, by about 60%. Second, we plug predicted cumulated investments directly into the regression equation and we find similarly a sizeable reduction in vulnerability as firms acquire more capital following temperature shocks.

Taken together, our results suggest that adaptation is an ongoing process among Italian farms. By not taking this process into account, a naive panel approach would average the heterogeneity of impact between adapted farms and non-adapted ones, therefore being unable to capture the true relationship between temperature and agricultural output. At the same time, the cross-sectional Ricardian approach is unable to distinguish farms that may be exposed to similar climatic conditions, but with different levels of adaptation driven by past shocks. Finally, our work proposes a new avenue for gauging evidence of adaptation efforts, without access to specific qualitative information.

The rest of the paper proceeds as follows. Section 2 describes the data used in the analysis. Section 3 discusses the empirical strategy. Section 4 presents the descriptive statistics. Section 5 reports the results.

2 Data

In order to study the impact of weather and extreme temperature on firms' behavior, we combine different panel datasets at different spatial levels: financial information at the firm level, gridded weather information, and gridded points about the presence of irrigation systems.

2.1 Financial information

We obtain firm data from Bureau van Dijk's AIDA ("Analisi informatizzata delle Aziende Italian", Italian company information and business intelligence) dataset, which corresponds to the Italian subdivision of the larger ORBIS database. AIDA contains balance sheet data of Italian corporations ("Società di capitali"), which are required by law to deliver their balance sheets to the local chambers of commerce. We obtain from AIDA the complete balance sheets, allowing us to observe detailed financial information. The dataset contains the municipality where the firms' headquarters are located, allowing us to match each firm with the actual weather conditions they were exposed to. We consider only firms belonging to the agricultural sector defined under the NACE Rev. 2 code 011 ("Growing of non-perennial crops") and 012 ("Growing of perennial crops"). ORBIS data are widely used in the economic literature, but they require extensive data cleaning: we follow the steps suggested by Kalemli-Ozcan et al. (2015); further details can be found in Appendix A. As a measure of firm output, we collect data for sales revenues ("Ricavi vendite e prestazioni"), which importantly does not include insurance payments and subsidies. Then, we correct this variable by changes in inventories ("Variazione rimanenze prodotti") since these have been shown to affect the former as a mechanism to attenuate weather shocks (Roberts & Schlenker, 2013). We also derive information about firms' investments, which we compute as the variation in assets (total, tangible, and intangible), plus the depreciation[3]. We collect information about 9,160 farms, observed between 2011 and 2021.

2.2 Weather data

We employ ERA 5 Land (Muñoz-Sabater et al., 2021) as our main dataset to derive firm exposure to weather realizations. ERA 5 Land belongs to the fifth generation of the European ReAnalysis (ERA) family of datasets, which have been extensively used for economic applications (Holtermann, 2020; Kotz et al., 2022; Pankratz & Schiller, 2024). These data are produced by the European Centre for Medium-Range Weather Forecasts in the framework of the Copernicus Climate Change Service of the European Commission. From a technical point of view, reanalysis data are generated by combining real observations with climatic models in order to produce a globally complete and consistent dataset. In this way, ERA 5 Land is able to provide time series beginning in 1950 of a wide range of meteorological variables at an hourly frequency and it offers a highly granular spatial resolution of about 0.1° (9×9 km). Such precise spatial resolution makes ERA 5 Land particularly desirable for our application for a practical reason, since we use their reported municipality in order to locate the firms in the sample. We match weather data and farms at the municipality level and we interpolate weather data using areal weights, i.e., by the surface of each grid square inside the municipality: the high spatial resolution

[3]This is a straightforward extension of the Perpetual Inventory Method, see for example Gal (2013).

allows us to retain substantial variation in weather shocks between units[4]. We further refine the precision of the interpolation by considering only agricultural areas within the municipalities, obtained from the Coordination of Information on the Environment (CORINE) Land Cover dataset (Büttner, 2014). The CORINE program is an initiative of the European Union aimed at collecting information about land cover and land use in Europe, grouped into 44 classes. The spatial resolution of the dataset is 100 metres, although only areas with an extension of at least 25 hectares are mapped. Specifically, we employ the 2012 version, which is the closest to the first year of our firm-level dataset. We define as agricultural areas the following land typologies: non-irrigated arable land, permanently irrigated land, rice fields, vineyards, fruit trees and berry plantations, olive groves, annual crops associated with permanent crops, complex cultivation patterns, land principally occupied by agriculture with significant areas of natural vegetation, and agro-forestry areas.

2.3 Irrigation data

In order to investigate the mechanisms behind firms' investments, we focus on the adoption of irrigation systems, since it is one of the most important practices that can help plants resist increasing temperatures (Auffhammer, 2018; IPCC, 2022; Schauberger et al., 2017; Schlenker et al., 2005; Wing et al., 2021). Since this information is not available in the AIDA dataset, we obtain it separately from the Land Use/Cover Area frame Survey (LUCAS) (d'Andrimont et al., 2020), which is produced by the European Union. The dataset is composed by *in situ* observations by surveyors, who periodically visit predefined locations and report the land use and cover of the particular point. The data are collected in two phases. In the first phase, a 2 km grid of evenly spaced points is defined and classified into broad classes based on orthophotos or satellite imagery. In the second phase, a sample is extracted for field visit or, in the case of accessibility difficulties, further photointerpretation. In this phase more detailed information, including the presence and type of irrigation are collected. About one third of the original points are thus further investigated. In order to understand the drivers of the adoption of irrigation systems, we create a dummy variable which is equal to 1 if for a given point any form of water management is reported (namely, any one of irrigation, i.e., if an irrigation system is present, potential irrigation, i.e., if the field is not currently irrigated but will be during the year, or has been in the previous years, and irrigation and drainage). The waves of the survey that we consider are 2009, 2012, 2015, 2018 and we retain those points that are classified as cropland and destined to agricultural production. We merge these points at the municipal level in order to match weather information.

[4] On average, Italian municipalities have an extension of 38 km^2, meaning that even though we observe the municipality rather than the exact position of a farm, we are not losing an excessive amount of information by aggregating weather variables at the municipal level.

3 Empirical approach

3.1 The impact of temperatures on production

We investigate the impact of temperatures on farms' revenues. Considering revenues rather than yields allows us to capture the substitution between crops that is endogenous to climatic conditions (Deschênes & Greenstone, 2007). Our specification is grounded in the panel approach, since we exploit within farm variation. Following Schlenker and Roberts (2009), we model exposure to temperatures during the growing season through 5-degrees-wide temperature bins which measure the number of hours h, spent by farm i, in temperature range k between March and September of year t:

$$T_{it}^{k} = \sum_{h} \mathbf{1}\left[\tau_h \in k\right], \tag{1}$$

where

$$k \in \{(-\infty, 0)[0, 4), [4, 9), [9, 14), [14, 19), [19, 24), [24, 29), [29, 3), [34, \infty)\}. \tag{2}$$

Our baseline specification is the following:

$$y_{it} = \sum_{k} \beta^{k} T_{it}^{k} + \gamma_1 rain_{it} + \gamma_2 rain_{it} + \alpha_i + \delta_t^{p} + \epsilon_{it}, \tag{3}$$

where y_{it} are revenues adjusted by the change in inventories for firm i in year t. More specifically, we use the semilog specification in order to account for the skewed distribution of the dependent variable (Schlenker et al., 2006). T_{it}^{k} are the temperature bins that measure firm i's exposure to temperatures during the growing season. Coefficients β^{k} indicate the net effect of substituting the exposure to reference bin $k^{R} = [19, 24)$ with temperature bin k. We include the total amount of rainfall during the growing season as a second-degree polynomial. α_i is the firm-specific fixed effect, which we include to control for time invariant unobserved confounders, such as land quality and farmer's characteristics, and δ_t^{p} are year-by-province fixed effects, that absorb area and time specific shocks, such the prices of local markets and farmers' expectations, which we assume to be homogeneous within that area (Ji & Cobourn, 2021). Following Zeilinger et al. (2022) we cluster standard errors at a radius of 25 km (Conley, 1999) in order to account for spatial correlation[5].

[5]Results do not change substantially when clustering by municipality.

3.2 The impact of temperature shocks on investments

We investigate whether past exposure to temperature shocks makes it more likely for a farmer to carry out investments in equipment and technologies to better cope with future higher temperatures. Similarly to Pankratz and Schiller (2024), we define a temperature shock using a local threshold in order to account for geographical differences in expectations about temperature realizations and current practices. We define expected temperatures as the average number of hours $\bar{T}_i^{34+}$ during the growing season with temperatures higher than 34°C between 1981 and 2000. We choose temperatures larger than 34°C since they are increasingly harmful for plant health (Gammans et al., 2017; Schauberger et al., 2017; Schlenker & Roberts, 2009). Then, we define a shock as a binary variable which is equal to 1 if the number of hours in the $T \geq 34$°C bin for a given year t in farm i is larger than 3 times its standard deviations:

$$shock_{it}^{34+} = \mathbf{1}[T_{it}^{34+} - \bar{T}_{it}^{34+} > 3\sigma_i^{34+}]. \tag{4}$$

In practice, $shock_{it}^{34+}$ is a binary variable that indicates an unexpectedly warm year, in comparison to the local climate distribution. We study its impact on the extensive and the intensive margin of investments:

$$i_{it} = \sum_j \phi_j shock_{i,t-j}^{34+} + \alpha_i + \delta_t^p + \epsilon_{it}, \tag{5}$$

where i_{it} is a measure of investments. We study two sets of measures of firm investments, in terms of extensive and intensive margin. In the case of the extensive margin, we obtain a binary variable that is equal to 1 if the firm has positive investments a given year, and 0 otherwise[6]. Since the variation in assets can be very low in absolute terms, and therefore unlikely to constitute a type of investment that is relevant for our research question, we also consider variations in assets larger than a relative threshold, i.e., 5 or 10% of assets of that particular type in the previous year. In the case of the intensive margin of investments, we consider two variables: either the logarithm of 1 plus the actual value of the variation in assets, censored at zero, or the investment rate defined as the variation in assets divided by the value of that particular type of assets during the previous year. In order to exclude outliers, we drop observations with investment rate below (above) the 1st (99th) percentile. After testing the lag structure, we include the contemporaneous shock and its lagged value. We include as controls farm and year-by-province fixed effects. In our baseline specification, we do not add any covariate in order to have a clean interpretation of

[6]We use a linear probability model since due to the large number of fixed effects we might incur in the incidental parameter problem.

the estimated coefficients, but results are robust to the inclusion of weather and firm-level controls[7]. In our main specification, we look at investments in tangible fixed assets, which include land, buildings, plants and machinery, and therefore the acquisition of adaptation technologies, such as irrigation equipment, will be reported in this category. As a placebo test, we also look at investments in intangibles, e.g., patents and intellectual property rights, which we do not expect to be affected in the same way.

3.3 Uptake of irrigation systems

In order to understand how farmers might invest in adaptation measures following a climate shock, we investigate whether irrigation systems are more likely to be present in an agricultural field after an unexpected shock as defined above. We estimate the following regression:

$$Irrigation_{lt} = \sum_j \phi_j shock^{34+}_{l,t-j} + \alpha_l + \delta_t + \epsilon_{lt} \tag{6}$$

where $Irrigation_{it}$ is a dummy variable taking the value of 1 if unit l, i.e., the survey point as discussed in Section 2.3, is reported to have a water management system. In order to account for location specific unobservables and time shocks we include point and year fixed effects. Results remain qualitatively similar when including both year × province fixed effects and weather covariates.

3.4 The effect of adaptation

Since investments are likely to contribute to firm's operations throughout time, we do not measure exposure to shocks as above through yearly observations. Therefore, in order to understand the effectiveness of the adaptation efforts, we define a variable S_{it} that captures exposure to past shocks. This variable is defined as the moving average of past single shocks $shock^{34+}_t$ over time horizon p:

$$S_{it} = \frac{1}{p} \sum_{j=t-p}^{t-1} shock^{34+}_{ij}. \tag{7}$$

In this way, the current implicit stock of investments in adaptation measures is a function of multiple periods. In our estimates, we compare the results for different time horizons ranging from $p = 3$ to $p = 9$, in order to account for different possible dynamics in the process of acquiring capital by farmers. We then modify Equation 3 by interacting variable S_{it} with the $T \geq 34$°C bin, so that the sum of coefficients $\beta^{34+} + \omega_1$ indicates the net, mitigated effect of higher temperatures on revenues.

[7]Following the literature about firms' investments, in the robustness checks we include cashflow ratio, sales growth, EBIT to assets ratio, tangibility, and total assets (e.g., Bai et al., 2020; Bond et al., 2003). Results are reported in Appendix B, Tables B1 and B2.

$$y_{it} = \sum_k \beta^k T_{it}^k + \omega_1 S_{it} T_{it}^{34+} + \omega_2 S_{it} + \gamma_1 rain_{it} + \gamma_2 rain_{it} + \alpha_i + \delta_t^p + \epsilon_{it}, \tag{8}$$

In addition, we estimate the effect of adaptation using predicted investments in an approach based on the control function method (Wooldridge, 2015). We include investments in tangible assets directly into Equation 3 in a two-step process. In the first step, we estimate the effect of temperature shocks on different measures of investments in tangible assets (Equation 5). In the second step, we obtain the predicted investments by multiplying the estimated coefficients for the number of shocks a firm was exposed to and cumulating them over time. We do this at the municipality level in order to avoid any bias from panel attrition. In this way, we obtain a measure of investments that is exogenous to time-varying firm specific unobservables. We estimate the following regression specification:

$$y_{it} = \sum_k \beta^k T_{it}^k + \pi_1 \hat{i}_{it} T_{it}^{34+} + \pi_2 \hat{i}_{it} + \gamma_1 rain_{it} + \gamma_2 rain_{it} + \alpha_i + \delta_t^p + \epsilon_{it}. \tag{9}$$

As in Equation 8, the sum of coefficients $\beta^{34+} + \pi_1$ indicates the mitigated effect of very high temperatures, through the investment in tangible assets explained by past temperature shocks.

4 Descriptive statistics

Our final dataset is an unbalanced panel made up by 9,160 firms, observed between 2011 and 2021. Table 1 presents the descriptive statistic of the meteorological variables. The average temperature during the growing season is 18.79°C with a rainfall of 47 cm. In our period of analysis, 19% of the farms are exposed to a temperature shock as described above. The most frequent temperature bin is the one that ranges from 19 to 24°C, accounting on average for almost 27% of the time spent by farms in the growing season.

Table 2 presents descriptive statistics of firms' variables. The median value of production amounts to €161,777 and the median farm has a value of assets of €993,576; the ratio of tangible to total fixed assets is reaches 86% on average. Investment is common among farms, with 66% of observations reporting a positive change in tangible fixed asset. Large investments are however less frequent: for instance, changes above 5% of previous year's value of tangible fixed assets takes place in 36% of observations. Finally, irrigation equipment is observed at 27% of survey points.

Table 1: Summary statistics for meteorological variables

Variable	min	mean	median	max	s.d.	N
Temperature	3.39	18.79	18.96	22.67	1.89	55,379
Rainfall	0.05	0.47	0.45	2.31	0.22	55,379
$shock^{34+}$	0.00	0.19	0.00	1.00	0.40	52,763
Temperature bins						
T < 0	0.00	17.62	0.04	1683.95	73.01	55,379
T ∈ [0, 4)	0.00	81.05	52.37	1350.92	104.37	55,379
T ∈ [4, 9)	0.00	372.34	381.23	1738.00	185.35	55,379
T ∈ [9, 14)	414.00	858.73	847.57	1850.00	143.87	55,379
T ∈ [14, 19)	119.99	1180.65	1156.87	2190.35	189.81	55,379
T ∈ [19, 24)	1.41	1377.55	1374.03	2362.20	218.00	55,379
T ∈ [24, 29)	0.00	899.71	892.79	1965.00	262.56	55,379
T ∈ [29, 33)	0.00	311.22	312.00	797.55	174.15	55,379
T ≥> 34	0.00	37.13	11.43	443.25	61.47	55,379

This table contains descriptive statistics for the meteorological variables in the dataset. All variables refer to the growing season, considered from March to September. *Temperature* indicates the average temperature. *Rainfall* indicates the total rainfall in metres. $shock^{34+}$ indicates the occurrence of a high temperature shock as defined in the text. The remaining variables are temperature bins expressed in hours. All variables are at municipal level.

Table 2: Summary statistics of firm variables and irrigation data

Variable	min	mean	median	max	s.d.	N
Cashflow ratio[1]	-0.56	0.03	0.02	0.57	0.12	45775
Sales growth[1]	-0.86	0.24	0.02	8.28	1.10	45775
EBIT to assets ratio[1]	-0.61	0.01	0.01	0.56	0.12	45775
Tangibility	0.00	0.90	0.99	1.00	0.21	45775
Total assets	6.96	13.84	13.92	19.93	1.68	45775
$I_{Tangibles}$	-25236.24	136.32	5.39	349346.65	1849.26	45775
$I_{Intangibles}$	-7445.27	16.82	0.00	88041.80	519.54	45775
$i_{Tangibles}$	0.00	0.69	1.00	1.00	0.46	45775
$i_{Tangibles,>5\%}$	0.00	0.35	0.00	1.00	0.48	45775
$i_{Tangibles,>10\%}$	0.00	0.26	0.00	1.00	0.44	45775
$i_{Intangibles}$	0.00	0.27	0.00	1.00	0.44	45775
$i_{Intangibles,>5\%}$	0.00	0.23	0.00	1.00	0.42	45775
$i_{Intangibles,>10\%}$	0.00	0.20	0.00	1.00	0.40	45775
Investment rate (Tangibles)[1]	-0.58	0.19	0.01	7.00	0.61	45775
Investment rate (Intangibles)[1]	-1.00	0.72	0.00	24.69	3.15	45775
Irrigation	0.00	0.27	0.00	1.00	0.44	34,845

[1]Winsorized between 1 and 99%.

This table reports the descriptive statistics of firm specific variables, and the presence of irrigation systems, which is matched at the municipal level (see Section 2.3 for further details). *Value of production* is the logarithm of firm sales revenues adjusted by the change in inventories. *Cash flow ratio* is the cash flow divided by lagged total assets. *Sales growth* indicates the growth rate of firm revenues. *Tangibility* is the ratio of tangible assets to total fixed assets. *EBIT to assets ratio* is the EBIT (operating margin) divided by lagged assets. *Total assets* is the logarithm of the total assets of the firm. $i_{Tangibles}$ and $i_{Intangibles}$ are binary variables equal to 1 if the firm reports a positive change in tangible or intangible fixed assets larger than €1. $i_{X,>5\%}$ and $i_{X,>10\%}$ are binary variables equal to 1 if the firm reports a positive change, in either tangible or intangible assets, larger than respectively 5 or 10% of that particular type of assets. $I_{Tangibles}$ and $I_{Intangibles}$ report the variation in tangible assets or intangible assets plus the depreciation in thousands of euros. *Investment rate (Tangibles)* and *Investment rate (Intangibles)* report the ratio of investments in tangible (intangible) to the lag of tangible (intangible) fixed assets. *Irrigation* is a binary variable equal to 1 if in the surveyed location is present an irrigation system.

5 Results

5.1 Impact of temperatures on output

Table 3 reports the results of regressing the logarithm of net revenues on different measures of temperature, i.e., temperature bins and a polynomial of second order of average temperature, and precipitation. Columns 1 to 4 model the impact of temperature through temperature bins. First, we estimate a pooled OLS regression (Column 1), which does not take into account the panel structure of our data: the coefficient of top temperature bin $T \geq 34$ is positive and significant, suggesting that there is unobserved heterogeneity introducing bias in the estimated parameters. Once we introduce farm fixed effects (Column 2), thus controlling for firm-level time invariant variables, our results indicate that temperatures away from the reference bin have a negative effect, in a similar fashion to the concave effect of temperatures that is usually found in the agroeconomic literature. With the addition of time fixed effects (Column 3), the inverted-U shaped relationship between output and temperatures becomes more evident and the impact of very high temperature is negative and significant. In Column 4, our preferred specification, we introduce year-province fixed effects, which control for location specific idiosyncratic shocks, that may correlate with weather realizations: an example might be prices in the local markets, that influence the use of inputs or the value of outputs. However, the robustness of the identification comes at the cost of larger standard errors. Figure 1 displays the estimated temperature-revenues relationship for this specification: additional 10 hours with temperature between 24 and 29°C lead to a change in output of about -0.16%; the figure for the 29-34°C temperature bin is similar (-0.13%), but not statistically significant, while for very high temperatures, i.e., above 34°C, the decrease is as large as 0.40%. The impact of this bin nearly doubles in comparison with the model in Column 3, indicating that omitted variables are producing a downward bias in the magnitude of the effect. On the other hand, we do not find a significant impact of rainfall on firm production, albeit the signs of the coefficients suggest an inverted-U shape. Column 5 and 6 report the estimation of a more parsimonious model, where temperature enters the regression specification as a polynomial of second degree. Similarly to our temperature bins specification, we find a concave relationship between average temperature and net revenues that peaks between 15 and 17°C, depending on the model. At the same time, we find again that the inclusion of the more granular year $\times$ province fixed effects leads to a stronger, negative effect as the average temperature moves away from the stationary point of the quadratic curve.

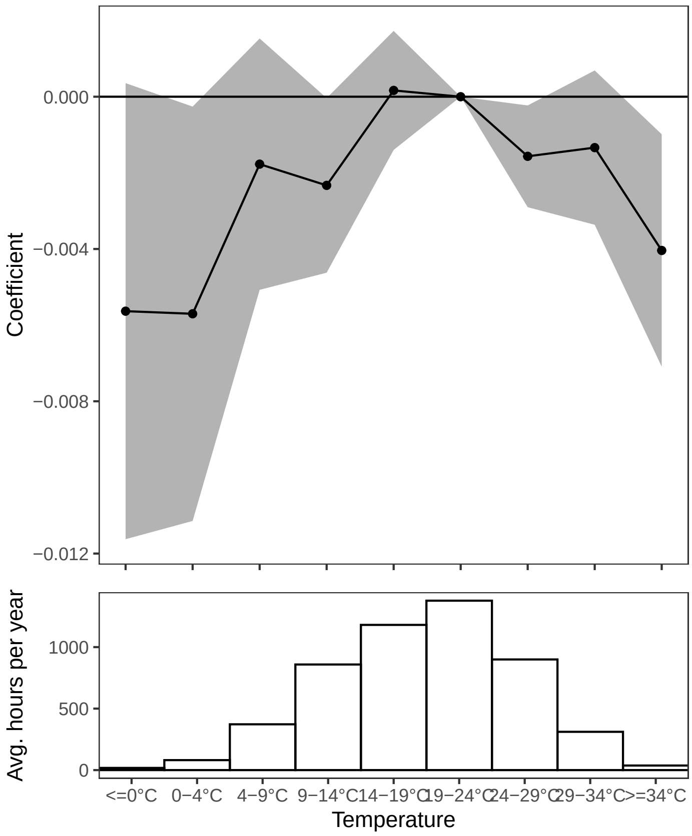
Table 3: The effect of temperature on agricultural production

Dep. Var.:	Net revenues					
	Temperature bins				Temperature polynomial	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
(Intercept)	11.65***					
	(0.8190)					
T < 0	-0.0080	0.0029*	0.0009	-0.0056		
	(0.0075)	(0.0017)	(0.0017)	(0.0036)		
T ∈ [0, 3)	0.0157*	-0.0002	-0.0017	-0.0057*		
	(0.0083)	(0.0011)	(0.0014)	(0.0033)		
T ∈ [4, 9)	-0.0055*	-0.0015**	-0.0009	-0.0018		
	(0.0029)	(0.0006)	(0.0008)	(0.0020)		
T ∈ [9, 14)	0.0006	-0.0010***	-0.0018***	-0.0023*		
	(0.0024)	(0.0003)	(0.0007)	(0.0014)		
T ∈ [14, 19)	0.0003	-0.0024***	-0.0012*	0.0002		
	(0.0031)	(0.0005)	(0.0006)	(0.0009)		
T ∈ [24, 29)	0.0046	0.0002	-0.0012*	-0.0016*		
	(0.0032)	(0.0006)	(0.0006)	(0.0008)		
T ∈ [29, 34)	-0.0049	-0.0016***	-0.0018***	-0.0013		
	(0.0030)	(0.0005)	(0.0007)	(0.0012)		
T ≥ 34	0.0077*	-0.0003	-0.0021**	-0.0040**		
	(0.0046)	(0.0010)	(0.0009)	(0.0018)		
Rain	-0.0019	-0.1941*	-0.1784	0.1141	-0.1986*	0.1245
	(0.6106)	(0.1090)	(0.1187)	(0.2594)	(0.1073)	(0.2524)
Rain^2	0.3114	0.0677	0.1094	-0.2163	0.1169	-0.2225
	(0.4635)	(0.0887)	(0.0924)	(0.1697)	(0.0865)	(0.1663)
T mean					0.1166*	0.2085*
					(0.0617)	(0.1198)
T mean^2					-0.0036**	-0.0069**
					(0.0016)	(0.0029)
Fixed-effects						
Firm		Yes	Yes	Yes	Yes	Yes
Year			Yes		Yes	
Year-province				Yes		Yes
Fit statistics						
Observations	55,379	55,379	55,379	55,379	55,379	55,379
Adjusted R^2	0.0045	0.9026	0.9030	0.9036	0.9030	0.9036
Within Adjusted R^2		0.0034	0.0004	0.0002	0.0001	0.0001
Std. Dev. y	1.943	1.943	1.943	1.943	1.943	1.943

Conley (25km) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

This table reports the estimated coefficients of Equation 3. The dependent variable is the logarithm of net revenues, obtained by subtracting the variation in inventories to sales revenues. Variables $T < 0$ through $T \geq 34$ are temperature bins, indicating the number of hours spent within the particular temperature range during the growing season; they are divided by ten for readability. Rain is the amount of rainfall during the growing season. *T mean* is the average growing season temperature.

Figure 1: The effect of temperature on agricultural production



This figure reports the estimated coefficients of Equation 3 (top panel). The shaded area indicates the 90% confidence interval. The bottom panel reports the average distribution of temperatures in the sample.

5.2 Impact of temperature shocks on investments

We next look at the impact of unexpected temperature shocks on investments. Table 4 presents the results of regressing a binary measure of investment on our measure of unexpected temperature shock, as described in Section 3.2. We find a positive and significant effect for contemporaneous shocks and their first lags, which indicates that firms react quickly after the shock. In a more general model we included two additional lags, i.e., up to $t - 3$, but their coefficients were not statistically significant. This result is similar to Ji and Cobourn (2021), who report that farmers give more weight to recent weather realizations in their decisions. We find that experiencing a heat shock increases the likelihood of carrying out an investment by 4.04%, which corresponds to about 8.71% of a standard deviation of the dependent variable. In Columns 2 and 3, we find similar results when considering different thresholds for defining investments, namely positive variations larger than 5 or 10% of the stock of tangible assets. Then, we look at the intensive margin of investments: a positive change in this variable would mean that farmers are not only more likely to invest, but also to invest more. We look at the logarithm of investments[8], which is likewise positively and significantly affected by shocks. The same holds for the investment rate, which can take also negative values, e.g., in the case firms are dismissing their assets or the depreciation of assets exceeds investments.

Our hypothesis is that farmers are investing to acquire technologies to better cope with high heat, but our firm data do not allow us to examine the content of these investment. Therefore, as as a placebo test, we look at changes in intangible assets. If farmers are investing in equipment, we should not observe an impact on this different type of assets. Table 5 reports the results: we do not find any significant effect of temperature shock on any measure of investment in intangibles.

[8]Our results are similar when dropping zero and negative observations.

Table 4: Impact of temperature shocks on investments (tangible fixed assets)

Dep. Var.:	$i_{Tangibles}$	$i_{Tangibles,>5\%}$	$i_{Tangibles,>10\%}$	$\log(I_{Tangibles}+1)$	Inv. rate (Tangibles)
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
shock^{34+}	0.0404***	0.0286**	0.0173	0.3671***	0.0326**
	(0.0101)	(0.0125)	(0.0112)	(0.1126)	(0.0146)
shock^{34+} (t-1)	0.0075	0.0329***	0.0203**	0.1553	0.0589***
	(0.0101)	(0.0096)	(0.0097)	(0.0976)	(0.0175)
Fixed-effects					
Firm	Yes	Yes	Yes	Yes	Yes
Year-province	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	43,533	43,533	43,533	43,533	43,533
Adjusted R^2	0.3722	0.3404	0.3086	0.4764	0.1665
Within Adjusted R^2	0.0003	0.0003	0.00009	0.0003	0.0004
Std. Dev. y	0.4640	0.4759	0.4390	4.958	0.6064

Conley (25km) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

This table reports the results for the estimated coefficients in Equation 5. The dependent variable in column 1 is a dummy variable taking the value of 1 in the presence of positive investments in tangible fixed assets. In columns 2 and 3 the dependent variable is a dummy taking the value of 1 if the firm is investing in tangible assets at least respectively 5 or 10% of its tangible fixed assets in the previous year. In column 4 the dependent variable it the logarithm of 1 plus the value of investments in tangible fixed assets, where negative variations are censored at 0. In column 5 the dependent variable is the ratio of investments in tangible fixed assets divided by previous year's value of tangible fixed assets; it is winsorized between 1 and 99%. $shock^{34+}$ is a dummy variable taking the value of 1 if the firm experienced a deviation from the historical distribution of the $T \geq 34$ bin larger than 3 standard deviations.

Table 5: The Impact of temperature shocks on investments (intangible fixed assets)

Dep. Var.:	$i_{Intangibles}$	$i_{Intangibles,>5\%}$	$i_{Intangibles,>10\%}$	$\log(I_{Intangibles}+1)$	Inv. rate (Intangibles)
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
shock^{34+}	0.0074	0.0075	0.0081	0.1044	0.0259
	(0.0101)	(0.0101)	(0.0109)	(0.0929)	(0.0606)
shock^{34+} (t-1)	0.0073	0.0003	0.0019	0.0648	-0.1044
	(0.0088)	(0.0086)	(0.0082)	(0.0808)	(0.0717)
Fixed-effects					
Firm	Yes	Yes	Yes	Yes	Yes
Year-province	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	43,531	43,531	43,531	43,531	29,040
Adjusted R^2	0.3841	0.2994	0.2585	0.4321	0.0352
Within Adjusted R^2	-0.00003	-0.00004	-0.00004	-0.00001	0.00004
Std. Dev. y	0.4431	0.4170	0.4007	4.108	1.960

Conley (25km) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

This table reports the results for the estimated coefficients in Equation 5. The dependent variable in column 1 is a dummy variable taking the value of 1 in the presence of positive investments in intangible fixed assets. In columns 2 and 3 the dependent variable is a dummy taking the value of 1 if the firm is investing in intangible assets at least respectively 5 or 10% of its intangible fixed assets in the previous year. In column 4 the dependent variable it the logarithm of 1 plus the value of investments in intangible fixed assets, where negative variations are censored at 0. In column 5 the dependent variable is the ratio of investments in intangible fixed assets divided by previous year's value of intangible fixed assets; it is winsorized between 1 and 99%. $shock^{34+}$ is a dummy variable taking the value of 1 if the firm experienced a deviation from the historical distribution of the $T \geq 34$ bin larger than 3 standard deviations.

5.3 Temperature shocks and adoption of irrigation systems

Finally, we turn to the mechanisms that might explain this increase in investments. We are not able to gather qualitative information about them at the firm level, but using land survey data, as described in Section 2, we can look at the likelihood that in an agricultural field irrigation systems have been installed between consecutive survey waves, in the wake of a heat shock. Table 6 reports the results: we find that lagged shocks[9] increase the likelihood to find irrigation system by about 10%. When testing for further lags of temperature shocks, we do not find any significant effect. This result is robust to the inclusion of weather covariates, as Column 4 shows.

Table 6: The impact of temperature shocks on the adoption of irrigation systems

Dep. Var.:	Irrigation			
Model:	(1)	(2)	(3)	(4)
Variables				
$shock^{34+}$	0.0076	0.0095	-0.0003	0.0006
	(0.0155)	(0.0152)	(0.0153)	(0.0164)
$shock^{34+}$ (t-1)		0.1050***		0.1007***
		(0.0307)		(0.0308)
Fixed-effects				
point id	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Weather controls	No	No	Yes	Yes
Fit statistics				
Observations	28,045	28,018	28,045	28,018
Adjusted R^2	0.5544	0.5567	0.5546	0.5567
Within Adjusted R^2	0.00001	0.0047	0.0005	0.0048
Std. Dev. y	0.4451	0.4451	0.4451	0.4451

Conley (25km) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

This table reports the results for the estimated coefficients in Equation 6. The dependent variable is a dummy that is equal to 1 if at the survey point is present an irrigation system and 0 otherwise. $shock^{34+}$ is a dummy variable taking the value of 1 if the firm experienced a deviation from the historical distribution of the $T \geq 34$ bin larger than 3 standard deviations.

[9] Note that 98% of observations in the LUCAS dataset have been collected before September, i.e., before the end of the growing season; on the contrary, firms' balance sheets are closed at the end of December. This means that if investments are carried out after the growing season, i.e., the timing of the shock, they can still be reported in the same year of the shock, but the same investment is more likely to appear in the subsequent year in LUCAS data.

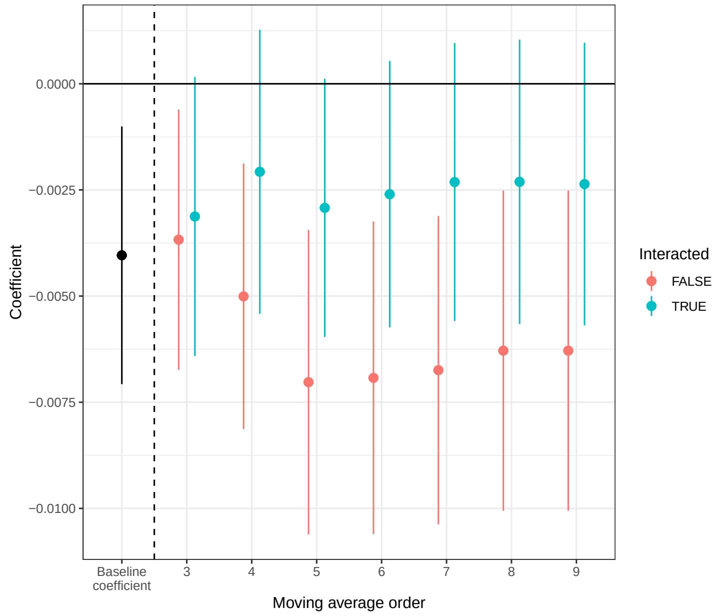
5.4 The effect of past exposure to temperature shocks on future vulnerability to extreme temperatures

The above section presented the evidence that while very high temperatures decrease farm net production, unexpected temperature shocks induce investments. Our results suggest that these investments are directed at acquiring technologies that alleviate the impact of very high temperatures: we find evidence that the installation of irrigation systems becomes more likely after temperature shocks. We turn to evaluate whether these investments are effective in protecting farms from higher temperatures in the years following their occurrence. In order to capture this effect, we estimate a reduced form model where past shocks proxy for potential investments in adaptation (Equation 8). In the previous sections we looked at a binary measure of temperature shocks and its effect on yearly investment: however, since we expect these investments to continue contributing to production over time, we compute a moving average of past shocks, rather than including single lags of the shock. Our measure of exposure to unexpectedly high temperatures thus becomes the average number of single shocks experienced in the recent past, over different time periods. We test different orders of moving average, from 3 up to 9. Figure 2 compares the main coefficient for high temperatures and the sum of the coefficient with the interaction term, taking the moving average of past shocks at the sample mean[10]. In addition, we report the baseline result for the $T \geq 34$ bin from Table 3. We find that the difference in impacts becomes larger as we take into consideration longer time horizons. This might due to the fact that new investments take time before contributing to the farm's operations and becoming profitable. In addition, we find that the impact for unexposed farms is larger than the baseline estimate: in the model with moving average of order 6, the coefficient of variable $T \geq 34$ is 55.62% larger; on the contrary, the coefficient for an exposed farm is 35.60% smaller when past exposure is taken at the sample mean. In relative terms, the impact of temperatures higher than 34°C for a firm that was exposed to unexpected shocks in the past at the sample average is around 40% of one that was not exposed. This difference implies that farmers are investing in adaptation measures to counterbalance future adverse weather conditions with effective results. At higher levels of past exposure, the effect of higher temperatures is not statistically different from zero: nevertheless, our confidence intervals are large and therefore we cannot rule out a residual impact of higher temperatures that albeit smaller remains economically meaningful.

We then include investments in tangibles that are explained by exposure to temperature shocks, as discussed in Section 3.4, in order to measure their effect in reducing the vulnerability to higher temperatures. Table 7 reports the results: we find that cumulative investments have a significant and positive effect when interacted with the highest temperature bin, while not by themselves. This finding might indicate that these increases in assets do not affect a farm's productivity by themselves, but they

[10] Full results are reported in Table B3.

Figure 2: The impact of extreme temperatures on agricultural production (reduced form model)



This figure reports the estimated coefficients for the top temperature bin T^{34+} (in red) and its sum with the interaction term (in blue) of the moving average of past temperature shocks, taking the moving average at the sample mean. The confidence intervals are at the 90% level. On the left, the coefficient of T^{34+} from our baseline model is reported (Table 3)

only contribute to the production process when the farm is exposed to intense heat. The magnitude of the economic effect is sizeable: at the sample average of each measure of cumulative investment in tangibles, the effect of investments roughly halves the impact of temperatures. Similarly to the results obtained above, these results suggest that by investing farmers are able to significantly reduce the vulnerability of their crops to very high temperatures.

Table 7: The effect of adaptation on production

Dependent Variable:	Net revenues				
Model:	(1)	(2)	(3)	(4)	(5)
Investment Variable:	$i_{Tangibles}$	$i_{Tangibles,>5\%}$	$i_{Tangibles,>10\%}$	$\log(I_{Tangibles}+1)$	Inv. rate (Tangibles)
Variables					
T < 0	-0.0036	-0.0035	-0.0035	-0.0036	-0.0036
	(0.0057)	(0.0056)	(0.0056)	(0.0056)	(0.0056)
T ∈ [0, 3)	-0.0023	-0.0022	-0.0022	-0.0024	-0.0024
	(0.0033)	(0.0033)	(0.0033)	(0.0033)	(0.0033)
T ∈ [4, 9)	-0.0003	-0.0003	-0.0003	-0.0004	-0.0003
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
T ∈ [9, 14)	-0.0013	-0.0012	-0.0012	-0.0013	-0.0013
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
T ∈ [14, 19)	0.00009	0.0001	0.0001	0.00002	0.00005
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
T ∈ [24, 29)	-0.0016*	-0.0016*	-0.0016*	-0.0016*	-0.0016*
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
T ∈ [29, 34)	-0.0016	-0.0016	-0.0016	-0.0016	-0.0016
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
T ≥ 34	-0.0062***	-0.0061***	-0.0061***	-0.0067***	-0.0060***
	(0.0020)	(0.0020)	(0.0020)	(0.0021)	(0.0020)
Rain	0.0614	0.0602	0.0602	0.0630	0.0533
	(0.2963)	(0.2975)	(0.2975)	(0.2955)	(0.2972)
Rain^2	-0.1789	-0.1787	-0.1787	-0.1776	-0.1734
	(0.2165)	(0.2177)	(0.2177)	(0.2165)	(0.2176)
Cum. Investments	-0.4694	-0.3282	-0.5359	-0.0682	-0.2319
	(0.4808)	(0.3894)	(0.6372)	(0.0782)	(0.2596)
T ≥ 34 × Cum. Investments	0.0766**	0.0534**	0.0873**	0.0118**	0.0409**
	(0.0338)	(0.0243)	(0.0398)	(0.0048)	(0.0185)
Fixed-effects					
Firm	Yes	Yes	Yes	Yes	Yes
Year-province	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	43,529	43,529	43,529	43,529	43,527
Adjusted R^2	0.9140	0.9140	0.9140	0.9140	0.9140
Within Adjusted R^2	0.0002	0.0001	0.0001	0.0002	0.0001
Std. Dev. y	1.905	1.905	1.905	1.905	1.905

Conley (25km) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

This table reports the estimated coefficients of Equation 9. The dependent variable is the logarithm of net revenues, obtained by subtracting the variation in inventories to sales revenues. Variables $T < 0$ through $T \geq 34$ are temperature bins, indicating the number of hours spent within the particular temperature range during the growing season; they are divided by ten for readability. Rain is the amount of rainfall during the growing season. $Cum.\quad Investments$ is the cumulative sum of predicted investments from Equation 5.

6 Conclusions

The agricultural sector is one of the economic sectors most vulnerable to global warming, due to the role played by the weather in determining crop yields. How much of this impact can be attenuated by adaptation efforts remains an open question in the economic literature, but it remains relevant in order to understand the value of the damages that climate change will entail for the sector. At the same time, studying the drivers of the uptake of adaptation measures is another topic of importance for policy-makers. We look at both questions by studying a panel of Italian agricultural firms between 2011 and 2021. We find that higher temperatures pose a risk for farms, because they decrease their output. On the other hand, we find that temperature shocks lead farmers to make investments in equipment and other tangible assets. When accounting for this past exposure to temperature shocks, we find a considerable heterogeneity in farms' vulnerability to higher temperatures. The farms that were hit by a shock become less affected: the size of the impact decreases with past exposure and it is not statistically different from zero in those with a higher exposure in the past. These results are therefore compatible with a pattern of investment in adaptation. Exploring possible mechanism that can help explain these results, we find that irrigation systems become more likely to be installed in agricultural fields after a temperature shock.

Our contribution to the agroeconomic literature is two-fold. First, we show that the panel approach might fail to account for the heterogeneous impact across farms with different levels of equipment: in that case, a naive regression would be unable to capture the temperature-yield relationship. On the other hand, by comparing farms with similar climates, the Ricardian approach might not be able to uncover the path-dependency that is caused by the difference in beliefs among farmers. Second, we propose an indirect way to uncover both investment in adaptation and to measure its efficacy against future higher temperatures.

Finally, our work is not exempt from limitations. Namely, we cannot gauge the content of farmers' investment and we rely on the union of a behavioural insight about salience of climate change, with a robust econometric specification. However, we validate in part this hypothesis by exploiting an external source of data, i.e., the presence of irrigation systems, which we show to react to the same shocks that drive investments.

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7 Appendix

A Data cleaning of firm data

We clean the firm data obtained from AIDA following the literature, e.g., Andrews et al. (2016) and Kalemli-Ozcan et al. (2015). The steps are detailed below.

1. If the closing date of the balance sheets is before June 30$^{\text{th}}$, we assign that observation to the previous year; if a firm has multiple observations per year, we keep the one with the latest closing date.
2. We drop observations for which the competence period is not 12 months.
3. We drop firms with large variations (±500 or $\pm1/500$) in assets, revenues and net production.
4. We drop firms with spikes, i.e., changes of 50 or $1/50$ from a year to the other, in assets.
5. We drop firms with negative fixed assets, fixed tangible assets, fixed intangible assets, and revenues.
6. We drop firms with a growth rate in assets in the bottom (top) 2.5% (97.5%).

B Additional Tables

Table B1: Impact of temperature shocks on investments (extensive margin), with weather and firm-level covariates

Dependent Variables:	$i_{Tangibles}$	$i_{Tangibles,>5\%}$	$i_{Tangibles,>10\%}$	$\log(I_{Tangibles}+1)$	Inv. rate (Tangibles)
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
shock^{34+}	0.0392***	0.0377***	0.0335***	0.4014***	0.0323**
	(0.0123)	(0.0137)	(0.0130)	(0.1356)	(0.0140)
shock^{34+} (t-1)	-0.0012	0.0368***	0.0177	0.0950	0.0514***
	(0.0115)	(0.0121)	(0.0109)	(0.1167)	(0.0169)
T mean	0.1120	0.2403*	0.0360	0.7324	0.1878
	(0.1122)	(0.1379)	(0.1198)	(1.145)	(0.1298)
T mean^2	-0.0021	-0.0057	-0.0018	-0.0172	-0.0050
	(0.0028)	(0.0036)	(0.0032)	(0.0292)	(0.0035)
Rain	0.3421	-0.0318	-0.0191	4.070**	0.3750
	(0.2196)	(0.2091)	(0.2089)	(2.045)	(0.2979)
Rain^2	-0.2316	0.0748	-0.0193	-2.623	-0.1654
	(0.1602)	(0.1661)	(0.1669)	(1.603)	(0.2262)
T mean (Lag 1)	-0.2269*	-0.2169*	-0.2247**	-2.466**	-0.1866*
	(0.1189)	(0.1252)	(0.1050)	(1.159)	(0.1111)
T mean^2 (Lag 1)	0.0069**	0.0048	0.0051*	0.0688**	0.0037
	(0.0032)	(0.0032)	(0.0028)	(0.0307)	(0.0029)
Rain (Lag 1)	0.1010	-0.6463***	-0.3581*	0.2078	-0.0603
	(0.2342)	(0.2485)	(0.2127)	(2.175)	(0.2730)
Rain^2 (Lag 1)	-0.0031	0.3488*	0.1616	0.0572	0.0646
	(0.1657)	(0.1821)	(0.1508)	(1.538)	(0.1968)
Cash flow ratio (t-1)	0.0536	0.0773	0.0367	0.9894	-0.1241
	(0.0771)	(0.0835)	(0.0835)	(0.7168)	(0.1435)
Sales growth (t-1)	0.0097***	0.0090***	0.0055***	0.1021***	0.0079***
	(0.0020)	(0.0022)	(0.0018)	(0.0200)	(0.0025)
EBIT/Assets ratio (t-1)	0.0496	0.1015	0.1714**	0.4475	0.4843***
	(0.0732)	(0.0776)	(0.0782)	(0.6660)	(0.1507)
Tangibility (t-1)	-0.0702**	-0.2633***	-0.3162***	-1.164***	-0.8891***
	(0.0283)	(0.0342)	(0.0364)	(0.2856)	(0.0787)
log(Assets) (t-1)	-0.0122	-0.1391***	-0.1725***	-0.2608***	-0.3021***
	(0.0083)	(0.0117)	(0.0120)	(0.0855)	(0.0234)
Fixed-effects					
Firm	Yes	Yes	Yes	Yes	Yes
Year-province	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	34,839	34,839	34,839	34,839	34,839
Adjusted R^2	0.3838	0.3594	0.3262	0.4900	0.1840
Within Adjusted R^2	0.0019	0.0125	0.0194	0.0032	0.0421
Std. Dev. y	0.4643	0.4713	0.4306	4.979	0.5448

Conley (25km) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

This table reports the results for the estimated coefficients in Equation 5. The dependent variables are a dummy variable taking the value of 1 in the presence of positive investments in tangible fixed assets. In columns 2 and 3 the dependent value is a dummy taking the value of 1 if the firm is investing in tangible assets at least respectively 5 or 10% of its tangible fixed assets in the previous year. In column 4 the dependent variable is the logarithm of 1 plus the value of investments in tangible fixed assets, where negative variations are censored at 0. In column 5 the dependent variable is the ratio of investments in tangible fixed assets divided by previous year's value of tangible fixed assets; it is winsorized between 1 and 99%. $shock^{34+}$ is a dummy variable taking the value of 1 if the firm experienced a deviation from the historical distribution of the 34+ temperature bin larger than 3 standard deviations. *Cash flow ratio* is equal to the ratio of profit (loss) plus depreciation and amortization to lagged assets. $Sales\_growth$ is the growth rate of revenues. $Tangibility$ is the ratio of tangible fixed assets to total fixed assets. *Cash flow ratio*, $Sales\_growth$, and *EBIT/Assets ratio* are winsorized at 1-99%.

Table B2: Impact of temperature shocks on investments (intensive margin), with weather and firm-level covariates

Dep, Var.:	$i_{Intangibles}$	$i_{Intangibles,>5\%}$	$i_{Intangibles,>10\%}$	$\log(I_{Intangibles}+1)$	Inv. rate (Intangibles)
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
shock^{34+}	0.0159	0.0141	0.0142	0.1553	0.0252
	(0.0123)	(0.0121)	(0.0128)	(0.1122)	(0.0655)
shock^{34+} (t-1)	0.0105	0.0006	0.0014	0.0713	-0.0990
	(0.0102)	(0.0104)	(0.0105)	(0.0967)	(0.0848)
T mean	0.1289	0.0061	-0.0056	0.4422	0.0603
	(0.1110)	(0.1134)	(0.1056)	(0.9811)	(0.7270)
T mean^2	-0.0033	-0.0006	0.0003	-0.0125	0.0040
	(0.0028)	(0.0029)	(0.0027)	(0.0248)	(0.0196)
Rain	0.1726	0.0436	-0.1149	0.8612	1.478
	(0.1999)	(0.2117)	(0.2038)	(1.801)	(1.559)
Rain^2	-0.1610	-0.1254	0.0342	-1.139	-0.5534
	(0.1399)	(0.1640)	(0.1533)	(1.312)	(1.238)
T mean (Lag 1)	-0.1074	-0.0999	-0.1014	-1.276	-0.5410
	(0.1036)	(0.0975)	(0.0976)	(0.8977)	(0.6973)
T mean^2 (Lag 1)	0.0027	0.0021	0.0024	0.0314	0.0181
	(0.0026)	(0.0024)	(0.0025)	(0.0226)	(0.0170)
Rain (Lag 1)	0.2595	0.0675	0.0338	2.342	0.2751
	(0.1902)	(0.2008)	(0.1816)	(1.692)	(1.423)
Rain^2 (Lag 1)	-0.2366	-0.1582	0.0009	-2.105	0.8959
	(0.1503)	(0.1671)	(0.1430)	(1.397)	(1.038)
Cash flow ratio (t-1)	-0.0327	-0.0331	-0.0391	-0.6396	-0.5079
	(0.0555)	(0.0529)	(0.0547)	(0.5052)	(0.5141)
Sales growth (t-1)	0.0046**	0.0039*	0.0029	0.0527***	0.0223
	(0.0023)	(0.0022)	(0.0021)	(0.0202)	(0.0148)
EBIT/Assets ratio (t-1)	0.0450	0.0723	0.0905*	0.7499	0.6804
	(0.0529)	(0.0518)	(0.0538)	(0.4779)	(0.4611)
Tangibility (t-1)	0.1445***	0.2608***	0.3243***	1.567***	2.382***
	(0.0312)	(0.0346)	(0.0353)	(0.2927)	(0.2246)
log(Assets) (t-1)	0.0103	-0.0167*	-0.0302***	0.0376	-0.3307***
	(0.0094)	(0.0099)	(0.0095)	(0.0847)	(0.0874)
Fixed-effects					
Firm	Yes	Yes	Yes	Yes	Yes
Year-province	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	34,837	34,837	34,837	34,837	21,977
Adjusted R^2	0.3924	0.3096	0.2701	0.4455	0.0493
Within Adjusted R^2	0.0011	0.0036	0.0060	0.0018	0.0166
Std. Dev. y	0.4415	0.4142	0.3973	4.100	1.825

Conley (25km) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

This table reports the results for the estimated coefficients in Equation 5. The dependent variables are a dummy variable taking the value of 1 in the presence of positive investments in intangible fixed assets. In columns 2 and 3 the dependent value is a dummy taking the value of 1 if the firm is investing in intangible assets at least respectively 5 or 10% of its intangible fixed assets in the previous year. In column 4 the dependent variable is the logarithm of 1 plus the value of investments in intangible fixed assets, where negative variations are censored at 0. In column 5 the dependent variable is the ratio of investments in intangible fixed assets divided by previous year's value of tangible fixed assets; it is winsorized between 1 and 99%. $shock^{34+}$ is a dummy variable taking the value of 1 if the firm experienced a deviation from the historical distribution of the 34+ temperature bin larger than 3 standard deviations. *Cash flow ratio* is equal to the ratio of profit (loss) plus depreciation and amortization to lagged assets. $Sales \quad growth$ is the growth rate of revenues. $Tangibility$ is the ratio of tangible fixed assets to total fixed assets. *Cash flow ratio*, $Sales \quad growth$, and *EBIT/Assets ratio* are winsorized at 1-99%.

Table B3: The impact of extreme temperatures on agricultural production (reduced form model)

Dep. Var.: Model:	Net revenues (1)	Net revenues (2)	Net revenues (3)	Net revenues (4)	Net revenues (5)	Net revenues (6)	Net revenues (7)	Net revenues (8)
Order of MA:	–	3	4	5	6	7	8	9
Variables								
$T < 0$	-0.0056	-0.0022	-0.0021	-0.0024	-0.0028	-0.0030	-0.0028	-0.0025
	(0.0036)	(0.0056)	(0.0055)	(0.0056)	(0.0056)	(0.0055)	(0.0056)	(0.0056)
$T \in [0, 3)$	-0.0057*	-0.0045	-0.0049	-0.0046	-0.0044	-0.0044	-0.0045	-0.0044
	(0.0033)	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0035)
$T \in [4, 9)$	-0.0018	-0.0008	-0.0010	-0.0010	-0.0008	-0.0008	-0.0008	-0.0007
	(0.0020)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
$T \in [9, 14)$	-0.0023*	-0.0020	-0.0022	-0.0021	-0.0020	-0.0019	-0.0020	-0.0020
	(0.0014)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
$T \in [14, 19)$	0.0002	0.00005	-0.0002	-5.04×10^{-6}	4.71×10^{-6}	0.00005	0.00001	0.00007
	(0.0009)	(0.0010)	(0.0009)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
$T \in [24, 29)$	-0.0016*	-0.0014	-0.0013	-0.0014	-0.0015*	-0.0013	-0.0013	-0.0015*
	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
$T \in [29, 34)$	-0.0013	-0.0009	-0.0008	-0.0009	-0.0009	-0.0009	-0.0009	-0.0010
	(0.0012)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
$T \geq 34$	-0.0040**	-0.0037**	-0.0050***	-0.0070***	-0.0069***	-0.0067***	-0.0063***	-0.0063**
	(0.0018)	(0.0019)	(0.0019)	(0.0022)	(0.0022)	(0.0022)	(0.0023)	(0.0026)
Rain	0.1141	0.1878	0.2229	0.1812	0.1826	0.2075	0.1868	0.1555
	(0.2594)	(0.3048)	(0.3041)	(0.3019)	(0.3017)	(0.3010)	(0.3009)	(0.2998)
$Rain^2$	-0.2163	-0.3044	-0.3105	-0.2940	-0.2910	-0.3039	-0.2963	-0.2774
	(0.1697)	(0.2241)	(0.2240)	(0.2235)	(0.2222)	(0.2208)	(0.2204)	(0.2209)
MA $shock^{34+}$		-0.0038	-0.0745	-0.1167	-0.1773*	-0.2717**	-0.2054	-0.2243
		(0.0432)	(0.0606)	(0.0892)	(0.1015)	(0.1194)	(0.1393)	(0.1679)
$T \geq 34 \times$ MA $shock^{34+}$		0.0030	0.0174**	0.0258***	0.0285**	0.0306**	0.0286*	0.0248
		(0.0055)	(0.0073)	(0.0096)	(0.0119)	(0.0139)	(0.0161)	(0.0186)
Fixed-effects								
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	55,379	52,657	52,657	52,657	52,657	52,657	52,657	52,657
Adjusted R^2	0.9036	0.9016	0.9016	0.9016	0.9016	0.9016	0.9016	0.9016
Within Adjusted R^2	0.0002	0.00004	0.0002	0.0004	0.0004	0.0005	0.0003	0.0003
Std. Dev. y	1.943	1.920	1.920	1.920	1.920	1.920	1.920	1.920

Conley (25km) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

This table reports the estimated coefficients of Equation 8 for columns 2 to 9, while column 1 reports the baseline model (Equation 3). The dependent variable is the logarithm of net revenues, obtained by subtracting the variation in inventories to sales revenues. Variables $T < 0$ through $T \geq 34$ are temperature bins, indicating the number of hours spent within the particular temperature range during the growing season. Rain is the amount of rainfall during the growing season. *MA* $shock^{34+}$ is the moving average of lagged temperature shocks up to the lag reported. $T \geq 34\times$ *MA* $shock^{34+}$ is the interaction between the highest temperature bin the moving average of lagged temperature shocks.

Corporate cost of debt in the low-carbon transition: The effect of climate policies on firm financing and investment through the banking channel

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Abstract

This paper assesses to what extent markets with sophisticated investors and large firms price transition risks due to climate policies. We introduce an important innovation to previous studies by examining the impact of climate policy on the allocation of capital in the syndicated loan market, using country-by-year continuous variation in climate policy stringency interacted with firm-level performance measures to isolate the effect of mitigation policies on loan spreads. We provide three main results. First, stringent climate policies significantly lower the cost of debt of firms with good environmental performance (in terms of emission intensity or patenting activity in mitigation technologies). Second, ESG scores and their environmental pillar – which correlate poorly with firms' actual environmental outcomes – are not sufficiently informative to assess and price domestic climate policy risks. Third, more stringent mitigation policies can encourage investment in green firms by reducing the cost of debt.

1 Introduction

Reaching the climate-change mitigation goals of the Paris Agreement will require substantial investment in low-carbon infrastructure and technologies over the next decades. Global annual investments in low-carbon energy alone need to increase to USD 4.4 trillion by 2030, more than three times the level in 2022 (IEA, 2023). Private sector firms are expected to play a key role in the net-zero transition as they account for more than half of all climate-change mitigation finance (Andersson et al., 2016; Initiative, 2021).

The contribution of the private sector to the net-zero transition hinges on the capacity of markets to efficiently aggregate information on mitigation policies and their possible effects on firms. Investors responsible for capital-allocation decisions need to be capable of assessing and correctly pricing firms' transition risk, i.e. the risk that mitigation policies cause costly adjustments for firms, due to – for instance – technology changes, the stranding of emitting assets or lower demand (De Haas & Popov, 2019; Fried et al., 2022; Levine et al., 2018). However, not all financial intermediaries may have the information and capacity to assess the environmental profile of their investments and transition risks.

Since Chava (2014), several papers have analysed how financial markets incorporate information on firms' environmental performance by adjusting required returns and, in turn, the cost of capital. These papers show that investors require a premium when investing in firms with worse environmental performance (Bolton & Kacperczyk, 2021; Delis et al., 2019; Ehlers et al., 2022). This premium is often interpreted as evidence that investors price-in transition risk. However, it is also possible that financial intermediaries have other motives to prefer environmental sustainable assets, including environmental commitments (Bolton & Kacperczyk, 2021; Degryse et al., 2023) and portfolio management strategies (Degryse et al., 2022; Umar et al., 2021).

Concerns about the endogeneity of environmental performance to cost of capital are a common challenge for studies in this literature. In particular, firm-level unobservables like managerial quality might determine both the environmental performance and the cost of capital. If these unobservables correlate positively with the dependent and independent variables, the bias should be away from zero.

Taking into consideration climate policy stringency is crucial to understand the underlining cause of the variation in firms' cost of capital based on their environmental performance. First, policy shocks help identifying transition risks because, if investors expect climate policy to strengthen over time, firms exposed to such policy shocks will face a higher transition risk. Second, climate policy offers credible exogenous variation to identify their effect on firms' cost of debt, addressing the endogeneity problem of environmental performance. Increasing evidence show how premia changed after the Paris Agreement underlining the importance of climate commitments and announcements in shaping expectations and capital allocation decisions (Altunbas et al., 2022; Delis et al., 2019; Kruse et al., 2024; Mésonnier, 2022; Monasterolo & De Angelis, 2020; Seltzer et al., 2022) and the introduction of carbon pricing policies (Bernardini et al., 2021; Wen et al., 2020)[1].

One contribution of the paper is differentiating between measures of environmental performance and types of climate change mitigation policy. Regarding environmental performance, we compare emission intensities, green innovativeness (measured by patenting activity in mitigation technologies), and ESG scores. Having this rich setup allows us to assess jointly how banks respond both to downside risks and emerging opportunities associated with the low-carbon transition. Regarding policies, we compare market-pull policies, such as emission pricing, and technology-push policies, such as technology support subsidies. In contrast with previous papers looking at before and after the implementation of one individual policy (or international agreement), this provides deeper insights on the role of mitigation policies, which notwithstanding their relative effectiveness may have different levels of political feasibility (Carattini et al., 2018; Goulder & Parry, 2008; Rausch & Yonezawa, 2023; van der Ploeg et al., 2022). The literature has so far largely revolved around the risks associated with the low-carbon transition, focussing

[1] See Campiglio et al. (2023) for a recent review.

on firms' exposure in terms of their emissions or emission intensities. In addition to risks, in this paper, we assess jointly how banks also respond to emerging opportunities associated with the transition to climate neutrality using patents in mitigation technologies (Dechezleprêtre et al., 2021; Hege et al., 2022).

A first result is that firms' good environmental performance are rewarded with a lower cost of capital only when climate policies bite. This effect disappears when climate policies are lenient. Market-pull policies (i.e., carbon taxes) increase loan spreads for firms with high emission intensity and decrease them for green innovators. Technology-push policies (i.e., green technology support) decrease loan spreads for green innovators but do not have a significant effect on emission intensive firms. The effects are sizeable when mitigation policy is stringent. For example, when carbon prices are above €50/t CO_2, firms in the top quartile by patents in mitigation technology enjoy a loan spread 30% lower than firms at the bottom quartile. This is equivalent to 41 basis points or €1.5 million less in yearly interest payments for the median syndicated loan deal. This effect disappears when climate policies are lenient.

A second set of results indicates that the effect of ESG scores on loan spreads is disconnected from mitigation policy, contrary to the actual firms' environmental performance. Companies disclosing an ESG score benefit from lower loan spreads and this advantage increases with better scores, but mitigation policies do not mediate this relationship. This result, together with the low correlation of our ESG scores data with environmental performance, corroborates the view that they are weak proxies of firms' actual environmental performance (Berg et al., 2022; OECD, 2022).

Lastly, we provide back-of-the-envelope calculations on the effect of mitigation policies on firm investment through the cost-of-capital channel. These are based on the in-sample elasticity of real asset investment to cost of debt, estimated with an instrumental variable based on balance sheets and leveraging monetary policy shocks. If stringent climate policies decrease (increase) interest rates for green (brown) firms, these firms respond by increasing (decreasing) investments. We show that this effect is economically significant, reinforcing the idea that mitigation policy is an important driver in mobilizing large investments.

The analysis of investments is related to a strand of literature focusing on the role of finance in providing the resources to the net-zero transition. This literature is mostly concerned with studying the aggregate investment effects of introducing a new environmental policy. In contrast, this paper focuses exclusively on the cost of capital channel, helping to quantify the role of the financial sector in allocating capital in response to mitigation policies. Despite its importance, evidence on this channel is scant. Two related papers are Cohn and Deryugina (2018) and Goetz (2019), studying how two specific shocks to access to credit in the United States affected investment in technology to avert environmental spills and abate emissions. Kempa et al. (2021) assess the cost of debt for renewable and non-renewable energy sector firms. Instead, this paper produces more general back-of-the-envelope calculations on the effect of mitigation policies on investment through the cost-of-capital channel, differentiating between green and brown firms.

Finally, the paper also relates to the literature on the impact of Environmental, Social and Governance (ESG) scores on investment decisions (Houston & Shan, 2022). Unlike financial reporting, ESG reporting does not rely on well-defined quantitative metrics and is therefore less standardized. This makes it harder to assess and compare different ESG scores, which may be a poor proxy of environmental performances. Low correlation and inconsistencies of firms' ESG score across providers (Berg et al., 2022; Boffo & Patalano, 2020; OECD, 2022) raise questions on the quality and their relevance to investors (OECD, 2022)[2]. Several papers suggest that ESG ratings affect investment decisions and that firms that do not disclose them face a penalty in terms of higher financing costs (Matsumura et al., 2014; Pástor et al., 2022). Our results are in line with the explanations offered by two recent papers. Bingler et al. (2022) suggests that ESG disclosure is mostly "cheap-talk" and is associated with cherry-picked disclosure of information that is not relevant to the firm's exposure to climate change risks and policies. Giglio et al. (2023) argue that investors holding ESG assets do that principally because return-driven or because of ethical reasons and less because they hedge climate risk.

The paper is structured as follows. Section 2 provides details on syndicated loans and presents the construction of the data set; section 3 describes the empirical approach and presents the estimation results; section 4 estimates the effect of mitigation policies on investments through the cost of capital; section 5 concludes and discusses options to improve climate finance and to reduce environmental information asymmetries for different kinds of investors.

2 Data sources and sample construction

2.1 Syndicated loans: background and data

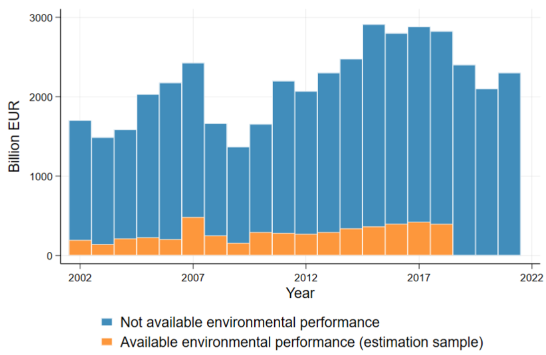
Syndicated loans involve several lenders. Lenders can be banks or non-bank financial institutions, such as finance companies and institutional investors. Loan syndication is a major contributor of debt finance, particularly of large-scale debt used, for instance, in project finance, infrastructure investment and leverage buyouts. It is an alternative source of finance to bilateral loans, corporate bonds and private debt placement. Because of their size, syndicated loans are a prerogative of sophisticated investors and large companies. Their main advantage is to spread the risk of borrower default across multiple lenders in addition to addressing a number of typical issues arising in lending markets, such as market matching problems, information asymmetry, and moral hazard (Commission et al., 2019).

In syndicated loans, one or more lenders (the lead arranger and its co-agents) take on information

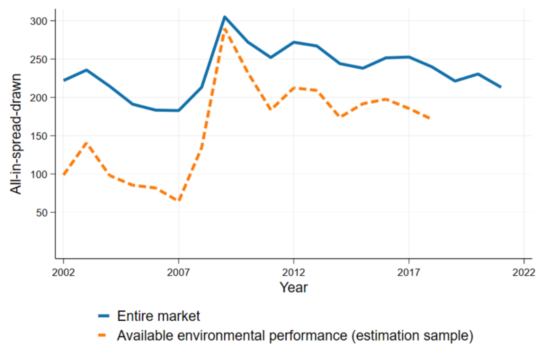
[2]This relates to the literature on bank financing and intangibles, which has shown that as banks find it difficult to price intangibles (Demmou & Franco, 2021).

Figure 1: Cost of debit and new syndicated loan volume in the syndicated loan market and estimation sample

(a) Volume of syndicated loans, billion €



(b) All-in-spread-drawn, bps



Panel (a) shows the total tranche value of loans (in billion euros at current prices) for the entire syndicated loan market (blue + orange bars) and for the firms with available environmental performance employed for estimation (orange bars). Panel (b) shows the average all-in-spread-drawn (in bps) in the entire syndicated loan market (blue solid line) and in the sub-sample of firms with available environmental performance metrics employed for estimation (dashed orange line). The all-in-spread drawn describes the amount the borrower pays in basis points over LIBOR for each dollar drawn down; it adds the spread of the loan with any annual (or facility) fee paid to the bank group.

collection and monitoring responsibilities and negotiate the contract terms (Sufi, 2007). As in other areas of the lending market, the monitoring of borrowers plays an important role in the syndicated loan market, with banks making considerable and costly efforts to overcome the information asymmetry between the borrower and lenders. Gustafson et al. (2021) measure how banks monitor borrowers receiving syndicated loans. They show that for twenty percent of loans banks engage in costly active monitoring, meaning that the lender or a third party regularly visits the borrower. Fifty percent of lenders require borrowers to provide information at least on a monthly basis, and 5% of lenders require this information daily. The monitoring activity of banks can significantly affect lending conditions, with more active monitoring being associated with significantly lower margins as the monitoring reduces asymmetric information. Banks issuing syndicated loans are thus sophisticated investors expending significant monitoring efforts for investment decisions, which may be different from other investors without the ability or capacity for extensive monitoring.

Syndicated loans are a large and increasingly important source of corporate finance. Over the past two decades, the volume of syndicated loans increased to about €2.3 trillion in 2021 (Figure 1, panel A). For comparison, new corporate bonds averaged to about $1.8 trillion (around €1.4 trillion) a year between 2008 and 2019 (Çelik et al., 2020). The syndicated loan volumes increased markedly during the second half of the 2000s to above €2 trillion but then declined by more than a third in the wake of Global Financial Crisis (GFC). Afterwards, they recovered gradually to reach their current level.

Syndicated loans can play an important role in the low-carbon transition by providing the financing for low-carbon energy infrastructure. For example, the Dogger Bank wind farm, one of the world's largest offshore wind farms, has been financed through a $5.5 billion syndicated loan in 2020, financed by a group of lenders comprising of 31 banks and credit agencies. When completed, it is estimated to supply 5% of the United Kingdom power demand and provide electricity for six million homes[3]. Other examples include the Northvolt battery factories built in Sweden, financed via a $1.6 billion syndicated loan[4], the Canberra Light Rail project, an electrified urban rail project, was financed through a $280 billion syndicated loan[5] and the 75MW Ishinomaki Hibarino Biomass Power Generation Project in Japan has been financed through a syndicated loan[6].

Data on syndicated loans is sourced from the Refinitiv LPC Loan Connector Dealscan database (Dealscan hereafter), which provides comprehensive loan-deal information at a global level. Dealscan contains detailed information about loan terms (e.g. loan amount, fees and spreads, maturity, loan type and purpose, and other features of the contracts). Refinitiv LPC combines different sources to produce this dataset, including information submitted directly by lenders, regulatory filings of borrowers, and financial news. Influential rankings based on the market share of lenders ("league tables") provide strong incentives to banks to report their loans to Refinitiv LPC and attract clients (Cohen et al., 2020; Ivashina, 2009). For the analysis below, only the origination of new loans is considered while loan extensions are excluded. An important benefit of using data on syndicated loans is that it provides precise information on the loan spreads and fees. Estimating the cost of financing from equity, another source of financing for firms, requires stronger assumptions and estimates can differ substantially depending on the chosen estimation method (Frank & Shen, 2016).

The average spread to the benchmark rate (LIBOR) rose during the GFC by more than 100 basis points (from 183 in 2007 to about 305 in 2009) and it has hovered at a higher level since (Figure 1, panel (b)). Reasons of this persistent increase in the syndicated loan spreads following the GFC include responses to Basel III regulation (Ma, 2016), increased market power in lending (Thia et al., 2022), and changes in lenders' risk aversion (Lee et al., 2017).

The syndicated loan market is most developed in the United States (accounting for 45% of total loan amount), followed by Japan (12%), United Kingdom (4%), France, Canada, Germany and Australia each at 3% (Appendix A, Figure A1, panel a). Firms across a large range of sectors use syndicated loans, the largest ones being manufacturing, financial services and utilities (Appendix A, Figure A1, panel b)[7].

[3]Source: https://doggerbank.com/press-releases/dogger-bank-wind-farm-a-and-b-reaches-financial-close; consulted on 20/06/2024.

[4]Source: https://www.nib.int/releases/nib-financing-for-northvolt-battery-plant-in-sweden; consulted on 20/06/2024.

[5]Source: https://institutional.anz.com/insight-and-research/Dec-20/canberra-metro-in-landmark-green-loan; consulted on 20/06/2024.

[6]Source: https://www.renovainc.com/en/business/power_plant/ishinomaki_hibarino_biomass/; consulted on 20/06/2024.

[7]To compare the distribution of firms between the estimation sample and the raw data, the Refinitiv Major Industry Group classification is used, which is available in the Dealscan database. Other sectoral classifications are not available for the raw loan-level data.

2.2 Sample construction

The dataset employed for the empirical analysis consists of micro-data combining loan-, firm-, sector- and country-level information. Loan-level information on syndicated loans from Dealscan is merged with several other data sources (Appendix A). The environmental performance metrics considered are firms' green innovation and emission intensity. Green innovation is measured by the stock of patents in mitigation technologies issued by the firm, sourced from PATSTAT. Firm-level emissions come from Refinitiv EIKON and are measured in CO_2 equivalents[8]. These emissions include both direct emissions from company-owned resources (Scope 1) and indirect emissions from the generation of purchased energy (Scope 2). Country-level data on policy comes from the OECD Environmental Policy Stringency (EPS) index and its sub-components (Botta & Koźluk, 2014; Kruse et al., 2022). Table 1 lists the data sources used in the empirical analysis. Appendix A contains additional details about each source.

Table 1: Data sources

Type of data	Datasets
Deal-level data on the universe of syndicated loans • All-in-spread-drawn, deal amount, maturity, etc.	LPC Loan Connector Dealscan
Firm-level financial data • Assets, return on assets, debt, etc.	BvD ORBIS
Country-level environmental policy indicators	OECD EPS indicators
Firm-level exposure variables • Green innovativevess • Emission intensity and ESG scores, including E pillar	 Climate-change mitigation patents (PATSTAT Y02 classification) Refinitiv EIKON

This table reports the type of data and the datasets used in the empirical analysis.

The panel dataset for the regression analysis consists of just above 6,000 observations (loans) across nearly 1,400 firms for the years 2002–2018, distributed in 33 countries and 71 sectors. The regression sample is unbalanced, as some firms do not receive a loan each year (90% of firms receive less than 10 loans over the period), while a few have more than one. The summary statistics of the main variables in the estimated sample are reported in Table A1 in Appendix A.

Firms distribute across countries similarly in the universe and estimation samples with the most remarkable differences being Japan, a large market for syndicated loans where environmental disclosure is not common, and other countries, including Hong Kong and Singapore, for which EPS data is unavailable. Firms from the United States represent a large share of syndicated loans (45% of the universe and 69% and estimation sample), although results are not driven by these firms, as discussed below. The distribution of

[8]We use the variable *ENERDP123* in the Refinitiv database, which is used widely in the literature to measure firms CO_2 equivalent emissions (Altunbas et al., 2022; Hege et al., 2022; Homroy, 2023).

firms across sectors is also similar in our estimation sample compared the universe of syndicated loans.

The availability of data on firms' emission intensity (from Refinitiv's EIKON database) that are included in the merged Dealscan-Orbis sample explains the limited number of observations in the estimation sample compared with the raw data. The estimation sample covers about 10% of the total loan value of the syndicated loan market. The size of the estimation sample is compared with the full sample in Figure 1. Firms have higher returns on assets and general patenting activity (Table A2 in Appendix A). Reassuringly three main variables of interest: the all-in-spread-drawn, emission intensities and mitigation patent stock are not very different. Nonetheless, in our empirical analysis we introduce a Heckman-type instrument in order to show that sample selection on emission intensity is not important in determining our results.

3 Empirical approach

3.1 Research hypotheses

We distinguish between "market-pull" and "technology-push" climate policies, following Jaffe et al. (2005). We employ CO_2 taxation as a representative market-pull policy[9]. By introducing a price on emissions, firms internalize emission externalities responding to market incentives. We use green technology support as a measure of technology-push policy, combining public green technology support and subsidies for renewable energy. These measures support the development of green technologies, providing incentives investing in them, and make it easier for firms to benefit from knowledge spillovers of public research (Jaffe et al., 2005).

We expect these policies to affect differently firms based on their relative environmental performance. First, emission intensity can be seen as an indicator of transition risk in the strict sense, as carbon intensive firms will stand to lose more with increasingly stringent regulation of pollution. On the other hand, the stock of green patents can become an increasingly valuable asset as policies penalise carbon intensive technologies (Delis et al., 2019).

We obtain four interactions between policies and firms' environmental performance metric (Table 2). First, we expect market-pull policies to reduce the spread for firms that are green innovators. These firms could deploy their innovations to reduce their abatement costs and benefit from the rise in the demand for clean technology that higher carbon prices engender (panel A). At the same time, market-pull policies impose compliance costs for high emitting firms, worsening their financial and economic prospects and raising lending risks. If priced in, these risks should lead to lower loan spreads for green firms relative to

[9]We focus on carbon taxes rather than carbon pricing in emission trading schemes as the latter are presumably more endogenous to lending spreads. While changes in carbon taxes are statutory, ETS prices are determined in the allowance market and are more likely affected by unobservable shocks to the business cycle, which might also affect borrowing conditions.

brown firms (panel C).

Second, we expect technology-push policies (Table 2, column 2) to reduce the spread for green innovators as banks price into loans the opportunities for these firms to benefit from technology support policies (panel B). The effect of technology support policies on emission intensive firms is instead more ambiguous. The policy could increase the cost of debt for emissions intensive firms if emission intensive firms are not eligible or have the expertise to benefit from technology support policies, for example because they do not have the knowledge or capacity to use or develop low-carbon technologies. However, technology support policies could also lower the spread for emission intensive firms if they are seen as an opportunity and financial incentive for such firms to lower their emission intensity (panel D).

Table 2: Expected effects of mitigation policy by firms' degree of green innovation and emission intensity

	Policies	
Firm environmental performance	**CO_2 Tax** *Market-pull effect* (1)	**Green technology support** *Technology-push effect* (2)
Innovation in green technologies	(Panel A) Ability to innovate CO_2 or sell abatement technology is priced-in Expected sign of effect on loan spreads (−); the green premium increases	(Panel B) Ability to capitalize no technology support policies is priced-in Expected sign of effect on loan spreads (−); the green premium increases
Emission intensity	(Panel C) Additional cost from CO_2 tax is priced-in Expected sign of effect on loan spreads (−); the green premium increases	(Panel D) Opportunity cost and ability to capitalise on technology support policies is priced-in Expected sign of effect on loan spreads (+/−); the green premium may increase or decrease

The table describes the two main hypotheses tested in the paper, the technology-push and the market-pull effects. It also shows the expected signs of the coefficient for the respective interaction of the policy variable with the firm characteristic.

3.2 Empirical strategy

The empirical model estimates the effect of climate policies on borrowing firms' loan spreads. The main hypothesis tested is whether or not mitigation policies affect the green premium (i.e. the loan spread of brown firms minus that of green firms, everything else equal).

To test the hypothesis, we use the following empirical model:

$$AISD_{dfct} = \beta_1 \mathbf{E}_{ft} + \beta_2 \mathbf{P}_{ct} \times \mathbf{E}_{ft} + \beta_3 \mathbf{X}_{dft} + \delta_{ct} + \delta_{it} + \epsilon_{dfct} \tag{1}$$

where d denotes the loan deal, f the firm, c the country, t the year, and i the industry. The dependent variable, $AISD_{dfct}$, is the logarithm of the all-in-spread-drawn. It is the loan interest rate spread over

LIBOR for each dollar drawn down from the loan, measuring the cost of the syndicated loan (Chava, 2014). E_{ft} denotes the firm-level environmental performance metrics; P_{ct} is the domestic climate mitigation policy indicator[10]. In line with the existing literature (De Haas & Popov, 2019; Delis et al., 2019), the vector X_{dft} collects both firm level controls (such as log total assets, return-on-assets, debt-to-total-assets), deal-level controls (log tranche amount, tenor or maturity, secured deal, number of lenders, provisions, covenant) and deal-type dummy variables, controlling for the deal seniority, the type (term loan, credit line, other), and one of 28 primary purposes (e.g., acquisition, back-up line of credit, etc.). The deal-level controls also include country of syndication by year dummies, controlling for differences and changes in the rule of law across countries.

We include in the baseline two sets of fixed effects to control for unobservable shocks: δ_{ct} is a vector of country-by-year fixed effects to control for country-specific shocks that may be correlated with both mitigation policy and the loan spread. More generally, country-specific time fixed effects allow us to control for macro-economic shocks at the country-level, for example the effects of increasing globalisation and trade openness. δ_{it} are industry by year fixed effects, controlling for sector-specific shocks, such as global changes in demand for products coming from a particular sector and shifts in technological adoption. In the robustness checks, country-sector-year fixed effects are included to control for country-sector specific shocks, such as country-specific shifts to low-carbon technologies. Finally, ϵ_{dfct} is an error term assumed independent to the covariates of interest. It is allowed to correlate within firm: while this provides conservative estimates, it is important to allow firm-level dependence of disturbances to take into account unobservables.

The coefficient of interest is β_2, as the main variable of interest is the interaction between policies and firms' environmental performances $\mathbf{P}_{ct} \times \mathbf{E}_{ft}$ to identify the effect of the climate policies on cost of debt. This identification strategy combines within-country variation in climate policy and firm-level variation in exposure to climate policy to plausibly identify the effect of policies on firms' cost of capital. $\mathbf{P}_{ct}$ contains information on mitigation policy stringency, including the Environmental Policy Stringency (EPS) index and its sub-components relating to CO_2 taxes and green technology support (as further detailed below). $\mathbf{E}_{ft}$ contains information on firm-level environmental performance (i.e., green innovativeness and emission intensity), which is interpreted as the exposure to such policies. These variables vary by firm and year. To compare the relative magnitude of the effects of the main variables of interest $\mathbf{E}_{ft}$, we standardize these variables, so that the coefficient can be interpreted as the approximate percentage change in cost of debt associated with one standard deviation in the variables. An advantage

[10]The model does not evaluate whether investors assess the exposure to foreign policy stringency. If multinationals systematically relocate production in jurisdictions with lower policy stringency (the 'pollution haven' hypothesis) to reduce their exposure to domestic policies, then domestic policy might be of limited importance for investors. It is Reassuringly for the analysis, the empirical results below show that this is not the case and that exposure to domestic mitigation policy is taken into account by investors.

of interacting mitigation policy stringency with firm-level green innovativeness and CO_2 intensity is that it reduces concerns of omitted variable bias in our estimation. Any omitted variable that correlates with the country-level policy variables would only pose a problem if it were also similarly correlated to the firm-specific environmental exposure variables. For example, unobserved managerial quality could correlate with environmental performance, but firms with different managerial quality would not be affected differently, conditional on environmental performance, by changes in mitigation policy. This approach also rules out country-level confounders that might correlate with environmental policy and affect the cost of debt but are orthogonal to environmental performance, such as labour regulation. In the robustness checks, we also estimate the model with firm-specific fixed effect and time-invariant environmental performance metrics to account for potential endogeneity.

A limitation of this approach is that it does not evaluate whether investors assess firms' exposure to foreign policy stringency. If multinationals systematically relocate production in jurisdictions with lower policy stringency (the 'pollution haven' hypothesis) to reduce their exposure to domestic policies, then domestic policy might be of limited importance for investors. As policy variations correlate positively, this could potentially introduce a bias towards zero, as unilateral changes to environmental policy are partially offset by foreign ones. Systematically testing policy differences is beyond the scope of this paper, but existing evidence shows that relocation risks are small (D'Arcangelo & Galeotti, 2022; Dechezleprêtre et al., 2022).

4 Results

4.1 Baseline results

The estimation starts with a simple specification including only firm-level environmental performance metrics ($\mathbf{E}_{ft}$), namely green innovativeness and emission intensity. Further regressions add progressively policy variables and interaction terms to yield the baseline specification as presented in Equation 1.

The specification with no policy variable interaction (Table 3, column 1) shows that the environmental performance variables are not significantly different from zero[11]. he coefficients on the control variables show the expected sign. They are also stable across different specifications (columns 2 – 5). Larger, more profitable and more innovative firms (as measured by general patenting) pay a lower cost on their capital, while firms with a high debt-to-asset ratio have a higher spread. Larger tranche amounts and loans with performance pricing provisions are associated with a lower spread. Secured loans, loans with

[11]This specification without policy interactions raises concerns about the endogeneity of the variable of interest. In particular, firm-level unobservables like managerial quality might determine both the environmental performance and the loan spread. If these unobservables correlate positively with the dependent and independent variable, the bias should be away from zero. Interestingly, the estimated effect is instead precisely estimated around zero. This concern is assuaged in the other specifications because other potential omitted variables should be equally correlated with the mitigation policy variable

longer tenors, loans with covenants, and loans with a larger number or lenders have higher spreads[12].

The coefficients on firms' environmental performance variables (green innovativeness and firms' emission intensities) and their interactions with the EPS index are the main parameters of interest in Table 3, column 2. The coefficient of the linear terms should be interpreted as the effect on loan spreads of increasing green innovation or emission intensity by one standard deviation, when EPS is zero (i.e. minimum level of policy environmental policy stringency). A positive significant coefficient for green innovation suggests that, when mitigation policy is absent, green innovators face higher loan spreads. The negative and significant coefficient on the interaction between EPS and green innovativeness means that this effect is reversed when mitigation policy is sufficiently stringent. The next section quantifies the size of this effect. On the contrary, the interaction term between the EPS index and emission intensity is very close to zero and not statistically significant, suggesting that higher emissions intensity is not significantly associated with the loan spread even for high level of EPS.

The bottom rows of the table show the marginal effect on loan spreads of green innovativeness and emission intensity i.e., the overall change in loan spreads for a unitary change in each of these variables. In this specification, the point estimates of these marginal effects are not statistically different from zero. In aggregate, this suggests that firms' environmental performance have no bearing on loan spreads unless mitigation policy is sufficiently strong.

When the EPS index is replaced by the two specific policy variables: carbon taxes (to capture market-pull effects) and clean technology support measures (to capture technology-push effects), the results are consistent with the hypothesis described in Table 2 that the syndicated loan market is a conduit for technology-push and market-pull effects (Table 3, columns 3 and 4).

Carbon taxes are associated with higher loans' spread for emission intensive firms and lower spreads for green innovators, as shown by the significant interaction terms and consistently with Table 2, panel (c) (Table 3, column 3). This is suggestive that sophisticated investors, such as banks operating in syndicated loan markets, can appraise the potential impact of market-pull policies on firms based on their level of emission intensity and green innovation.

Market-pull policy affect loan spreads through the syndicated loan markets (Table 3, column 4). The statistically significant negative coefficient on the interaction of technology support and green innovation suggests that green innovators face lower loan spreads when technology support is high, as banks might assess that these firms can capitalise on such support polices (Table 2, panel (b)). Similarly, the effect of the green technology support policies for emission intensive firms is positive, although only marginally

[12] The positive correlation between secured loans and the spread is discussed in previous research, showing that secured loans tend to be riskier loans and tend to be issued by younger firms with lower cash flows, explaining the positive correlation (Erel et al., 2012; Lim et al., 2014). Similarly, many lenders on a deal could be caused by the necessity to share a higher risk among many participants. The positive correlation between loan spread and number of lenders may also be explained by higher loan fees that may be associated with more lenders.

Table 3: The effect of mitigation policy on syndicated loans' spread

	log($AISD$)				
Model:	No policy variable (1)	EPS (2)	CO_2 tax (3)	Tech. support (4)	Tech. support & CO_2 tax (5)
Green innovativeness	0.001	0.162***	0.006	0.160***	0.136***
	(0.024)	(0.063)	(0.024)	(0.047)	(0.047)
Green innovativeness×EPS		-0.067***			
		(0.024)			
Green innovativeness×Tech. support				-0.073***	-0.061***
				(0.019)	(0.019)
Green innovativeness×Carbon tax			-0.176***		-0.117***
			(0.050)		(0.040)
Emission intensity	0.021	0.033	0.017	-0.030	-0.039
	(0.017)	(0.054)	(0.017)	(0.033)	(0.033)
Emission intensity×EPS		-0.006			
		(0.022)			
Emission intensity×Tech. support				0.028*	0.031**
				(0.015)	(0.016)
Emission intensity×Carbon tax			0.131***		0.107***
			(0.041)		(0.039)
(Log) Tranche amount	-0.043***	-0.043***	-0.043***	-0.043***	-0.043***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Tenor or maturity	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Secured	0.406***	0.405***	0.407***	0.404***	0.405***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Number of lenders	0.004**	0.003**	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Performance pricing provisions	-0.063**	-0.062**	-0.059**	-0.063**	-0.060**
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Presence of covenants	0.078***	0.080***	0.075***	0.079***	0.077***
	(0.027)	(0.027)	(0.027)	(0.026)	(0.026)
(Log) Total Assets	-0.100***	-0.101***	-0.101***	-0.103***	-0.103***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
ROA	-1.329***	-1.302***	-1.317***	-1.332***	-1.323***
	(0.165)	(0.165)	(0.165)	(0.165)	(0.165)
Debt to Asset	0.462***	0.454***	0.461***	0.455***	0.456***
	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)
General patenting	-0.098***	-0.100***	-0.095***	-0.102***	-0.100***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Observations	6,029	6,029	6,029	6,029	6,029
Number of firms	1,384	1,384	1,384	1,384	1,384
Degrees of freedom lost due to f.e.	1,101	1,101	1,101	1,101	1,101
Green innovativeness marginal effect	0.001	0.007	-0.028	0.018	-0.004
p-value	0.962	0.783	0.274	0.433	0.860
Emission intensity marginal effect	0.021	0.020	0.042**	0.024	0.042**
p-value	0.215	0.239	0.018	0.153	0.017

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The environmental performance variables (emission intensity and green innovativeness) are standardized to have mean 0 and standard deviation 1. For these variables, the coefficient estimated can be interpreted as the % change in AISD corresponding to 1 standard deviation change in the independent variable. All specifications contain country×year, industry×year and deal-type fixed effects. The marginal effects reported are the average (across observations) predicted change in the dependent variable to a unit change in the independent variable, keeping the other variables at the observational value. Standard errors clustered at the firm level in parentheses.

significant.

The baseline estimate, which will be used later, considers the two policy dimensions (technology-push and market-pull factors) at the same time (Table 3, column 5). The estimates reflect those in columns 3 and 4. More generous technology support policies lower the spread for green innovating firms and increase the spread for emission intensive firms, although the latter result is only marginally significant. Higher carbon taxes increase the spread for emission intensive firms and lower it for green innovating firms.

The marginal effects of the environmental performance variables, reported at the bottom of the table along their p-values (Table 3), provide additional insights. In particular, the average marginal effect masks heterogeneity across firms depending on the level of countries' policy stringency. The marginal effect of green innovativeness is very close to zero across specifications. This means that, given the policy stringency level in the countries and period covered by the dataset, green innovativeness has on average no effect on spreads. In contrast, the marginal effect of emission intensity is positive and different from zero at a 5% confidence level, at least in the richer specifications (columns 3 and 5), though it is quantitatively small[13]. This latter finding is consistent with previous papers reporting small or no carbon premia associated with emission intensity (Bolton & Kacperczyk, 2021). More stringent policy across countries would further induce banks operating in the syndicated loan markets to discriminate between them, resulting in larger marginal effects.

The difference in the average marginal effects of green innovation and emission intensity can be explained as follow. Given the average mitigation policy stringency, in the countries and period covered in this study, firms' green innovation is still too difficult to assess for banks to offer a green premium to green-innovating firms. On the contrary, emission intensity of firms and the ease with which banks can observe and assess this information allows them to price in higher transition risks when offering loans to high emission firms, given the average mitigation policy stringency in the sample.

The results in this section are robust to alternative specifications (presented in Appendix B). First, firm-fixed effects control for unobservable time-invariant characteristics of the firm, such as management quality, which could invalidate the identification strategy. Results are largely robust to including firm-fixed effects, although the interpretation slightly changes as effects are now related to departures from firm-level averages (within-firm effects, Table B1 in Appendix B1). A second robustness check consists in using a time-invariant (within-period average) measure of policy exposure to account for the possibility that cheaper access to credit may encourage firms to invest in green innovativeness or emission abatement, potentially introducing reverse causality in the estimation.

Results are also robust to including a richer fixed effect structure (industry × year × country), using

[13]One standard deviation above the mean emission intensity is associated with -4% in loan spreads. For the median deal (137bps), this is equivalent to -5bps.

value added to compute emission intensity instead of total assets, and including energy prices as additional control (Table B2 in Appendix B1). One additional robustness check replicates the analysis without the firms from the United States (which make up around two thirds of the sample) yielding similar quantitative results (Table B2 in Appendix B1). Finally, results are robust to alternative transformations of the green innovativeness variable (i.e. number of patents relating to mitigation technologies), including the use of alternative constants and of the inverse hyperbolic sine transformation, to avoid the problem of missing values in case of zero patents (Table C1 in Appendix B1).

4.2 Magnitude of the effects

The effects in Table 3 are economically meaningful. As regards green innovativeness as mediated by EPS (column 2), a unit increase in the EPS is associated with a 7% decline in the cost of debt for firms with a green innovativeness one standard deviation above the mean (or the 87th percentile of the green innovativeness distribution) and with average emission intensity. For the median deal (spread: 137bps, size: €366 million), this is equivalent to a decline in 9bps or €0.3 million in annual interests.

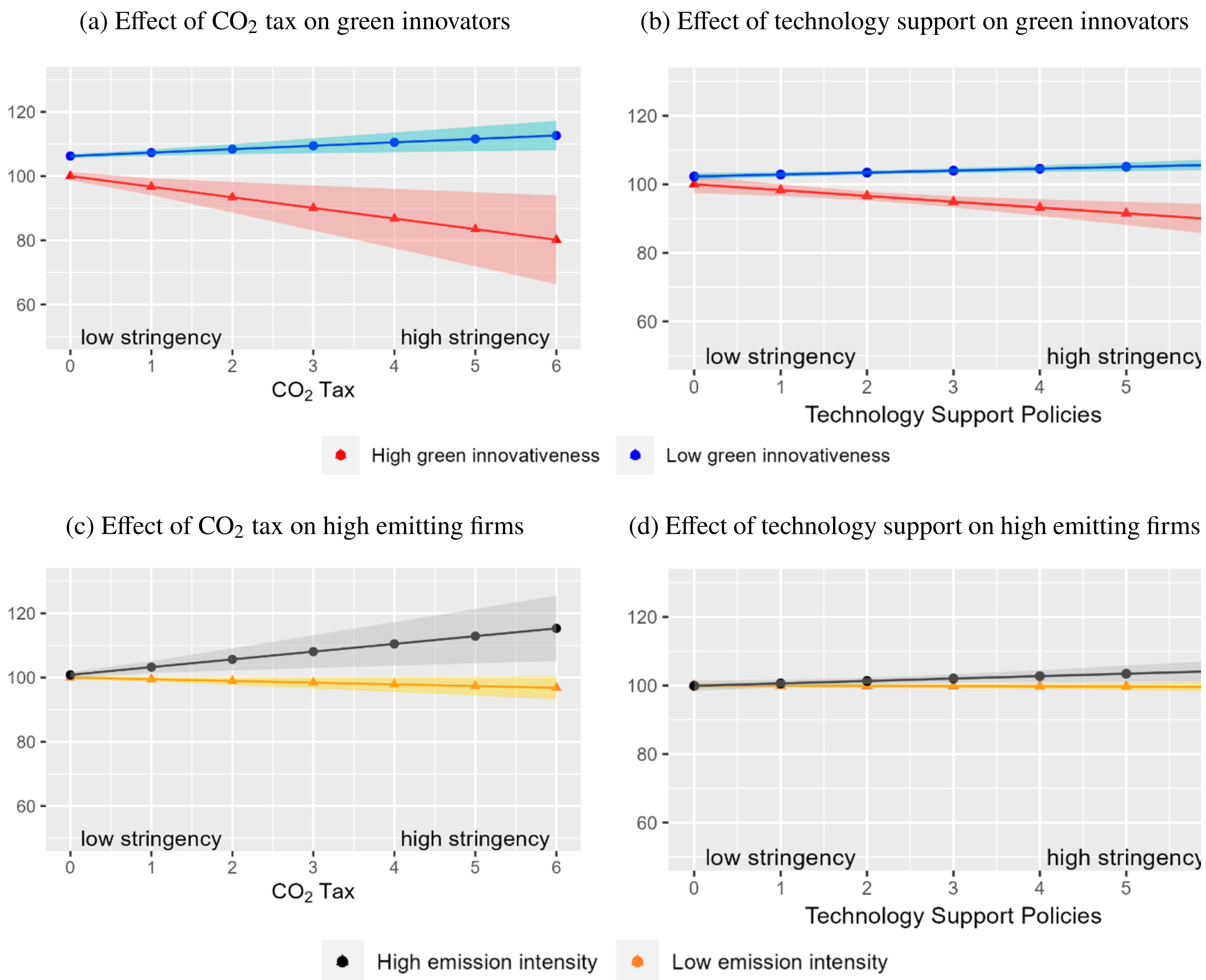
Figure 2 shows the effect of carbon taxes and technology support policies using the baseline specification in column 5 of Table 3. Firms are divided into two groups: top 25% and bottom 25% based on the in-sample distributions of the emission intensity and green innovativeness measures. The other loan and firm-level controls are fixed at their mean[14]. For ease of interpretation, a unitary increase in the two policy sub-indices is about equal to the in-sample average change between 2002 and 2018, although some countries have increased their policy stringency more than others. The figures show the predicted values of the loan's spread (re-scaled to 100 for the greenest firms in absence of policy).

Overall, the results in Figure 2 indicate that green innovators enjoy lower loan spreads due to both market-pull and technology-push policies, while emission intensive firms face higher loan spreads due to carbon taxes but not technology-push policies:

- The predicted loans' spread for the most green-innovative firms is almost 20% lower with a high carbon tax (score of six, equivalent to a carbon price above €50/t CO_2) than with no carbon tax (Figure 2, panel (a)). Even for relatively low carbon prices, i.e., from an indicator score of two onwards (equivalent to a carbon price above €10/t CO_2), the loan spread is significantly lower for firms with the highest green innovation level. For firms in the bottom 25% of the green innovativeness distribution, the loan spread increases by about 8% as the carbon tax increases from no carbon tax to a carbon tax score of six. With high carbon prices (score of six on the CO_2 tax sub-index), the difference in the predicted spread between top and bottom green innovators is about

[14]This helps to isolate the effect of policies for comparisons keeping constant all the other variables. Because green innovativeness correlates negatively with emission intensity, the two effects reinforce each other. For example, a firm that is in the top 25% of firms by green innovativeness is more likely to be in the bottom 25% of emission intensive firms. For that firms, the policy effects discussed here should be summed.

Figure 2: Effects of carbon taxes and technology support policies on loans' spreads



(a) Effect of CO_2 tax on green innovators

(b) Effect of technology support on green innovators

(c) Effect of CO_2 tax on high emitting firms

(d) Effect of technology support on high emitting firms

The figure shows the linear predicted effects of the policy interactions from Equation 1, based on the baseline regression results shown in Table 3, column 5. The effects are re-scaled to 100 for the green firm (high green patenting share or low emission intensity, respectively) at zero policy stringency. All other variables are fixed at their mean. Confidence bands at 95% level are calculated with the delta method and reflect the estimation uncertainty on β_1 (coefficient of the environmental performance variable) and β_2 (coefficient of the interaction term between the environmental performance and policy variables). As usual in these cases, the prediction is mechanically more imprecise for higher levels of the changing variable in the interaction term (the policy variable in this case). Panel (a) and (b) show the linear predicted effects for firms among the top 25% and the bottom 25% of green innovators for different levels of the CO_2 tax and technology support. Panel (c) and (d) show the linear predicted effects for higher emission intensive firms (top 25%) and low emission intensive firms (bottom 25%) at different levels of a CO_2 tax and technology support.

30%. For the median deal (spread: 137bps, size: €366 million) this difference is equal to 41 bps or €1.5 million of annual interest payments.

- Regarding technology support policies, at the highest level of the technology support sub-index, top green innovators benefit from a 15% lower spread than the bottom green innovators. The average change in the technology support policy stringency over the sample period is equal to a one unit increase in the index.

- The predicted effects on loan spreads for firms with a high and low emission intensity at different levels of carbon tax are shown in panel (c). Higher carbon pricing is associated with a significantly higher spread for the most emission intensive firms (top 25% of the emission intensity distribution). For these firms, increasing the carbon tax score from zero to six is associated with a 15% higher spread. The effect on firms with a low emission intensity is markedly lower with the spread declining by only 6% (and statistically only weakly significant). Together with the results of CO_2 taxes on green innovators (panel (a)), this shows how market-pull policies can have significant effects on the syndicated loans' spreads, lowering the cost of debt for firms innovating in green technologies and increasing the cost for the most emission intensive firms.

- The effect of green technology support policies on firms with different emission intensity is small, although statistically significant, with small positive effects only on the spread for the most emission intensive firms (panel (d)). Comparing these results with those in Panel (b) indicates that the effect of technology-push policies is larger when discriminating among firms based on their green innovativeness (panel (b)) than emission intensity (Panel (d)). This is to be expected, as technology support do not aim at penalising high-emission firms.

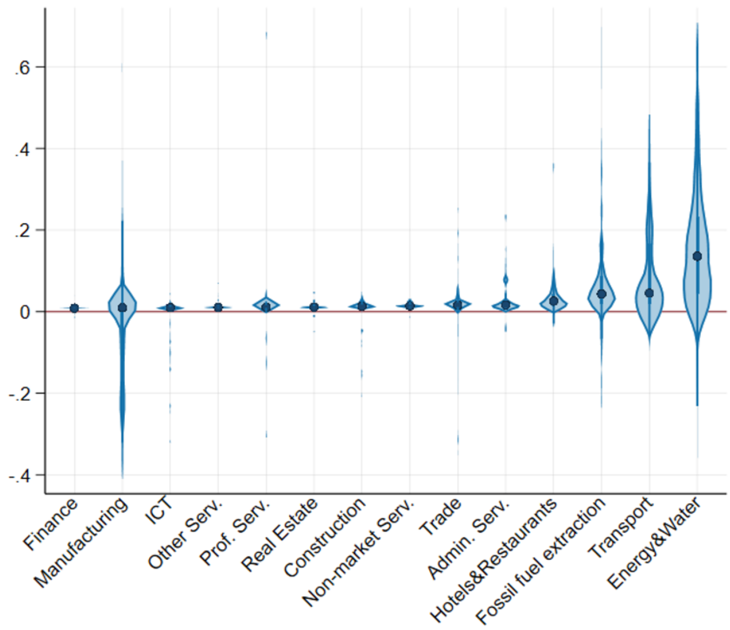
These results lead to the following policy insights. First, strengthening mitigation policies can be an effective way to reduce the cost of debt of green innovators. Both market-pull and technology-push policies have large positive effects on green innovators, reducing their loan spreads substantially (Figure 2, panel (a) and (b)). These policies are also associated with a moderate increase in the loans' spread of firms that do not engage or engage only to a limited extent in green innovation. Second, raising carbon taxes increases the cost of debt of highly emitting firms. Higher carbon taxes penalise firms with high emissions by raising their tax burden and banks operating in the syndicated loan markets respond to this by increasing loan spreads.

Increasing the carbon tax index will have widely different effects across firms (within and between sectors), depending on firms' environmental performance. The majority of firms in each sector will experience an increase in loan spreads following a one unit increase in the carbon tax index (around 10 €/tCO_2) (Figure 3). The median predicted change in loan spreads (the dot in Figure 3) is above zero in each sector[15]. Some sectors, such as Energy and Water, Transport, and Fossil fuel extraction, feature a large share of firms with low environmental performance. However, even in these industries, there are firms with high environmental performance, which could benefit from higher carbon taxes though lower loan spreads. Firms in the Manufacturing sector show stark heterogeneity in environmental performance and thus in the predicted change in loan spreads. Most firms are predicted to experience an increase in loan spreads (as the median change, i.e. the dot, is above zero), but a significant share of firms in this sector have good environmental performance and could enjoy lower loan spreads due to higher carbon taxes.

Overall, these results suggest that sophisticated investors, such as banks participating in syndicated loan markets, are forward-looking and price-in transition risk. Green innovation captures firms' future exposure to more stringent mitigation policies (in addition to exposure to existing policies), as green technologies will be key to reducing emissions and keeping abatement costs low. That green innovation is an important mediating factor of the effect of mitigation policies on loan spreads point to the ability of sophisticated investors, such as banks operating in the syndicated loan market, to incorporate expectations on future effects of current policies and future policy changes in their decision making. Banks issuing syndicated loans make considerable efforts to monitor corporate borrowers, reflecting large loan volumes and their associated risks (Gustafson et al., 2021). Detailed monitoring of corporate borrowers – including site visits, and regular information sharing – can enable large banks to effectively monitor firms' actual environmental performance (as measured by carbon emissions and green innovativeness) and their exposure to environmental policies.

[15] The deal-level predicted percentage change in loan spread associated with an increase in the carbon tax index is calculated as $\hat{\Delta}_{\%} = \left[\exp\left(A\hat{I}\hat{S}D_{dfct}\,(CO2_{ct}+1)\right) - \exp\left(A\hat{I}\hat{S}D_{dfct}\,(CO2_{ct})\right)\right] / \exp\left[\right] A\hat{I}\hat{S}D_{dfct}\,(CO2_{ct})\big]$, where $CO2_{ct}$ is the observed value of CO_2 tax and $A\hat{I}\hat{S}D_{dfct}(x) = \hat{\beta}_1^{EI} EI_{ft} + \hat{\beta}_1^{Pat} Pat_{ft} + \hat{\beta}_{21}^{EI}(x \times EI_{ft}) + \hat{\beta}_{21}^{Pat}(x \times Pat_{ft}) + \hat{\beta}_{22}^{EI}(TS \times EI_{ft}) + \hat{\beta}_{22}^{Pat}(TS \times Pat_{ft}) + \hat{\beta}_3 \mathbf{X}_{dft} + \hat{\delta}_{ct} + \hat{\delta}_{it}$.

Figure 3: Distribution of effects of a carbon tax across firms and industry



The figure shows the distribution of percent predicted changes in loan spreads (using the baseline regression results shown in Table 3, column 5) from increasing the carbon tax index by one unit (around 10 €/tCO_2). The blue dots represent the median predicted change in firms' loan spreads within each industry. Differences across and within industries are driven by the variation in deal- and firm-level characteristics (including environmental performance).

4.3 Sample selection and emission disclosure

Emission disclosure is voluntary for some firms in our sample, raising a potential problem of sample selection. Sample selection can bias estimates if management chooses to disclose emissions based on firm characteristics unobserved by the researcher that also affect loan spreads. For example, ownership or governance structures affect the disclosure decision (Christensen et al., 2021). Low emitters could have an incentive to strategically disclose their emissions if they are more credit-worthy and the incentive would be stronger if environmental policy is more stringent.

We address the problem of sample selection implementing a two-step estimator à la Heckman (1979). This involves two steps: modelling the firm's decision to disclose and compute the inverse Mill's ratio, and inserting the inverse Mill's ratio in the loan spread specification to correct for possible sample selection bias.

In the first step, we estimate the selection process on the full sample of firm-level data (i.e., firm level data including data with missing data on emissions). We use peer pressure as an instrument, defined as the share of competing disclosing firms at the country-industry-year level (unweighted or weighted by either assets or total revenues), lagged by one year[16]. Firms mimic their peers and competitors when disclosing sustainable practices, for example because they learn about the associated benefits or to compete for stakeholder engagement (Cao et al., 2019; Matsumura et al., 2014; Misani, 2010). The use of an instrumental variable approach has the advantage of not relying on the assumption of a normal distributional form of the error term, otherwise necessary for identification of the Heckman estimator (Puhani, 2000). Rather, identification hinges on the exclusion restriction of peer pressure in the spread equation. In other words, this assumes that a firm's spread does not depend on the decision of other firms to disclose emissions, if not through their own disclosure decision.

The results of the first step (Table 4, panel A) indicate that our instrument is relevant and it has the expected sign. The probability of a firm to disclose its emissions increases as the share of peers and competitors within country and industry disclosing their emissions (during the previous year) increases. In the second step, we include the inverse Mill's ratio in our preferred specification to control for selection bias (table 4, panel B), the corresponding coefficient is not statistically different from zero, implying that sample selection does not affect significantly our main results.

4.4 The effect of ESG information on loan spreads

Investors are increasingly incorporating environmental, social and governance (ESG) factors into asset allocation and risk decisions. The environmental (i.e., E pillar) score of ESG ratings has gathered increasing attention as investors' concerns about exposure to climate risks intensify. In principle, investors

[16] A similar approach appears in Ilhan et al. (2021).

Table 4: Heckman two-step correction

Panel A: Selection equation			
	Peer Pressure		
Weights:	Unweighted	Total assets	Total revenues
Model:	(1)	(2)	(3)
Peer Pressure	0.445***	0.103*	0.114**
	(0.093)	(0.054)	(0.053)
(Log) Total Assets	0.598***	0.598***	0.598***
	(0.015)	(0.015)	(0.015)
ROA	1.675***	1.691***	1.687***
	(0.172)	(0.172)	(0.172)
Debt to Asset	-0.756***	-0.765***	-0.764***
	(0.077)	(0.077)	(0.078)
General patenting	0.059**	0.057***	0.058***
	(0.015)	(0.015)	(0.015)
Green innovativeness	0.063**	0.064**	0.063**
	(0.031)	(0.031)	(0.031)
Observations	171,934	171,621	171,178
Number of Firms	17,615	17,559	17,564

Panel B: Regression equation			
		$\log(AISD)$	
Model:	(4)	(5)	(6)
Inverse Mill's Ratios	-0.0506	-0.0506	-0.0548
	(-0.641)	(-0.642)	(-0.695)
Green innovativeness	0.109**	0.109**	0.111**
	(2.139)	(2.138)	(2.207)
Green innovativeness × Carbon tax	-0.148**	-0.148**	-0.147**
	(-2.237)	(-2.245)	(-2.238)
Green innovativeness × Tech. support	-0.0536**	-0.0536**	-0.0545***
	(-2.578)	(-2.579)	(-2.656)
Emission intensity	-0.0407	-0.0408	-0.0405
	(-1.199)	(-1.201)	(-1.193)
Emission intensity × Carbon tax	0.106***	0.106***	0.105**
	(2.623)	(2.616)	(2.576)
Emission intensity × Tech. support	0.0313*	0.0314**	0.0311*
	(1.960)	(1.964)	(1.947)
Loan characteristics	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes
Observations	6,029	6,029	6,029
Number of Firms	1,384	1,384	1,384

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

All specifications contain country × year, industry × year,deal-type (seniority, loan type and loan purpose), and country of syndication × year fixed effects.

could use reliable E pillar scores as a screening device to easily assess firms' climate transition risks and make investment decisions in light of those risks. In the absence of informative E pillar scores banks and investors would need to expend more efforts and resources in monitoring firms so as to assess firms' transition risks.

However, ESG and E pillar scores capture only imperfectly firm's environmental performance and their exposure to climate and policy-related risks. Firms with an ESG score may devote substantially more financial resources to information disclosure than firms without an ESG score while having similar environmental performances. ESG scores can be unrelated to environmental performance, in terms of emission or green innovativeness, raising questions on the quality and usefulness of the information provided by ESG (OECD, 2022).

This section investigates whether ESG scores (sourced from Refinitiv) alter the impact of environmental performance measures (i.e. firms' green innovativeness and emission intensity) on loans spread with respect to the baseline specification. If the impact of firm's environmental performance metrics on the loan spread is entirely or partially explained by the introduction of the ESG or E-pillar scores, then one could conclude that banks use these scores as a tool to assess firms' environmental performance and transition risks in their loan disbursement decisions. For this to happen, the following three conditions must realise: 1) ESG scores need to correlate with environmental performance; 2) ESG scores need to correlate with spreads; 3) the magnitude on the coefficients of the environmental performance variables needs to decrease (in absolute value) with respect to the baseline specification.

Overall, the results suggest the following. First, firms with higher ESG or E pillar scores are rewarded by the market with lower interest rates. Second, ESG and E pillar variables do not correlate (or correlate weakly) with green innovativeness and emission intensity (Appendix C). Third, mitigation policies do not mediate the effect of ESG scores. Put together these results suggest that ESG information is financially material to investors, but as they may provide little information on a firms' actual environmental performances and their transition risks, they are not useful instruments to price the effect of mitigation policies in loan decisions.

The effect of ESG scores on the loan spreads is analysed in Table 5. Column 1 reports the baseline estimates (from Table 3, column 5) to facilitate comparison. Two variables (and their interactions) are added to the baseline: an ESG (or E-pillar) disclosure dummy variable (equals to 1 for firms with an ESG (or E-pillar) score and zero otherwise) and the level of the (standardized) ESG (or E-pillar) score. Adding a disclosure dummy has two purposes: 1) capturing the effect of disclosing information about firms' environmental metrics regardless of the actual score; 2) imputing an ESG (or E-pillar) score of zero to firms that do not have one, so as to preserve the baseline dataset and compare results.

Firms that disclose an ESG score (Table 5, column 2) or E pillar (Table 5, column 3) in addition to

Table 5: The effect of mitigation policy on syndicated loans' spread

	log($AISD$)		
	Baseline	General ESG	E pillar
Model:	(1)	(2)	(3)
Green innovativeness	0.136***	0.157***	0.165***
	(0.047)	(0.047)	(0.048)
Green innovativeness × Tech. support	-0.061***	-0.068***	-0.072***
	(0.019)	(0.020)	(0.020)
Green innovativeness × Carbon tax	-0.117***	-0.117***	-0.116***
	(0.040)	(0.040)	(0.040)
Emission intensity	-0.039	-0.028	-0.030
	(0.033)	(0.034)	(0.033)
Emission intensity × Tech. support	0.031**	0.027*	0.027*
	(0.016)	(0.016)	(0.016)
Emission intensity × Carbon tax	0.107***	0.101**	0.100**
	(0.039)	(0.040)	(0.041)
Discloses ESG (dummy)		-0.078**	-0.088**
		(0.040)	(0.040)
ESG score		-0.134***	-0.152***
		(0.042)	(0.049)
ESG score × Tech. support		0.046**	0.058**
		(0.019)	(0.023)
ESG score × Carbon tax	0.014	0.000	
		(0.015)	(0.019)
Green innovativeness marginal effect	-0.004	0.002	0.004
p-value	0.860	0.951	0.869
Emission intensity marginal effect	0.042**	0.042**	0.042**
p-value	0.017	0.017	0.018
ESG marginal effect		-0.042***	-0.039**
p-value		0.006	0.016

Signif. Codes: ****: 0.01,* ***: 0.05,* **: 0.1*

The environmental performance variables (emission intensity and green innovativeness) are standardized to have mean 0 and standard deviation 1. For these variables, the coefficient estimated can be interpreted as the % change in AISD corresponding to 1 standard deviation change in the independent variable. All specifications contain country×year, industry×year and deal-type fixed effects. The marginal effects reported are the average (across observations) predicted change in the dependent variable to a unit change in the independent variable, keeping the other variables at the observational value. Standard errors clustered at the firm level in parentheses.

their green innovativeness and emission intensity face lower syndicated loan spread. Also, among the firms with an ESG or E pillar score, a higher score is associated with a lower spread. The interactions of the ESG or E pillar scores with the policy variables indicate that carbon pricing does not mediate the effect of the ESG or E pillar score on firms' cost of debt of firms. Against expectations, more generous green technology support is associated instead with a higher spread for firms with a better ESG score.

The marginal effects at the bottom of the table are the average predicted change in loans when ESG or E pillar scores increase by one (i.e. one standard deviation), keeping policies at their observational value. Firms with an ESG score one standard deviation above the mean experience a 4% reduction in the loan spread, equal to 5 bps for a median loan. The findings are similar when replacing the ESG score by the E pillar score. Higher ESG scores are associated with lower firms' loan spreads, regardless of mitigation policy. Banks may reward firms with high ESG or E pillar scores with lower loan spreads, irrespective of mitigation policy stringency, because of banks' corporate plans, ESG investing mandates or other factors (i.e., shareholder pressures) pushing them to shift investment and activity towards such firms. In these regards, portfolio management could be targeting ESG or E pillar scores as an 'output', rather than as an input to manage transition risk.

The results also show that adding the ESG or E pillar scores does not significantly alter the impact of the environmental performance variables (i.e. green innovativeness and emission intensity) on loan spread as compared with the baseline regression in column 1[17]. Overall, these findings are consistent with viewing banks operating in the syndicated loan marker as sophisticated investors. They are able to assess firms' transition risks based on the level of mitigation policy stringency and firms' actual environmental performance but use ESG scores for other motives than managing borrowers' transition risks. For example, certain banks maintain ESG targets in their portfolio for commercial reasons or they might actively seek investments that have a positive sustainability impact, regardless of price-risk considerations.

5 The effect of mitigation policy on investment

5.1 Empirical strategy and estimation

The previous section quantified the effect of mitigation policies on syndicated loan spreads; this section investigates the additional investment that mitigation policies can engender through lower spreads.

Investment elasticities with respect to cost of debt has been estimated across several papers: Schaller and Voia (2017) estimate and elasticity of -0.8, Gilchrist and Zakrajšek (2007) obtain -0.75 in the short

[17]The interactions of the environmental performance variables with the policy variables remain significant and similar to the baseline results. The marginal effect of green innovativeness and emission intensity also remain similar across specifications. Sophisticated investors, such as banks, do not rely exclusively on ESG scores as a proxy for environmental performance in their loan disbursement decisions.

run and -1 in the long run, Wen et al. (2020) get -1.3 specifically for equipment; finally, the review of Hassett and Hubbard (2002) favours -1.

One approach to quantifying the effect on investment is to apply the range of estimates from previous studies in a back-of-the-envelope calculation. In addition, we also estimates the investment elasticity to loan spreads using our own firm-level data on investments and syndicated loans, using an Instrumental Variable-Generalised Method of Moments (IV-GMM) approach. The approach is described in detail in Appendix D and the results of regressing investment on loan spreads by IV-GMM are reported in Table D in Appendix D. The main estimate of interest is the investment elasticity with respect to cost of debt, which ranges in our estimation from -1 to -1.4, suggesting that a 10% increase in loan spreads causes a 10 to 14% decrease in investments. The coefficients are statistically different from zero, although confidence intervals are large, possibly because loan spreads are a noisy proxy of the average cost of capital. The point estimates are similar to previous findings reported in the previous paragraph.

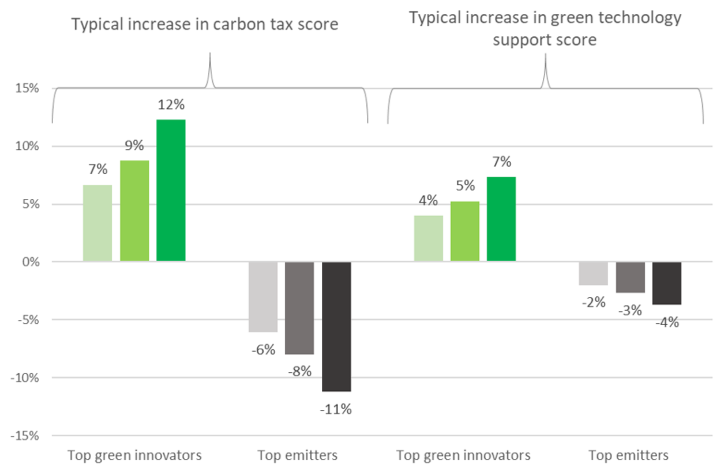
5.2 Quantification of the investment effect on green firms

These elasticity estimates can be used to perform back-of-the-envelope calculation on the effects of changes in mitigation polices on investment. In practice, the change in investment can be calculated as follows:

$$\hat{\Delta}_{\%} I_{fct} = \hat{\gamma} \times \hat{\Delta}_{\%} AISD_{fct} = \hat{\gamma} \times \hat{\beta} \times \Delta\mathbf{P}_{ct} \times \mathbf{E}_{ft} \tag{2}$$

where $\hat{\Delta}_{\%}$ denotes a predicted percentage change in the variable of interest; I_{fct} is investment of firm f, in country c and year t; $\hat{\gamma}$ is the estimated elasticity of investments to cost of debt; $AISD_{fct}$ is the average loan spread of firm f in year t; $\hat{\beta}$ is the estimated coefficient of interest from equation 1, multiplying the observed environmental performance $\mathbf{E}_{ft}$ and the considered change to policy $\Delta\mathbf{P}_{ct}$. Mitigation policies can have a large positive effect on top green innovators investments and an equally large negative effect on investments of large emitters. Figure 4 shows a range of estimates for a change in investment for a typical (one standard deviation) increase in the carbon tax and the technology support policy scores, using an upper- and a lower-bound for elasticity (taken from Table D in Appendix D and the literature (Gilchrist & Zakrajšek, 2007)). A typical increase in the carbon tax score is associated with a 7 to 12% increase in investment for top green innovators and a 6 to 11% decline in investment for the top emitters. A typical increase in the green technology support score is associated with a 4 to 7% increase in investment for top green innovators and a 2 to 4% decline in investment for top emitters. The magnitude of these effects is economically meaningful. Using our estimated elasticity, the investment effects are however statistically not different from zero because the elasticity of investments to cost of debt is not precisely estimated[18].

Figure 4: The investment effect of mitigation policies through cost of debt



The figure shows the range of changes in investment associated with a one standard deviation increase in the carbon tax and the technology support score for top green innovators and top emitters. The darker shades show the effects estimated with the upper bound elasticity estimated in this paper (-1.38). The medium-light shades show the effects estimated with the lower elasticity estimated in this paper (-0.99). The light shades show the effects estimated with the lower bound elasticity from Gilchrist and Zakrajšek (2007)(-0.75). Using our estimated elasticity of investments from equation 2, the investment effects are however not statistically significant because the elasticity of investments to cost of debt is not precisely estimated.

6 Discussion and conclusion

This paper shows that climate policies impact investors' reaction to firms' environmental performance. We make an important contribution to the previous literature by examining the effect of climate policy on the allocation of capital in the syndicated loan market, using country-by-year continuous variation in climate policy stringency interacted with firm-level performance. We are able to isolate the effect of mitigation policies on firms' cost of debt in the syndicated loan market. Our results show that climate policies, that vary in nature and stringency across countries and time, have financially material impacts on green and brown firms' cost of debt.

The analysis yields three important findings. Firstly, firms with strong environmental performance (measured by low emission intensity or high patenting activity in mitigation technologies) enjoy lower cost of capital, reflected in lower syndicated loan spreads, if climate policies are stringent. The effect is substantial under stringent mitigation policies but diminishes under lenient ones. Carbon taxes increase loan spreads for emission-intensive firms while decreasing them for green innovators, whereas green technology support policies reduce loan spreads for green innovators but have little impact on emission-intensive companies. Secondly, ESG scores, including their environmental pillar, do not adequately

[18]The quantification of investment effects of mitigation policies for companies whose environmental performance is expressed in standard deviations above the mean, rather than for the top and bottom quartiles of companies, are presented in Appendix E.

gauge the influence of climate mitigation policies on firms. Firms disclosing ESG scores experience lower loan spreads, escalating with better scores, yet this advantage is decoupled from policy stringency and lacks correlation with actual environmental performance. Thirdly, mitigation policies can induce capital reallocation, boosting investment in green firms while curtailing it in brown ones.

Overall, these results underscore investors' consideration of transition risks in capital allocation within the syndicated loan market, emphasizing the importance of accurate information and reducing informational disparities. Investors need such information to assess and manage climate-policy transition risks of investees so as to avoid locking investment in stranded assets and contribute to the financial sector net-zero pledges. Information on firms' environmental performance is often lacking, partial or incomplete. The information asymmetries are arguably larger for less sophisticated investors than those considered in this study. Less sophisticated investors likely face stronger barriers to collect or process information on investees' transition risks or their alignment with climate targets. Indeed, studies have reported the limited capacity of investors to process large and complex amounts of information, which may delay their reactions. Information reported in a non-standard format can be particularly difficult for investors to incorporate in investment decisions (DellaVigna & Pollet, 2007, 2009; Hirshleifer et al., 2009).

Improving the available information of firms' environmental performance metrics is important to enable investors to allocate capital in line with emission reduction targets. Mandating minimum environmental disclosure requirements could ameliorate this problem. The harmonisation of emission accounting standards and the improvement in data quality can be further encouraged. In addition, improving the transparency and credibility of ESG rating methodologies or other similar metrics is key to guide the financial assessment of climate policies on firms and firms' transition risks and contribute to the stability of the financial system.

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7 Appendix

A Data sources and descriptive statistics

A1 Environmental performance metrics: Green innovativeness, emission intensity and ESG

The environmental performance of firms is measured through their green innovation and emission intensity. Green innovation is measured by the stock of patents in mitigation technologies issued by the firm, sourced from PATSTAT. PATSTAT contains the universe of patents filed by firms. It is a globally comprehensive database – including all patents filed in any of the major patent offices – is maintained and regularly updated by the European Patent Office. Numerous papers have used this data source to measure firms' green innovation, e.g., Calel and Dechezleprêtre (2016) and Dechezleprêtre and Kruse (2022).

More specifically, this paper uses the number of patent applications in climate-change mitigation technologies, which are based on the "Y02" tagging system developed by the European Patent Office and available on all patent applications recorded in the global PATSTAT database. It includes inventions in climate-change mitigation technologies related to buildings (e.g. efficient home appliances), clean energy generation, smart grid technologies, transportation, as well as mitigation technologies in the production or processing of goods (e.g. metals, chemicals, minerals) among others (sustainable technologies in patents, 2016).

The analysis uses the accumulated stock of low-carbon patents as the explanatory variable instead of the flow of patents. This is because it takes time for firms to benefit from innovation, which first need to be turned into marketable products. Similarly, the uptake of new technologies by the market may not be immediate. Firm's patent stock in low-carbon technologies is therefore a more suitable measure to assess the effect of low-carbon innovation on economic performance than patent flows.

To compute the knowledge stock, we follow the literature and apply an annual 15% depreciation factor to patent filings using the perpetual inventory method (Dechezleprêtre & Glachant, 2014; Franco & Marin, 2017). The patent stock is expressed in logarithmic to limit the influence of extreme observations. A constant of one is added to the number of patents of all firms before applying the logarithmic transformation so as to avoid missing values for firms with zero patents. Results are robust to alternative transformation of the patent stock data to circumvent this problem (subsection 3 and Appendix B).

Firm-level emissions come from Refinitiv EIKON and are measured in CO_2 equivalents (in tons)[19]. These emissions include both direct emissions from company-owned resources (Scope 1) and indirect emissions from the generation of purchased energy (Scope 2)[20]. Emissions are reported either voluntarily

[19]We use the variable ENERDP123 in the Refinitiv database, which is used widely in the literature to measure firms CO_2 equivalent emissions (Altunbas et al., 2022; Hege et al., 2022; Homroy, 2023).

[20]Scope 3 emissions are excluded from the analysis as information on scope 3 emissions is largely imprecise and sparsely available.

or in compliance with existing regulation (for example the European Union Emission Trading System) and follow predominantly the GHG Protocol. Firms' emission intensity is computed as emissions over total assets. In the robustness check, emissions are alternatively divided by the firm's value added, although this variable is much sparser.

Environmental, social and governance (ESG) data is collected from the Refinitiv ESG database. The analysis below uses both the total ESG score and its Environmental Pillar Score. ESG scores are industry-adjusted ranking of firms according to their relative performance on various environmental performance metrics, such as the presence of an environmental management system, their resource use policies, environmental expenditures and others. Below a discussion of their use, strengths and weaknesses is included.

A2 Firm-level financial data

The BvD Orbis database provides firm-level variables, including firms' total assets, profitability and leverage. The steps to obtain the clean firm-level Orbis database, include keeping accounts that refer to entire calendar years, keeping only consolidated accounts, dropping observations with missing information on key variables as well as outliers identified as implausible changes or ratios (Andrews et al., 2016). Investment data, employed to estimate the elasticity of investment to loan interest rates, are calculated at the firm level as the change in fixed assets (including both tangible and intangible assets) between t and t-1 corrected for depreciation both at book values (Millot et al., 2020; Sorbe & Johansson, 2017). The cleaned firm-level Orbis database is merged to the loan-level Dealscan via the linking table built by Bottazzi et al. (2020), based on fuzzy text-matching algorithm.

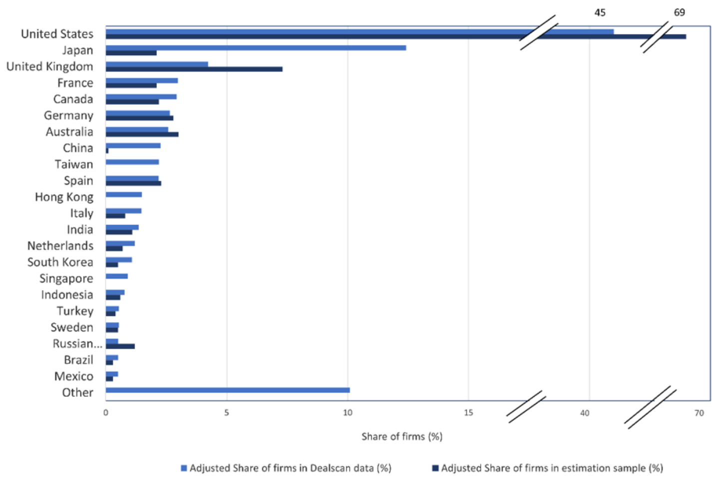
A3 Environmental policies

Country-level data on policy comes from the OECD Environmental Policy Stringency (EPS) index and its sub-components (Botta & Koźluk, 2014; Kruse et al., 2022). The OECD Environmental Policy Stringency (EPS) index is a widely used tool for policy analysis (Albrizio et al., 2017; OECD, 2021). One attractive feature of the EPS is that it compares policy stringency across countries and over time based on a homogeneous methodology. It focusses primarily on climate change and air pollution policies and covers 13 specific environmental policies. The index ranges from zero (least stringent policies) to six (most stringent policies) and is available from 1990 to 2020 for 40 countries.

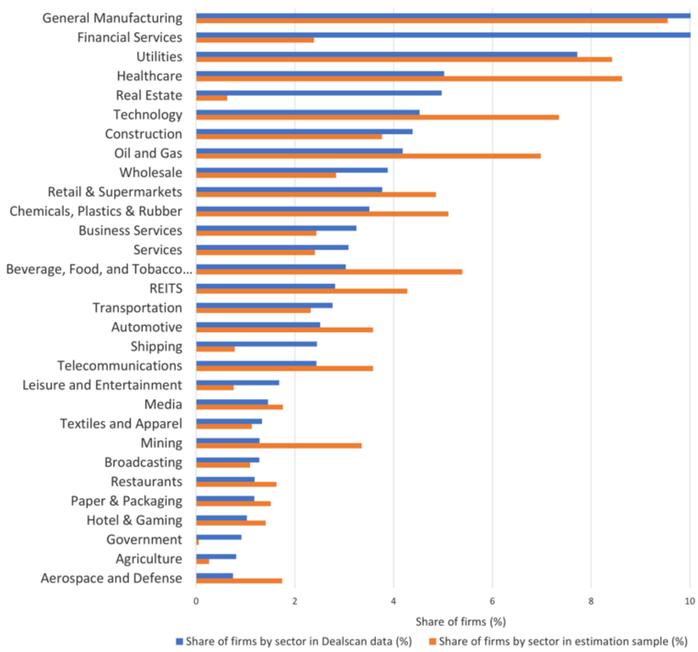
A4 Syndicated loans data

Figure A1: Share of firms using syndicated loans

(a) by country



(b) by sector



The figures show the share of firms by countries and sectors in the Dealscan data compared to the share of firms in the estimation sample. The Refinitiv Major Industry Group classification is used to classify sectors.

Table A1: Descriptive statistics of the estimation sample

Variable	N	Mean	s.d.	p25	p50	p75
Loan-level variables						
Log (All-in-spread-drawn) (AISD)	6,029	4.79	0.85	4.32	4.92	5.35
Tranche amount (m EUR)	6,029	771	1568	169	366	803
Tenor or maturity (months)	6,029	48.6	30	36	60	60
Secured (dummy)	6,029	0.25	0.43	0	0	0
Number of lenders	6,029	12.4	9.28	6	10	17
Performance pricing provisions (dummy)	6,029	0.38	0.49	0	0	1
Presence of covenants (dummy)	6,029	0.44	0.5	0	0	1
Firm-level variables						
Mitigation patent stock	6,029	0.53	1.14	0	0	0.36
Estimated intensity (tons CO_2 / EUR)	6,029	0.32	0.71	0.02	0.05	0.23
(Log) Total Assets	6,029	22.6	1.37	21.6	22.5	23.5
Return on assets	6,029	0.08	0.09	0.04	0.07	0.11
Debt to Asset	6,029	0.64	0.2	0.52	0.64	0.75
Discloses ESG score	6,029	0.86	0.35	1	1	1
Discloses E pillar score	6,029	0.86	0.35	1	1	1
Standardized firm-level variables						
Green patent stock sd.	6,029	1.93E-09	1	-0.46	-0.46	-0.15
Emission intensity sd.	6,029	-6.87E-10	1	-0.4	-0.35	-0.11
ESG score sd.	5,184	6.00E-10	1	-0.81	-0.12	0.72
E pillar score sd.	5,181	1.09E-08	1	-1.07	-0.22	0.86
General patenting sd.	6,029	2.20E-09	1	-0.8	-0.5	0.65
Policy variables						
EPS	6,029	2.32	0.76	1.67	2.42	2.94
Technology support policy	6,029	1.93	0.87	1.5	2	2.25
Carbon tax	6,029	0.19	0.76	0	0	0

The table shows the descriptive statistics of the estimation sample. s.d. is the standard deviation. P25, the 25th percentile, p50 the median and p75 the 75th percentile. Monetary values expressed at constant 2005 prices.

Table A2: Difference between full sample and estimation sample

	Estimation sample		Full sample		Difference	
	Mean	N	Mean	N	Value	%
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Loan-level variables						
Log (All-in-spread-drawn) (AISD)	4.790	6,029	5.056	1,7157	-0.266	-6%
Tranche amount (m EUR)	770.8	6,029	228.5	3,3859	542.3	70%
Tenor or maturity	48.60	6,029	50.89	3,5467	-2.302	-5%
Secured (dummy)	0.247	6,029	0.307	3,6585	-0.061	-25%
Number of lenders	12.36	6,029	6.262	3,6585	6.095	49%
Performance pricing provisions (dummy)	0.382	6,029	0.148	3,6585	0.234	61%
Presence of covenants (dummy)	0.444	6,029	0.286	3,6585	0.158	36%
Firm-level variables						
Mitigation patent stock	0.529	6,029	0.511	3,6585	0.019	4%
Emission intensity (tons CO_2 / EUR)	0.303	6,029	0.305	6,517	0	-1%
(Log) Total Assets	22.56	6,029	20.92	3,3576	1.637	7%
Return on assets	0.077	6,029	0.05	3,3244	0.027	36%
Debt to Asset	0.644	6,029	0.639	3,6008	0.005	1%
General patenting	1.849	6,029	1.522	3,6585	0.327	18%

Columns (1) and (3) show the mean in the estimation sample and full sample; columns (2) and (4) show the number of observations in the estimation sample and full sample; column (5) = (1) – (3); column (6) = (5)/(1). Monetary values expressed at constant 2005 prices.

B Robustness check

B1 Within-firm effects

The results with additional firm fixed effects remain stable (Table B1). The coefficients on the interaction of technology support with green innovativeness is smaller and not significant anymore in the specification with firm fixed effects. The coefficients on the other policy interactions remain significant.

By adding firm fixed effects, the specification controls for non-observable time-invariant firm characteristics, for example management quality (to the extent that it is stable within the sample period). Management quality could impact both the loan spread and the firms' decision to patent in green technologies, introducing endogeneity in our baseline specification. Adding firm fixed effects addresses this potential endogeneity. The sample size decline by about 6% to include only firms that receive more than one tranche amount over the sample period.

B2 Further robustness checks

A concern in our baseline specification may be that the cost of debt can impact firms' green innovation activity for example if cheaper access to credit may encourage firms to invest in R&D, introducing reverse causality in our estimates. To account for this, we use a time-invariant (within-period average) measure of policy exposure. The time-invariant measure helps break the potential inverse causation. The results are robust to using time-invariant environmental performance measures (Table B2, columns 1 and 2).

The results are also robust to an alternative fixed effects structure that controls for time-varying country-sector specific shocks that may impact environmental performance and cost of debt of firms, including for example the rise and subsequent decline of the solar power industry in Spain or Germany in the early 2000s, which was fuelled by generous FITs and declining technology costs (Table B2, column 3). In addition, the results are robust to an alternative emission intensity metric measuring emissions as a share of value added (Table B2, column 4). Furthermore, the results are robust to the inclusion of the oil price as an additional control variable, interacting with firm-specific environmental performance variables. Changes in oil prices may have similar effects on firms as environmental policies (in particular CO_2 pricing) as they increase input costs for energy-intensive firms. Indeed, we see that an increase in oil prices is associated with a lower spread for innovative green companies and a higher spread for emission-intensive companies (Table B2, column 5).

Applying a constant when log-transforming the green innovativeness variable could be problematic, as the constant is arbitrary. Results are however robust to the inclusion of a right-shifting constant, as shown in Table B3. Three alternative transformations are tested: log(x+0.1), log(x+10) and the inverse hyperbolic sine.

Table B1: The within-firm effect of mitigation policy on loan spread

	log($AISD$)			
	EPS	Tech. support	CO_2 tax	Tech. support & CO_2 tax
Model:	(1)	(2)	(3)	(4)
Green innovativeness	0.011	0.032	-0.033	0.026
	(0.108)	(0.091)	(0.075)	(0.091)
Green innovativeness × EPS	-0.023			
	(0.033)			
Green innovativeness × Tech. support		-0.037		-0.030
		(0.028)		(0.027)
Green innovativeness × Carbon tax			-0.177***	-0.155**
			(0.061)	(0.062)
Emission intensity	-0.019	-0.060	0.007	-0.074
	(0.054)	(0.045)	(0.021)	(0.046)
Emission intensity × EPS	0.013			
	(0.024)			
Emission intensity × Tech. support		0.040		0.046*
		(0.026)		(0.026)
Emission intensity × Carbon tax			0.093**	0.112***
			(0.037)	(0.039)
Observations	5,643	5,643	5,643	5,643
Number of firms	1,024	1,024	1,024	1,024
Green innovativeness marginal effect	-0.043	-0.039	-0.064	-0.058
p-value	0.561	0.593	0.390	0.432
Emission intensity marginal effect	0.011	0.017	0.023	0.034
p-value	0.590	0.427	0.262	0.113

Signif. Codes: ****: 0.01,* ***: 0.05,* **: 0.1*

Each regression includes the following deal-level controls: (log) tranche amount; tenor or maturity; number of lenders; performance pricing provisions; presence of covenants; dummies at the deal level (seniority, loan type, primary purpose); in addition to the following firm-level controls: (log) total assets; return on assets; debt to asset ratio; general patenting activity, and the following fixed effects: 1) firm; 2) country×year; 3) industry×year; 4) year×origination country. Observations: 5643; number of firms: 1024; degrees lost by fixed effects: 1053. Standard errors clustered at the firm level in parentheses.

Table B2: Additional Robustness checks

	log($AISD$)					
	Time invariant	Time invariant	C×I×Y f.e.	Value added EI	Oil prices	No USA
	(1)	(2)	(3)	(4)	(5)	(6)
Green innovativeness	0.152**	0.129***	0.270***	0.285**	0.666***	1.485***
	(0.064)	(0.048)	(0.061)	(0.125)	(0.155)	(0.415)
Green innovativeness × EPS	-0.065***					
	(0.024)					
Green innovativeness × Tech. support		-0.057***	-0.142***	-0.127**	-0.033	-0.068*
		(0.019)	(0.028)	(0.052)	(0.021)	(0.034)
Green innovativeness × Carbon tax		-0.128***	-0.173	-0.212***	-0.135***	-0.162**
		(0.045)	(0.106)	(0.081)	(0.040)	(0.064)
Emission intensity	0.079	0.013	-0.174*	-0.073	-0.471**	0.484
	(0.070)	(0.050)	(0.091)	(0.045)	(0.185)	(0.540)
Emission intensity × EPS	-0.022					
	(0.028)					
Emission intensity × Tech. support		0.008	0.093**	0.057**	0.034**	0.011
		(0.021)	(0.042)	(0.022)	(0.015)	(0.023)
Emission intensity × Carbon tax		0.091***	-0.023	0.115**	0.116***	0.202***
		(0.032)	(0.112)	(0.057)	(0.038)	(0.054)
Oil prices × Green innovativeness					-0.141***	
					(0.041)	
Oil prices × Emission intensity					0.101**	
					(0.042)	
Observations	6,029	6,029	5,538	1,977	6,029	1,718
Number of firms	1,384	1,384	1,213	582	1,384	464
Degrees of freedom lost due to f.e.	1,101	1,101	1,179	630	1,101	656
Green pat marginal effect	0.001	-0.006	-0.029	-0.058	-0.009	-0.003
p-value	0.954	0.826	0.349	0.192	0.713	0.963
Emission intensity marginal effect	0.028	0.045**	-0.001	0.087***	0.037**	0.224***
p-value	0.141	0.018	0.977	0.006	0.036	0.000

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Each regression includes the following deal-level controls: (log) tranche amount; tenor or maturity; number of lenders; performance pricing provisions; presence of covenants; dummies at the deal level (seniority, loan type, primary purpose); in addition to the following firm-level controls: (log) total assets; return on assets; debt to asset ratio; general patenting activity, and the following fixed effects: 1) country×year; 3) industry×year; 4) year×origination country. Column 1 and column 2 employ as policy exposure variables (green innovativeness and emission intensity) the average across the period in which the firm is observed; column 3 employs three-way fixed effects (country×industry×year); column 4 uses a different measure of emission intensity (emissions/value added); column 5 includes (log) oil prices interacted with the exposure variables as additional controls. Standard errors clustered at the firm level in parentheses.

Table B3: Alternative transformation of the green innovativeness variable

		log($AISD$)				
	Transformation	No policy variable	EPS	CO_2 tax	Tech. support	Tech. support & CO_2 tax
		(1)	(2)	(3)	(4)	(5)
Green innovativeness	Baseline	0.001	0.162***	0.006	0.160***	0.136***
		-0.024	-0.063	-0.024	-0.047	-0.047
	Log + 0.1	-0.016	0.122*	-0.014	0.131***	0.116**
		-0.027	-0.066	-0.027	-0.05	-0.049
	Log + 10	0	0.133**	0.011	0.128***	0.097**
		-0.02	-0.062	-0.02	-0.045	-0.045
	IHS	0.002	0.166***	0.006	0.164***	0.142***
		-0.024	-0.063	-0.024	-0.047	-0.047
Green innovativeness × EPS	Baseline		-0.067***			
			-0.024			
	Log + 0.1		-0.060**			
			-0.026			
	Log + 10		-0.053**			
			-0.022			
	HIS		-0.069***			
			-0.024			
Green innovativeness × Tech. support	Baseline				-0.073***	-0.061***
					-0.019	-0.019
	Log + 0.1				-0.073***	-0.065***
					-0.021	-0.021
	Log + 10				-0.053***	-0.038**
					-0.017	-0.017
	HIS				-0.076***	-0.065***
					-0.02	-0.019
Green innovativeness × Carbon tax	Baseline			-0.176***		-0.117***
				-0.05		-0.04
	Log + 0.1			-0.110***		-0.087***
				-0.035		-0.029
	Log + 10			-0.230***		-0.127
				-0.082		-0.087
	IHS			-0.160***		-0.109***
				-0.048		-0.037

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The table shows the estimates for the models contained in Table 3, applying different transformations of the green innovativeness variable. The green innovativeness variable is standardized after the transformation. Only the coefficients for the green innovativeness variable and its interaction are reported. Standard errors clustered at the firm level in parenthesis

C Additional ESG results

The data suggests that ESG scores weakly correlate with green innovation. The main coefficients from regressing the aggregate ESG score and the E pillar on green innovativeness and emission intensity are reported in Table C1. in Appendix C. Contrary to expectations, high emission intensities are associated with higher ESG and E scores (columns 1 and 3). Green innovativeness correlates with higher ESG and E Pillar scores, although this correlation is weak. Overall, green innovativeness and emission intensity explains little of the variation in ESG and E scores, as shown by the low regression R^2. Estimations reported in columns 2 and 4 also include the firm-level controls employed in the baseline regression (Table 3), as well as year by country and year by industry fixed effects. The positive correlation of emission intensity with both ESG scores disappears, while the overall correlation of environmental performance with ESG and E Pillar is even more tenuous.

Table C1: ESG scores relate only weakly with firms' environmental performance

	ESG		E Pillar	
Dep. Var:	(1)	(2)	(3)	(4)
Green innovativeness	0.175***	0.043	0.249***	0.119***
	-0.021	-0.039	-0.023	-0.035
Emission intensity	0.070***	0.024	0.119***	0.018
	-0.025	-0.034	-0.026	-0.032
Observations	3083	2878	3080	2875
R^2	0.04		0.08	
Firm-level controls		Yes		Yes
Fixed effects		Yes		Yes

Signif. Codes: ****: 0.01,* ***: 0.05,* **: 0.1*

Both dependent and independent variables of interest are standardized to have mean 0 and standard deviation 1. The regression coefficients are approximately equal to the coefficient of variation. Regressions in column (2) and (4) include the following controls: (log) total assets; ROA; debt to asset ratio; general patenting activity, as well as country×year and industry×year fixed effects. For consistency with the main results, these regressions are performed on the same observations of the baseline regressions, keeping one observation by firm-year. Standard errors clustered at the firm level in parentheses.

D Instrumental variable estimates

The main challenge in estimating the additional investment that mitigation policies can engender through lower spreads consists in isolating firms' demand elasticity of investments with respect to cost of debt from supply effects. Higher interest rates decrease firms' demand for debt and increase banks supply. The observed investment and loan spread are the equilibrium outcome of this system of demand and supply. Linear regressions that do not address this endogeneity problem would be biased. Table D1 in Appendix E (Columns 1 and 5) confirms this. In a simple OLS regression of investment (or alternatively investment over capital) on loan spreads, the coefficients of loan spreads are positive, counter-intuitively suggesting that higher interest rates are positively associated with investments (even after controlling for firm-level variables and including fixed effects).

Firms with different debt maturity are affected differently by fluctuations in access to credit, such as those caused by changes in monetary policy interest rates. Investors adapt portfolios maturity in response to changes in interest rates. Moreover, firms with a large share of loans close to expiration and looking for refinancing opportunity might have lower bargaining power when negotiating new loans and are thus more affected by policy interest rates. The exclusion restriction for an instrumental variable requires that it affects investment only through loan spreads i.e., the instrumental variable correlates with spreads but does not correlate directly with investments. The interaction of monetary policy interest rates with the average duration of syndicated loans provides a valid instrument. Arguably, monetary policy interest rates transmits to investments only through loans spreads. The instrument exogeneity is ensured by the fact that the debt structure is pre-determined with respect to announcements of changes in monetary policy. To reinforce exogeneity of the debt structure to loan spreads, the instrument is constructed using a one-year lagged debt duration so as to reduce the likelihood of firms' adjusting the debt structure in response to announced future changes in monetary policy.

The analysis relies on two instruments: the interaction of the duration of the firm's syndicated loans with the change in monetary policy interest rates and the interaction of the duration with the level of interest rates. Interest rate volatility could affect a loan's interest rate based on the firm's debt duration; for example, firms with short debt duration that are in the process of bargaining refinancing conditions could be more affected by a change in interest rates. Similarly, periods of tight (or loose) monetary policy could affect refinancing conditions based on a firm's debt duration: one possible channel is investors restructuring their portfolios in response to changes in monetary policy. Duration is calculated as the weighted average of the observed maturity for syndicated loans, weighted by tranche amount. As the model is overidentified (two instruments and one endogenous variable) and heteroskedasticity is probably present, the Instrumental Variable-Generalised Method of Moments (IV-GMM) provides a more efficient alternative to a standard two-stage least square.

One limitation of this approach is that omitted variables might exist that correlate both with the loan spreads and the instrument. The cost of other forms of investment financing, such as the cost of other types of debt and the equity returns, are likely to correlate with the instrument and with loans spread. To assuage these concerns, the observed capital and shareholders' funds are included in some specifications below but even including these variables is unlikely to fully control for the cost of all forms of financing. However, a possible approach consists in considering loan spreads as a good proxy for the unobserved average cost of capital. In other words, the average cost of capital is observed through loan spreads up to an error, which is assumed to be independent of the instruments conditional on the observables. This is a potentially strong assumption, for example if the cost of equity and the cost of debt do not correlate, but it provides a more prudent and general interpretation of the estimates. In particular, the elasticity estimate can be intended as the elasticity of investment to the average cost of capital, rather than exclusively to the cost of syndicated loans.

Table D1 shows the IV-GMM estimates of the investment elasticity with respect to loan spreads, in increasingly demanding specifications. The analysis relies on two instruments: the interaction of the duration of the firm's syndicated loans with the change in monetary policy interest rates and the interaction of the duration with the level of interest rates. The Hansen J-statistics, reported at the end of the table and used to test for overidentification, support the use of two instruments instead of each independently. The control variables have generally the expected sign: firms with higher debt-to-asset ratios, more assets and less current short-term assets invest more in fixed assets. A somewhat surprising result is the negative coefficient on return on assets, pointing to reverse causality.

The specification in columns 2 is chosen as baseline as it corresponds to a parsimonious model with a large number of observations and has a larger F-statistic, limiting concerns for weak instruments. Estimated elasticities in column 2 to 4 range between -1 and -1.4. As a robustness check, columns 5 to 7 show a similar analysis for the investment rate, offering an alternative interpretation to the result. The investment rate is elastic to loan spreads: a 10% increase in the loan spread causes a 17-40% increase in investment rates. These results are statistically significant, although confidence intervals are large, possibly due to unobserved heterogeneity.

Table D1: The effect of loan spreads on investments

	log($Investment$)				log(I/K)			
	OLS	IV-GMM			OLS	IV-GMM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(log) All-in-spread-drawn	0.071***	-0.988*	-1.381*	-1.274	0.190***	-1.723**	-3.067***	-3.954*
	-0.023	-0.567	-0.714	-0.908	-0.029	-0.71	-1.115	-2.06
Total Assets	1.543***	0.809***	0.713***	1.375***	0.223***	-0.423***	-0.697***	0.203
	-0.049	-0.108	-0.138	-0.085	-0.054	-0.137	-0.217	-0.157
Return on Assets	0.012	-1.668**	-2.253**	-1.719	0.245	-2.442***	-4.196***	-5.241*
	-0.131	-0.685	-0.905	-1.142	-0.179	-0.867	-1.447	-2.746
Debt to Total Assets	0.05	0.176	0.389*	0.568**	-0.152**	0.467**	0.952***	0.942*
	-0.056	-0.164	-0.223	-0.243	-0.073	-0.207	-0.352	-0.497
Turnover	-0.092***			-0.056	-0.199***			-0.168**
	-0.021			-0.037	-0.026			-0.069
Shareholders' funds	0.025			0.012	-0.081*			-0.516**
	-0.036			-0.104	-0.041			-0.256
Loans	0.009			-0.004	0.004			0.039
	-0.007			-0.013	-0.009			-0.031
Current assets	-0.513***			-0.600***	0.013			-0.371**
	-0.034			-0.075	-0.038			-0.17
Capital	-0.009*			-0.052**	-0.018***			-0.127**
	-0.005			-0.024	-0.006			-0.06
Observations	8,445	8,989	7,731	5,991	8,431	8,961	7,712	4,892
Number of firms	3,847	4,508	3,800	3,230	3,836	4,488	3,785	2,604
F statistic		10.9	9.2	4.6		12.3	9.7	4.2
Hansen J		0.139	0.198	0.985		4.043	0.066	0.632
Country×Year f.e.		Yes				Yes		
Industry×Year f.e.		Yes				Yes		
Country×Industry×Year f.e.	Yes		Yes	Yes	Yes		Yes	Yes

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The analysis considers all the firms that are active in the syndicated loan market and not only those with available environmental performance information. An F statistic larger than 10 passes the rule of thumb cut-off for weak instruments. The Hansen J statistics is used to test that instruments are valid and that the excluded instruments are correctly excluded: a lower statistic supports the use of overidentifying restrictions. Standard errors clustered at the firm level in parentheses.

E Investment effect of mitigation policies

Investment effects of mitigation policies can alternatively also be expressed in terms of firms' standard deviations of environmental performance. As $\mathbf{E}_{ft}$ (the observed environmental performance in Equation 2) are standardised to have mean zero and standard deviation one, the estimated percentage change in investment attributable to a unitary change in the policy variables for firms with environmental performance one standard deviation above the mean is $\hat{\gamma} \times \hat{\beta}_2$. A unitary increase in both policy variables is approximately equal to the average change observed between 2002 and 2018. Table E1. shows these calculations using the estimate $\hat{\beta}_2$ in Table 3 (columns 2 for EPS and 5 for the other two policies) and $\hat{\gamma}$ in Table E1 (column 2).

Mitigation policies can have a large positive effect on top green innovators investments and an equally large negative effect on investments of large emitters. With an estimated $\widehat{gamma}$ of -0.99, a unit increase in Environmental Policy Stringency decreases the cost of debt of green innovators by 6.7%, increasing their investments by 6.6%. As regards carbon taxes and technology support, both can foster investments in top green innovators (+11.5% and +6%, respectively), while reducing investments by heavy emitters (-10.5% and -3.1%, resp.). The confidence errors of the investment effects are large, mostly because the elasticity of investments to cost of debt is not precisely estimated.

Table E1: The investment effect of mitigation policies through cost of debt for top and bottom environmental performers

Policy (1)	Firms (2)	Change to cost of debt (3)	Change to investment (4)
EPS	Top green innovators	-6.7% [±4.0 ppt]	+6.6% [±7.4 ppt]
	Top emitters	not significant	
CO_2 Tax	Top green innovators	-11.7% [±6.7 ppt]	+11.5% [±12.6 ppt]
	Top emitters	+10.7% [±6.4 ppt]	-10.5% [±11.7 ppt]
Technology support	Top green innovators	-6.1% [±3.1 ppt]	+6.0% [±6.4 ppt]
	Top emitters	+3.1% [±2.6 ppt]	-3.11% [±3.8 ppt]

Green innovators' are firms with (log) green innovativeness 1 standard deviation above the median (84th percentile), 'Top emitters' are firms with emission intensity 1 standard deviation above the mean (88th percentile). Column 3 shows the semi-elasticity of loan spreads (AISD) to a unit change in the policy of column 1 for the type of firm of column 2. The semi-elasticities are the baseline coefficient estimates from Table 3, columns 2 and 5. Column 4 shows the semi-elasticity of investments to a unit change in the policy, obtained multiplying the coefficient in column 3 with the elasticity of investment to loan spreads (-0.99, Table C1. in Appendix C column 2). Confidence errors at 90% confidence level in parenthesis; calculated for column 4 with delta method assuming independence of the coefficients.

The impact of carbon taxation and carbon labelling on greenhouse gas emissions and welfare from food demand

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Abstract

Food production and consumption account for more than a third of global greenhouse gas emissions, but the mitigation potential remains large. Pollution externalities can be in part internalized on the demand side by policies such as carbon taxation and carbon labelling. These policies can help consumers reducing their impact by substituting towards less carbon intensive food products. However, these policies are expected to differ in terms of effectiveness and welfare impacts. In order to provide much needed evidence on this, we collect data from a survey-based randomized controlled experiment simulating an online supermarket, administered to a representative sample of the UK population. We use these data to estimate a structural demand system using the Exact Affine Stone Index model and accounting for censoring. We then estimate the greenhouse gas emissions reductions and welfare effects associated with a range of policy scenarios, combining carbon labelling and carbon taxation, and considering different household profiles. We find that the application of carbon labels leads to a 5.77% decrease in the carbon content of the average food basket. A £60 per CO_2e ton tax on the most carbon intensive products would yield a 10.20% reduction in the carbon footprint, but also generate a loss of £71.40 per person per year. However, combining carbon taxation and carbon labelling would allow to reach the same decrease in CO_2e content with a £27.78 carbon tax rate, reducing the welfare loss to £30.43. These results imply that carbon taxation and carbon labelling can be complementary policies to abate GHG emissions while limiting the negative impacts on welfare.

1 Introduction

In order to mitigate climate change impacts, we need to act swiftly and in a concerted way by decreasing the emission of greenhouse gases in the atmosphere, as envisioned by the Paris Agreement. In comparison with other sectors such as manufacturing and energy production, the food sector remains less targeted by policies, despite accounting for one third of global greenhouse gas (GHG) emissions (Crippa et al., 2021). Accordingly, the food system offers a large mitigation potential: on the demand side, the IPCC (2022) estimates that changes in socio-cultural factors can reduce by 44% projected related emissions in 2050.

However, achieving this ambitious goal requires the introduction of different policy instruments at the same time, ranging from 'soft' interventions, such as informational campaigns and information provision, to 'hard' measures, such as price interventions and regulations (European Commission, 2023; Willett et al., 2019). A mixture of hard and soft policies can therefore help consumers to shift their consumption from more GHG intensive products to less intensive ones. However, the interaction between different instruments remains understudied and hence their synergy is not clear, despite their importance in delivering a policy mix that is effective and fair.

This paper investigates the impact of a soft policy (i.e., carbon labelling) and a hard policy (i.e., carbon taxation), both alone and combined, on the demand of at-home food products in the UK. Employing a detailed experimental dataset about food demand of a representative sample of UK households, we study how the content of GHG emissions of the food basket and the consumer welfare vary across different policy scenarios for different types of households. To do so, in addition to the effect of prices, we model the effect of a soft policy, namely information provision through the labelling of carbon content in food products, using a structural demand system. Thanks to a rich set of covariates, we complement the analysis over an average household also studying the effect across different socio-economic groups of respondents.

The economic literature has investigated how different policies can lead the economy to become more environmentally sustainable and the costs that these entail. In our work, we focus on carbon labelling, a measure often advocated for its low cost and feasibility, and carbon taxation, a measure of strong impact but difficult implementation. Carbon labelling allows consumers to make informed choices aligned with their preferences (Edenbrandt & Nordström, 2023). By providing low-cost and low-effort information for consumers at the point of sale, carbon labels can thus affect food demand by increasing the salience of this attribute and correcting misperceptions that consumers may have regarding the environmental impact of their purchases (Camilleri et al., 2019). The starting assumption with carbon labels is nonetheless that consumers value a reduction in their carbon footprint (Rondoni & Grasso, 2021; Shewmake et al., 2015). Carbon labels have been shown to induce a reduction in carbon content to some extent (Taufique et al., 2022), but since existing types of labelling for food remain purely voluntary, they have been only studied in experimental settings either online (e.g., Muller et al., 2019), or in the field, such as in university cafeterias (e.g., Lanz et al., 2018; Lohmann et al., 2022).

On the other hand, carbon pricing in the form of carbon taxation is a theoretically desirable policy intervention, that allows consumers to internalize the cost of GHG emissions (Baranzini et al., 2017). Nevertheless, this kind of measure has not yet been introduced in the food sector[1], despite being increasingly advocated as urgent (European Commission, 2023; Katare et al., 2020). The study of the impact of

[1]The World Bank (2023) reports that New Zealand is going to be the first country to tax agricultural emissions from 2025.

carbon taxes has been carried out on an ex-ante basis and the main findings show that it would be effective in decreasing emissions (e.g., Caillavet et al., 2019; van der Ploeg et al., 2022), but regressive (Klenert et al., 2023) and in general difficult to implement (Carattini et al., 2018; Douenne & Fabre, 2022).

We contribute to the literature in different ways. First, we collected our data through a survey-based randomized controlled experiment taking place in a simulated online supermarket, where we introduced the policies of interest as experimental treatments. The survey contained a wide selection of products, thus resembling the real supermarket where respondents carry out their usual grocery shopping. We find that our baseline data compare well with the official statistics, thus showing that the realistic setting was able to alleviate concerns about the hypothetical bias. Through the experiment, we were able to introduce exogenous variation in prices reflecting a carbon tax and the provision of information about carbon content in products through carbon labels. Thus, carbon labelling was introduced on all products and in a consistent way, as if introduced by regulation. Currently, any similar initiative remains voluntary for producers and does not cover all available products. Even if they were introduced by regulation, their evaluation would be difficult due to the absence of an untreated control group, as in the case of nutritional labels. Our experimental setting thus approximated the real world implementation of the policies, both alone and combined, whereas in the current literature these measures are usually studied separately and often only for a subset of goods.

Second, by studying the simultaneous introduction of two policy instruments we contribute to the strand of the literature that looks at policy mixes. In order to support the shift towards a lifestyle that is more environmentally sustainable, policy-makers have at their disposal a number of measures that range from 'hard' policies (e.g., taxation and regulation) to 'soft' ones (e.g., educational campaigns and front-of-pack labels) (Mozaffarian et al., 2018; Willett et al., 2019). However, the introduction of any single policy in the food sector is likely to involve trade-offs between effectiveness and equity, casting doubt on its political feasibility (Carattini et al., 2018). Implementing different policies could thus limit or compensate negative impacts that might be induced by any single measure. Empirical evidence in the food sector remains scant. The existing literature typically investigates the impact of a single policy, or different policies in the same domain, as is the case for taxes and subsidies. Looking at two different interventions allows us to compare and evaluate their costs and benefits in the same framework, and evaluate their complementarity, or substitutability.

Third, we use our data to estimate a structural demand system (Lewbel & Pendakur, 2009). In this way, in addition to the variation in prices (due for instance to the application of a tax) we model the effect on demand of carbon labelling. Albeit there are some examples in the scientific literature of the evaluation of policies of information provision employing a demand system (e.g., dolphin-safe labels for tuna: Teisl et al., 2002; UK 5-a-day information campaign for the consumption of fruits and vegetables:

Capacci and Mazzocchi, 2011), to the best of our knowledge ours is the first work to empirically assess the impact of carbon labelling. Other works in the scientific literature typically resort to choice experiment, which may lack external validity due for instance to the limited number of choices, or field-experiments in specific settings, such as university canteens, which might not be representative of purchases conducted by heterogeneous households on a national scale. By estimating a demand system on a representative group of food products, we can account for substitution patterns and the role of sociodemographic characteristics of households. In this way, we are able to investigate the reduction in GHG content due to carbon labelling and/or price variation under different policy scenarios and for different types of households. In practice, we estimate an Exact Affine Stone Index demand system (Lewbel & Pendakur, 2009) through a system of simultaneous equations, while accounting for non-purchase of food items by employing a Tobit approach.

We investigate how food consumption changes under different policies. We find that carbon labelling and carbon taxation both cause a reduction in emission content, but through different channels. Under carbon labelling, there is a substitution from meat with a higher footprint to that with a lower intensity, resulting in a 5.8% reduction of emissions in the food basket of the average household. A carbon tax of £60 per CO2e on high-polluting products is almost twice as effective (-10.2%), but it induces consumers to compensate the loss in purchasing power by reducing the demand also for untaxed products. Then, we calibrate a tax rate that when introduced together with carbon labelling achieves the same emission reduction as a £60/CO2e ton rate. We find that the needed tax rate is substantially lower, at £27.78/CO2e ton. The effect of this policy combination is to decrease the demand for the highest taxed categories, beef, lamb, and cheese, and to increase it for fruits, vegetables, ready meals, and meat alternatives. The loss in consumer welfare is similarly much lower: from £71.40 per person per year, to £30.43.

We look at how these results vary for different types of households. When considering different diets, we find that those with a content high in meat, despite having a much larger footprint than other diets with a lower demand for animal products, react significantly to carbon labels (-6.6% change in carbon content), indicating that they have pro-environmental preferences. Households with an already low consumption of emission intensive products (pescatarian, vegetarian, and vegan diets) do not change demand with carbon labels and have a very small reduction with a tax. We also differentiate households between high and low-income. High-income households have a slightly larger per capita footprint (16% more than low-income). For these households, carbon labelling induces a reduction in emissions that is almost as large as the one by a carbon tax (respectively, -8.1% and -10.4%). To the contrary, the effect of carbon labels for low-income households is limited (-3.5%) in comparison with the impact of a carbon tax (-10.0%). If introduced with a carbon tax, carbon labelling can thus push more affluent households to make a larger effort in reducing their footprint: while this finding does not solve the issue of regressive taxation, it suggests a possibility in differentiating in the burden of climate change mitigation at different levels of income.

Our work stems from the strand of the economic literature that looks at the effect of policies on consumption. It is related to those works that investigate the impact of taxation on GHG emissions (e.g., Andersson, 2019) and social welfare, (e.g., Dubois et al., 2020). In particular, we contribute to the strand that looks at carbon taxation (e.g., van der Ploeg et al., 2022) and more specifically on food (e.g., Briggs et al., 2013). Finally, our work also draws from the literature that investigates policy interventions that are not based on price changes but rather on information provision (e.g., Lohmann et al., 2022; Shewmake et al., 2015).

The remainder of the article is organised as follows. Section 2 describes how our dataset was collected and provides descriptive statistics. Section 3 discusses our empirical approach to estimate the demand system and the estimation strategy. Section 4 presents the results. Section 5 discusses the limitations of our work. Section 6 concludes.

2 Data

2.1 Survey

In the UK the food system is responsible for almost a quarter of all GHG emissions (Crippa et al., 2021). This figure does not consider the carbon footprint of food imports produced abroad, which in 2022 accounted for 42% of domestic consumption (Department for Environment, Food & Rural Affairs, 2022). We collected the data for the present analysis as part of a broader project investigating the effect of taxation and information provision on the nutritional content and environmental impact of dietary choices (see Faccioli et al. (2022), for further information). The data were collected through a survey administered online in autumn 2020 to a representative sample of the UK population. In particular, the survey was aimed at the household member who regularly carried out the food shopping for their household. The survey presented a simulated online supermarket, displaying 72 types of food and beverage items to choose from. These products accounted for 72.8% of those reported in the Kantar FMCG panel[2] relative to Great Britain and represented 81.1% of the take-home expenditures of food and beverages. For each category, respondents found a short description of the products, with example pictures and the relative price. We derived the prices from the Kantar FMCG data: for each product category, we simulated a distribution of prices after omitting extreme values, and subsequently we drew respondent-specific prices from it. This way, respondents saw prices that were similar to those found in real supermarkets, but uncorrelated with individual-specific unobserved characteristics and therefore exogenous. For each product category, respondents had to specify both quantity (in units of product), and frequency of purchase (every week,

[2]Kantar FMCG is a database containing real-world scanner data on supermarket food purchases, which is often used in the analysis of demand (e.g., Caillavet et al., 2019).

every two weeks, or every month). In order to assess the validity of our data, we compared them with other sources in terms of weekly quantities, expenditure and carbon footprint, and we found that they were similar; details can be found in Appendix B.

In addition to requesting information on food and drinks purchased for home consumption under normal circumstances (Baseline scenario), we also asked each respondent to imagine how their food shopping behaviour would change in response to the introduction of food demand policies. Participants were therefore randomly assigned to one of three possible treatments (policy streams), each simulating the introduction of two different (but related) policies.. In our analysis for this paper, we focus on those observations subject to the introduction of carbon information and/or price increases due to the simulation of a carbon tax , while omitting the health focused treatments to avoid any confounding effect linked with preferences about the nutritional content of food. In the first policy stream, respondents were first provided with information about the carbon content of each food product (Carbon Information scenario), using a colour-coded graphical indicator, and subsequently they were additionally displayed a price increase (relative to the baseline) for those food products with a carbon content higher-than-average (Carbon Information & Tax scenario). To simulate the carbon tax, baseline prices for high carbon foods were increased proportionally to the carbon content by considering three different tax rates (£30, £60, or £90 per ton of CO_2e per kg of product) which were randomly assigned to respondents in that policy stream. In the third policy stream, respondents were first presented with price increases mimicking the application of a carbon and/or health tax on products (as explained above), without being informed about the reasons behind the price increases (Unlabelled tax scenario).

We perform data cleaning in order to drop implausible observations, following these steps:

1. We drop respondents for whom any expenditure share of a single item in any scenario is above 90% of their total expenditure;

2. We drop respondents who change their expenditure between any scenario to more than 100% or less than 50%;

3. We drop respondents who for any item have a quantity per member of their household in the top 1% for that item;

4. We drop respondents for whom we do not have complete observations, such as missing values in the sociodemographic variables.

In this way, we retain 3,925 respondents of the original 5,910[3].

[3]As a robustness check, we perform the analysis on the full sample for which we have complete observations, rather than the cleaned one but results do not vary substantially. Results can be found in Appendix E.

2.2 Aggregation of food items

We group the original 72 single items into 13 categories. These categories are reasonably homogeneous within and therefore theoretically justified by multistage budgeting (Edgerton, 1997), in other words we assume weak separability between our categories. The food groups are the following: Fruits and vegetables; Bread, pasta, rice and flour; Breakfast cereals; Milk and yoghurt; Cheese; Eggs; Beef and lamb; Pork; Poultry; Fish and seafood; Snacks; Beverages; and a residual category, i.e., Other food. This category includes milk and meat alternatives and ready meals, both with and without meat or fish. The composition of each category can be found in the Appendix Table A1.

We aggregate quantities Q for category R as the sum of the quantities q ofsingle products r of household h in scenario s:

$$Q_{hRs} = \sum_r q_{hrs}. \tag{1}$$

Furthermore, in order to assign a price to each category, we obtain the price index P_{hRs} as the weighted average of individual prices (p_{hrs}), where the weights are determined by the average quantity reported in each scenario s[4]:

$$P_{hRs} = \frac{\sum_r \left(\sum_h q_{hrs}\right) p_{hr}}{\sum_r \sum_h q_{hrs}} \tag{2}$$

We also compute the carbon intensity for each category as a weighted mean of the carbon content of the reported quantity of products in that category, where the weights are their quantities in the baseline[5]. We obtain carbon intensities for each food item mainly from the median values reported in Poore and Nemecek (2018), who have assembled a comprehensive database from existing studies about the environmental impact of food products estimated through a life cycle assessment approach.

2.3 Descriptive statistics

Our sample is composed by 7,869 observations for 3,925 respondents[6]. Table 1 reports the summary statistics for the main socio-demographic variables[7]. 58% of our respondents are female with a mean age

[4]Edgerton (1997) writes that the use of price indices is justified if "group price indices being used do not vary too greatly with the utility (or, equivalently, expenditure) level." A weighted average over the sample is the best choice in order to minimize variation in expenditure, approximated by the variation of expenditure by different households in our sample.

[5]Table A2 contains the CO_2e content of a unit of each category in the other survey scenarios; they do not change substantially.

[6]The difference between the number of respondents, or households, and observations comes from the fact that due to the structure of the survey we collect for all respondents three choice tasks, but we do not use all of these, as explained in Section 2.1

[7]For brevity, further summary statistics about region, occupation and ethnicity are reported in the Appendix (Table A4).

of 47: in comparison, the adult UK population is 51% composed by women and has an average age of 49. However, the survey was not aimed at all respondents, but at those that are responsible for food shopping in the household. The average household size in our sample is 2.7, ranging from 1 to 10 members, whereas the official figure for the UK is 2.4. The average number of children per household is 0.60 (0.51 in the official statistics), while the median household does not have any. On average, respondents have 13.7 years of schooling (compared with 13.2 reported in the Human Development Report, 2020) and report an income of £30,000 per household per year; this figure is substantially lower than the estimate by the Office for National Statistics (about £44,000) and closer to the figure for the median household disposable income (£30,500).

Table 1: Summary statistics for demographic variables

Variable	min	mean	median	max	std. dev.
Sex (Male = 1)	0	0.42	0	1	0.49
Age (years)	18	46.69	46	88	17.12
Household size (n. of individuals)	1	2.70	2	10	1.28
Nr. of children	0	0.60	0	7	0.96
Income (£'000)	10	35.63	30	110	23.27
Education (years of schooling)	6	13.67	13	19	2.81

This table contains descriptive statistics for selected socio-demographic characteristics of the sample. Sample size is 7,869, for 3,925 individuals. *Sex* is a dummy variable equal to 0 if the respondent self-reported as female. *Household size* indicates the number of people the respondent reported to normally do the food shopping for and *Nr. of children* reports how many of them are below 18. *Income* indicates the approximate annual gross income of the respondent's household in thousands of pounds. *Education* reports the number of years of schooling of the respondent. See Appendix Table A4 for the descriptive statistics relative to region, ethnic group and occupation.

Table 2 reports the descriptive statistics for the average weekly food shopping for all households in the sample by food category level; a disaggregated breakdown at single product level can be found in Table A3. The first column reports the average expenditure share: the food category with the largest share is Fruits and vegetables (18.3%), followed by Beverages (17.1%) and Snacks (10.8%). On the other hand, the categories with the lowest share of expenditure are Eggs (1.8%), Breakfast cereals (2.3%), and Bread, pasta, rice and flour (4.4%). The quantity, in terms of kg or litres, is reported in column 2: Fruits and vegetables remains the category with the largest quantity (8.02 kg) of reported food purchase.

The GHG content of food purchases differs largely between product categories (column 4). Beef and lamb has the largest footprint (61.1 CO_2e kg, contained in 1.07 kg of product, i.e., the average weekly purchase), followed by Milk and yoghurt (10.83 CO_2e kg, for 4.01 kg) and Fruit and vegetables (9.73 CO_2e kg for a consumption of 8.02 kg). Some food categories are more prone to corner solution (i.e., zero consumption), as reported in column 3. The category with the largest share of censored observations is Fish and seafood (26.5%), followed by Pork (17.9%) and beef and lamb (16.6%). Column 5 reports prices per kg or litre: the highest prices in the baseline are for Fish and seafood (£10.37 per kg), followed

Table 2: Summary statistics for expenditure shares, quantity, CO_2e emissions and prices

Category	Share (%)	Quantity (kg)	Censored (%)	CO_2e (kg)	Price (£ per kg/l)
Fruits/vegetables	18.26	8.02	0.41	9.73	1.63
Beverages	17.08	5.47	2.50	4.51	2.51
Snacks	10.77	1.46	4.13	4.05	5.52
Beef and lamb	10.77	1.07	16.64	61.10	8.59
Pork	6.60	0.85	17.94	8.95	6.07
Other food	6.58	1.20	15.29	8.04	3.94
Poultry	6.37	1.10	14.90	8.25	4.42
Cheese	5.23	0.61	4.61	7.88	6.10
Milk/yoghurt	5.19	4.01	3.64	10.83	0.91
Fish/Seafood	4.68	0.34	26.45	3.73	10.37
Bread/pasta/rice/flour	4.40	2.29	1.83	4.10	1.36
Breakfast cereals	2.25	0.52	15.03	1.35	3.22
Eggs	1.82	0.49	8.84	2.04	2.57

This table contains the descriptive statistics for prices and goods in our sample, in terms of the average weekly consumption by households. *Share* reports the average budget share for each food category (as a percentage), while *Quantity* reports the average quantity in kg. *Censored* indicates the percentage of observations that are equal to zero. *CO_2e* indicates the average CO_2e content (in kg) associated with the total reported quantities. *Price* reports the average price per unit in the baseline scenario, while *Price increase* indicates the average increase over the baseline in the scenarios where good were taxed.

by Beef and lamb (£8.59 per kg) and Cheese (£6.10 per kg), while the least expensive are Milk and yoghurt (£0.91 per kg), Bread, pasta, rice and flour (£1.36 per kg) and Fruits and vegetables (£1.63 per kg).

2.4 Policy scenarios

We investigate the impact of different policies aimed at encouraging respondents to take into account the environmental costs of their food purchases, in order to understand whether they are effective in reducing GHG emissions and what is their impact on consumer welfare. We simulate the following policy scenarios:

- Carbon labelling: a color-coded label indicating the carbon footprint is introduced on the packaging of all food items.
- Carbon tax: a tax on the carbon content is introduced on carbon intensive food categories, thus increasing their prices proportionally.
- Carbon labelling and tax: in this scenario, carbon labelling and a carbon tax on selected goods are introduced simultaneously.

In addition to different policy scenarios, we look at the heterogeneous impact across households, which are different in terms of income and diet.

When simulating food purchase under new scenarios, including those with a price increase, we keep the total expenditure of the representative household constant, because in our dataset the mean expenditure across different experimental scenarios displayed a low variation in economic terms (Table A5): in the survey, given the average expenditure in the baseline at £75.66, these results imply an average variation of -£1.38 in the labelling scenario, +£1.52 in the unlabelled tax scenario, and -£0.17 in the labelled tax scenario, which is not statistically different from zero.

In the scenarios where a carbon tax is introduced, similarly to Briggs et al. (2015) we introduce a tax on those categories that have a footprint larger than the average, namely beef and lamb (+34.9% price increase), cheese (+11. 8%), pork (+ 10.0%), and Fish and seafood (+6.3%), since a tax on every product is unlikely to be feasible (Faccioli et al., 2022). While these goods account for slightly more than a quarter of expenditures, they correspond to more than half of the total GHG content of food purchases (Table 3). The price increase is proportional to the carbon content of each of these categories and we choose a tax rate of £60 per CO_2e ton[8], which was the central value estimate of the UK Government for 2020 (Department of Energy & Climate Change, 2009) based on the marginal abatement cost approach.

In the Carbon labelling and tax scenario instead of the £60 per CO_2e ton rate, we calibrate a tax rate that equals the emission reduction as in the Carbon tax scenario, but exploiting the synergy with carbon labels. We find this rate to be £27.78/CO_2e ton.

Table 3: Price increase in taxation scenarios and carbon intensity

	Price increase (%)			
Category	Carbon tax (%)	Carbon labelling and tax (%)	CO_2e per kg of product (kg)	CO_2e per unit of product (kg)
Fruits/vegetables	0	0	1.22	0.58
Bread/pasta/rice/flour	0	0	1.79	1.28
Breakfast cereals	0	0	2.60	1.30
Milk/yoghurt	0	0	2.70	2.31
Cheese	11.83	5.49	12.92	3.29
Eggs	0	0	4.20	1.66
Beef and lamb	34.87	16.18	57.18	31.65
Pork	10.03	4.66	10.60	4.69
Poultry	0	0	7.50	5.66
Fish/Seafood	6.27	2.91	11.11	3.30
Snacks	0	0	2.79	0.74
Beverages	0	0	0.83	0.85
Other food	0	0	6.70	3.09

[8]This was also the central value for the tax rate applied in the survey-based experiment, which means that we are not extrapolating when projecting the new scenarios.

3 Empirical model

3.1 The EASI demand system

In order to model consumers' food demand under different prices and information scenarios, we specify a structural demand system consistent with microeconomic theory. We employ the Exact Affine Stone Index (EASI) approach (Lewbel & Pendakur, 2009), which improves upon the widespread Almost Ideal Demand System (Deaton & Muellbauer, 1980) by allowing non-linear Engel curves. Lewbel and Pendakur (2009) specify an expenditure function $\log C(\bullet)$ of the following form:

$$\log C(\mathbf{p}, u, \mathbf{z}, \epsilon) = u + \mathbf{p}' \left(\boldsymbol{\alpha} + \boldsymbol{\beta}\mathbf{u^k} + \boldsymbol{\delta}\mathbf{z} + \boldsymbol{\delta_u}\mathbf{z_u}u\right) + \frac{1}{2}\mathbf{p}' \left(\boldsymbol{\gamma} + \boldsymbol{\zeta}u\right)\mathbf{p} + \mathbf{p}'\epsilon, \tag{3}$$

where, u is the utility level attained by the consumer, $\mathbf{p}$ is the $R \times 1$ vector of the logarithm of prices for each commodity, $\mathbf{u^k}$ is the $k \times 1$ vector with values of the polynomial of k^{th} degree u^k, $\mathbf{z}$ is a $g \times 1$ vector of socio-demographic characteristics, $\mathbf{z_u}$ is $f \times 1$ subvector of $\mathbf{z}$ with socio-demographic characteristics interacted with u. ϵ is a $R \times 1$ vector of unobserved characteristics. $\boldsymbol{\alpha}$ $(R \times 1)$, $\boldsymbol{\beta}$ $(R \times k)$, $\boldsymbol{\delta}$ $(R \times g)$, $\boldsymbol{\delta_u}$ $(R \times f)$, $\boldsymbol{\gamma}$ $(R \times R)$, $\boldsymbol{\zeta}$ $(R \times R)$ are the parameters to be estimated.

Invoking Shepard's Lemma, the derivative in the logarithm of prices of (3) provides Hicksian budget shares $\mathbf{w}$ $(R \times 1)$:

$$\mathbf{w} = \boldsymbol{\alpha} + \boldsymbol{\beta}\mathbf{u^k} + \boldsymbol{\delta}\mathbf{z} + \boldsymbol{\delta_u}\mathbf{z_u}u + \boldsymbol{\gamma}\mathbf{p} + \boldsymbol{\zeta}\mathbf{p}u + \epsilon \tag{4}$$

By solving 3 for u, which is unobservable, Equation 4 can be expressed in terms of deflated expenditure, yielding y, a nonlinear function of expenditure and the other observed variables. We opt for the linear approximation of the model for computational simplicity, which remains a good approximation of the full model (Lewbel & Pendakur, 2009)) and it has been employed in the literature (e.g., Zhen et al., 2014). Hence, we define implicit utility (deflated expenditure) $\tilde{y} = \log x - \sum \bar{w}_{0i} \log p_i$, where $\bar{w}_{0i}$ is the average share for food category i in the sample. In this way, we obtain a system of estimable equations for each group i.

3.2 Elasticities

We further derive the expenditure, Hicksian (or compensated) and Marshallian (or uncompensated) elasticities. The expenditure elasticity e_i^E for category i is obtained as

$$e_i^E = \frac{\partial q_i}{\partial x}\frac{x}{q_i} \tag{5}$$

$$e_i^E = \frac{x}{q_i p_i}\frac{\partial w_i}{\partial x}x + w_i \tag{6}$$

$$e_i^E = \frac{1}{w_i}\left(\sum_k \beta_{ki} k \tilde{y}^{k-1} + \sum_j \zeta_{ij} \log p_j + \sum_f \delta_u z_{uf}\right) + 1. \tag{7}$$

Hicksian elasticity e_{ij}^H of category i with respect to price j is given by

$$e_{ij}^H = \frac{\partial q_i^H}{\partial p_j}\frac{p_j}{q_i^H} \tag{8}$$

$$e_{ij}^H = w_j + \frac{1}{w_i}\left(\sum_k \beta_{ki} k \tilde{y}^{k-1} + \gamma_{ij} + \sum_j \zeta_{ij}\tilde{y} - \bar{w_j}\sum_j \zeta \log p_j + \sum \delta_u z_{uf}\right) - \delta_{ij}, \tag{9}$$

where δ_{ij} is the Kronecker delta and it is equal to 1 if $i = j$ and 0 otherwise. Finally, Marshallian elasticities are obtained from the Slutsky equation as

$$e_{ij}^M = e_{ij}^H - e_i^E \times w_j. \tag{10}$$

3.3 Compensating Variation

In order to estimate the welfare effect of a price change, we employ the compensating variation (CV), which is equal to the change in expenditure required for a household to keep the same utility level after the variation in (log) prices from $\mathbf{p_0}$ to $\mathbf{p_1}$. Hence, the CV can be obtained as:

$$CV = C(\mathbf{p_0}, u_0, \mathbf{z}, \epsilon) \times (\exp(\log C(\mathbf{p_1}, u_0) - \log C(\mathbf{p_0}, u_0)) - 1) \tag{11}$$

where $C(\mathbf{p_0}, u_0, \mathbf{s}, \epsilon) = x$ is the observed expenditure at baseline prices $\mathbf{p_0}$. The change in expenditure $\Delta \log C_0^1 = \log C(\mathbf{p_1}, u_0) - \log C(\mathbf{p_0}, u_0)$ is thus equal to

$$\Delta \log C_0^1 = (\mathbf{p_1} - \mathbf{p_0})' \left(\boldsymbol{\alpha} + \boldsymbol{\beta}\mathbf{\tilde{y}^k} + \boldsymbol{\delta}\mathbf{z} + \boldsymbol{\delta_u}\mathbf{z_u}\tilde{y} + \epsilon\right) + \frac{1}{2}(\mathbf{p_1} - \mathbf{p_0})'(\boldsymbol{\gamma} + \boldsymbol{\zeta}\tilde{y})(\mathbf{p_1} - \mathbf{p_0}) \tag{12}$$

$$\Delta \log C_0^1 = (\mathbf{p_1} - \mathbf{p_0})'\mathbf{w_0} + \frac{1}{2}(\mathbf{p_1} - \mathbf{p_0})'(\boldsymbol{\gamma} + \boldsymbol{\zeta}\tilde{y})(\mathbf{p_1} - \mathbf{p_0}) \tag{13}$$

where $\mathbf{w}_0$ is the vector of baseline budget shares and can be substituted in 12 from 4. The first term in 13 captures the first order effect of a price change, while the second term describes substitution effects

(Lewbel & Pendakur, 2009).

3.4 Empirical specification

From Equation 4, we obtain a system of equations that can be jointly estimated for categories $i = 1, ..., 12$:

$$w_i = \alpha_i + \sum \beta_{ik}\tilde{y}^k + \sum_j \gamma_{ij} \log p_j + \sum_j \zeta_{ij} \log p_j \tilde{y} + \sum_g \delta_{ig} z_g + \sum_f \delta_{iu} z_{uf} \tilde{y} + \theta_i D^c + \sum_d \theta_{id} D^c z_{d(c)} + \epsilon_i \tag{14}$$

where w_i is the expenditure share for category i of household h (subscript h and s are omitted for simplicity), α_i is the intercept, p_j is the price of category j and $\tilde{y}$ is the linear approximation of deflated expenditure. Parameters β capture how the demand for a good changes with the expenditure; following Lewbel and Pendakur (2009), expenditure enters the model as a polynomial of 5$^{\text{th}}$ degree ($k = 5$) thus allowing highly flexible Engel curves. z_g are socio-demographic characteristics: we control for sex, age, household size, number of children in the household, income, education, occupation, region, ethnic group, two dummy variables indicating if the household is in the bottom or top quartile for meat consumption. Parameters ζ_{ij} and δ_u allow respectively the effect of prices and socio-demographic variables z_{uf} (i.e., sex, age, income, education, and meat consumption) to vary with the level of expenditure. In addition, we include a dummy variable D^c for the carbon information treatment, which captures how much respondents adjust their desired share of food group i as a linear shift, and interact it with the subset of household characteristics $z_{(c)}$, i.e., sex, age, income, education and meat consumption. We also tested the interaction of prices with the carbon information dummy, thus allowing a variation in price elasticity, but a Likelihood Ratio test resulted in a non-rejection of the null hypothesis of equivalence between the two models (p-value = 0.34). Therefore, we opted for the more parsimonious one. Finally, ϵ_{ih} is the error term of the regression, which is assumed to be uncorrelated with the other variables and to be normally distributed.

We impose the following restriction of the parameters (Lewbel & Pendakur, 2009):

$$\sum_i \alpha_i = 1 \tag{15}$$

$$\sum_i \beta_{ik} = \sum_i \gamma_{ij} = \sum_j \gamma_{ij} = \sum_i \zeta_{ij} = \sum_j \zeta_{ij} = \sum_i \delta_{ig} = \sum_i \delta_{iu} = \sum_i \theta_i = \sum_i \theta_{id} = 0 \tag{16}$$

$$\gamma_{ij} = \gamma_{ji} \tag{17}$$

$$\zeta_{ij} = \zeta_{ji} \tag{18}$$

These restrictions allow us to obtain a system of demand functions adding up to total expenditure $\sum_i w_i = 1$, homogeneous of degree zero in prices and total expenditure, and satisfying Slutsky symmetry. These restrictions and the presence of a residual category ensure the consistency of the model with microeconomic theory (Lewbel & Pendakur, 2009; Wales & Woodland, 1983). The parameters of the last equation ($i = 13$) are obtained through the imposed restrictions.

3.5 Estimation

Our data display a substantial amount of censoring (Table 2), which implies that OLS estimates would be inconsistent (Tobin, 1958). In order to derive a consistent estimate of the parameters, we follow Tobin's approach (Tobin, 1958), extended to a multivariate setting of simultaneous equations (Amemiya, 1974). In general, a Tobit model assumes a latent (unobserved) variable y^*, related to the observed dependent variable y such that

$$y^* = \mathbf{x}'\boldsymbol{\beta} + \epsilon \tag{19}$$

$$y = \begin{cases} y^* & \text{if } y^* > 0 \\ 0 & \text{if } y^* < 0 \end{cases} \tag{20}$$

By imposing a distributional form on the residual term ϵ_i (i.e., a multivariate normal), the parameters $\boldsymbol{\beta}$ can be recovered by maximum likelihood. Following Amemiya (1974), the likelihood for this problem is

$$L = \prod_1 f(\epsilon_1, \ldots, \epsilon_{12}) \prod_2 \left[1 - \int_{-\epsilon_1}^{\infty} \cdots \int_{-\epsilon_{12}}^{\infty} f(\epsilon_1, \ldots, \epsilon_{12}) d\epsilon_1 \ldots d\epsilon_{12}\right] \tag{21}$$

where $\prod_j$ is the product over the observation where $j = 1$, if $y_i = y_i^*$ because $\mathbf{x}'\boldsymbol{\beta} > \epsilon$, and $y = 0$, i.e., censored observations or $\mathbf{x}'\boldsymbol{\beta} < \epsilon$. f is the density of the multivariate normal distribution $N(\mathbf{0}, \boldsymbol{\Sigma})$. In practice, this likelihood function involves higher dimension integrals, which are difficult to estimate. For this reason, we employ a maximum simulated likelihood approach, which we estimate in Stata using the 'cmp' command (Roodman, 2011).

Since the estimated coefficients $\boldsymbol{\beta}$ are the marginal effect of the $\mathbf{x}$'s on the unobserved variable y^*, when estimating the elasticities we use following Greene (2018):

$$\frac{\partial E[y|\mathbf{x}]}{\partial x_i} = \beta_i \Phi\left(\frac{\mathbf{x}'\boldsymbol{\beta}}{\sigma}\right) \tag{22}$$

and the predicted dependent variable as

$$E[y|\mathbf{x}] = \Phi\left(\frac{\mathbf{x}'\boldsymbol{\beta}}{\sigma}\right)\left(\mathbf{x}'\boldsymbol{\beta} + \sigma\frac{\phi(\mathbf{x}'\boldsymbol{\beta}/\sigma)}{\Phi(\mathbf{x}'\boldsymbol{\beta}/\sigma)}\right) \tag{23}$$

which correspond to respectively the marginal effect on the observed dependent variable y and the expected value of the y, which may be censored at 0 (Greene, 2018).

4 Results

We estimate 804 equation parameters across 12 equations as described in Section 3.4, and 349 of them are statistically significant at the 10% level. A likelihood ratio test rejects the hypotheses that the parameters are jointly not significant. The R^2 is 0.541[9].

Table 4 reports the change in demand following the introduction of carbon labels. Beef and lamb and pork, which are carbon intensive animal meats, are associated with negative and statistically significant parameters θ_i, meaning that consumers decrease their demand after being reminded of the cabron footprint of these products, while the coefficients of poultry and bread and other carbohydrates are positive and significant. These results suggest a substitution between carbon intensive products and less intensive ones when carbon labelling is introduced.

Table 4: Estimates for parameter θ_i

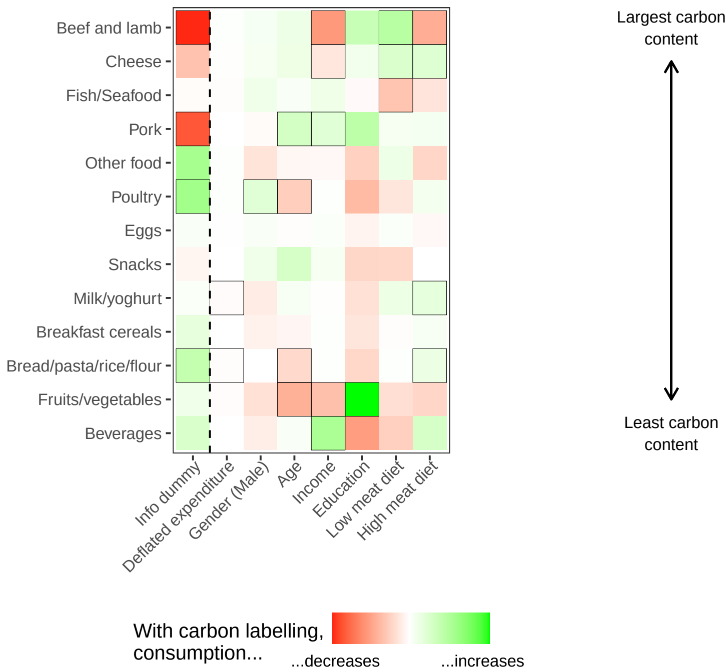
shareNames	value2	sd
Fruits/vegetables	0.227	1.12
Bread/pasta/rice/flour	0.87**	0.35
Breakfast cereals	0.369	0.33
Milk/yoghurt	0.078	0.55
Cheese	-0.693	0.54
Eggs	0.096	0.22
Beef and lamb	-2.074*	1.17
Pork	-1.774**	0.79
Poultry	1.261*	0.72
Fish/Seafood	-0.039	0.86
Snacks	-0.107	0.96
Beverages	0.572	1.68

Figure 1 shows what is the effect of interacting the sociodemographic variables and the information dummy. For example, older respondents tend to buy less poultry, bread and other carbohydrates, and fruits and vegetables, and more of pork in the presence of carbon labels. Households with higher income tend to substitute beef, lamb and cheese, with pork, but they also decrease their demand for fruits and

[9]Following Wooldridge (2010), we obtain it as the square of the correlation between y_i, the observed shares, and $\hat{y}_i$, the predicted shares as in Equation 23.

vegetables and increase the demand for beverages. Schooling only affects the demand for fruits and vegetables, with higher purchase as a result of with carbon labelling among highly educated respondents. Surprisingly, households with a low-meat diet increase their demand for beef, lamb, and cheese, but decrease that for fish and seafood, while high-meat households substitute beef and lamb with dairy products and carbohydrates such as bread and pasta. The overall effect is discussed in detail in Section 4.2 for the average household and in Section 4.3 for households with different diets and income.

Figure 1: Effect of information dummy and its interactions

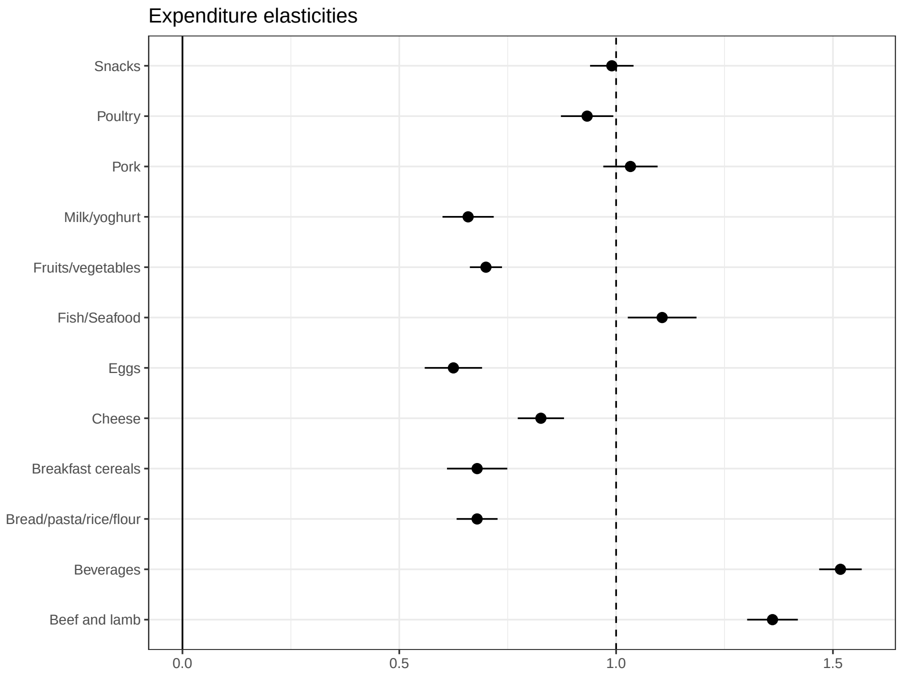


This figure reports the effect of the information dummy, obtained as the estimated parameter multiplied by the value of the sociodemographic characteristics. Deflated expenditure, age, income, and education are taken at the sample average. Gender is set to 1 (males), as well as low meat and high meat diet. The black border of a cell indicates that the parameter is statistically different from 0 at the 90% level.

4.1 Expenditure and price elasticities

Expenditure elasticities, which measure the variation in quantity of food demanded following an increase in expenditure, are shown in Figure 2. Goods with an elasticity to income larger than one are luxury goods, namely goods whose demand tends to increase more than proportionally with income: these are Beverages (1.52), Beef and lamb (1.35), and Fish and seafood (1.10). Estimates of expenditure elasticities in the literature tend to vary, but beef is usually above 1 (e.g., Caillavet et al., 2016; Roosen et al., 2022). On the other hand, Tiffin et al. (2011) report a low elasticity for both fish and beverages. Full Engel curves for each food category are reported in Figure A1: they display significant nonlinearities, which would not be captured by linear, or quadratic, functional forms, that are assumed by AIDS and QUAIDS.

Figure 2: Expenditure elasticities



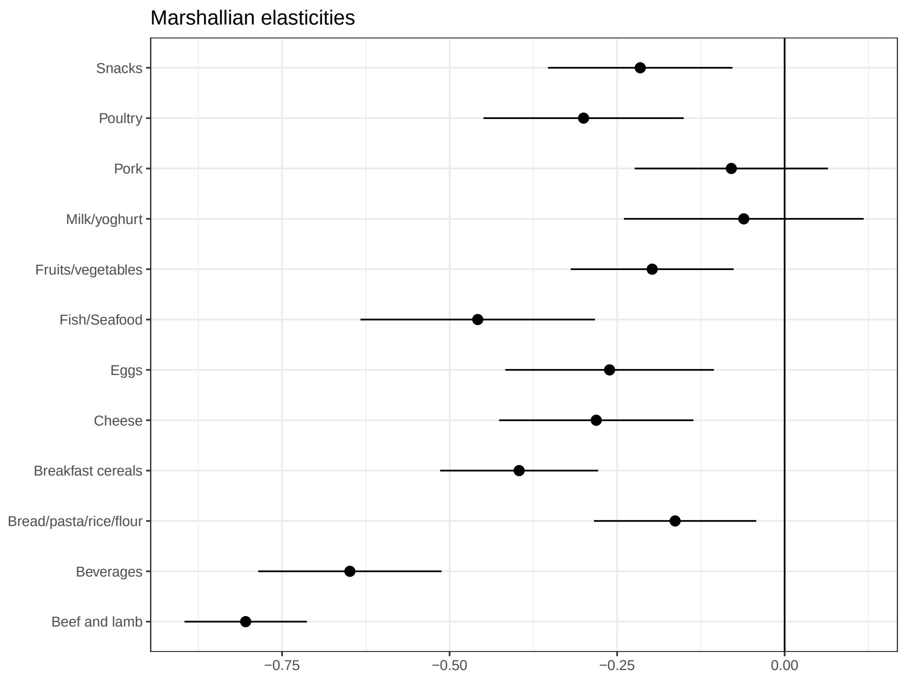
This figure shows the estimated expenditure elasticities. The error bars report the 90% confidence interval.

We also compute Marshallian, or uncompensated, elasticities (Figure 3, Figure A2 and Table A6), and Hicksian, or compensated, elasticities (Table A7), which measure the sensitivity of demand to changes in prices. As expected, we find fairly inelastic demands as own-price elasticities are all negative and lie in the interval between -1 and 0, which means that the quantities purchased of the food products decrease less than proportionally with an increase in prices. These results are in line with other studies in the literature based on official survey data (Kehlbacher et al., 2016, 2020; Tiffin & Tiffin, 1999; Tiffin et al., 2011). We find an own-price elasticity for beef and lamb that is the largest in absolute terms: this implies that imposing a tax on this category will have a strong effect in terms of demand reduction, leading to a decrease in the carbon content of the food basket. The same is also true for fish, seafood, and cheese, but the demand for pork meat does not appear to be sensibly affected by price and hence is not clear a priori to what extent a carbon tax would be able to decrease the carbon content of the food basket.

4.2 Impact of the different policy scenarios on household food demand, GHG emissions and welfare

We now investigate how the different policies under investigation affect the desired bundle of at-home food that would be purchased by the average household. We look at three policy scenarios: (1) the provision to consumers of information about the carbon footprint, through graphical indicators (Carbon labelling); (2) a price increase due to a tax on the most polluting items, proportional to the carbon content

Figure 3: Marshallian elasticities



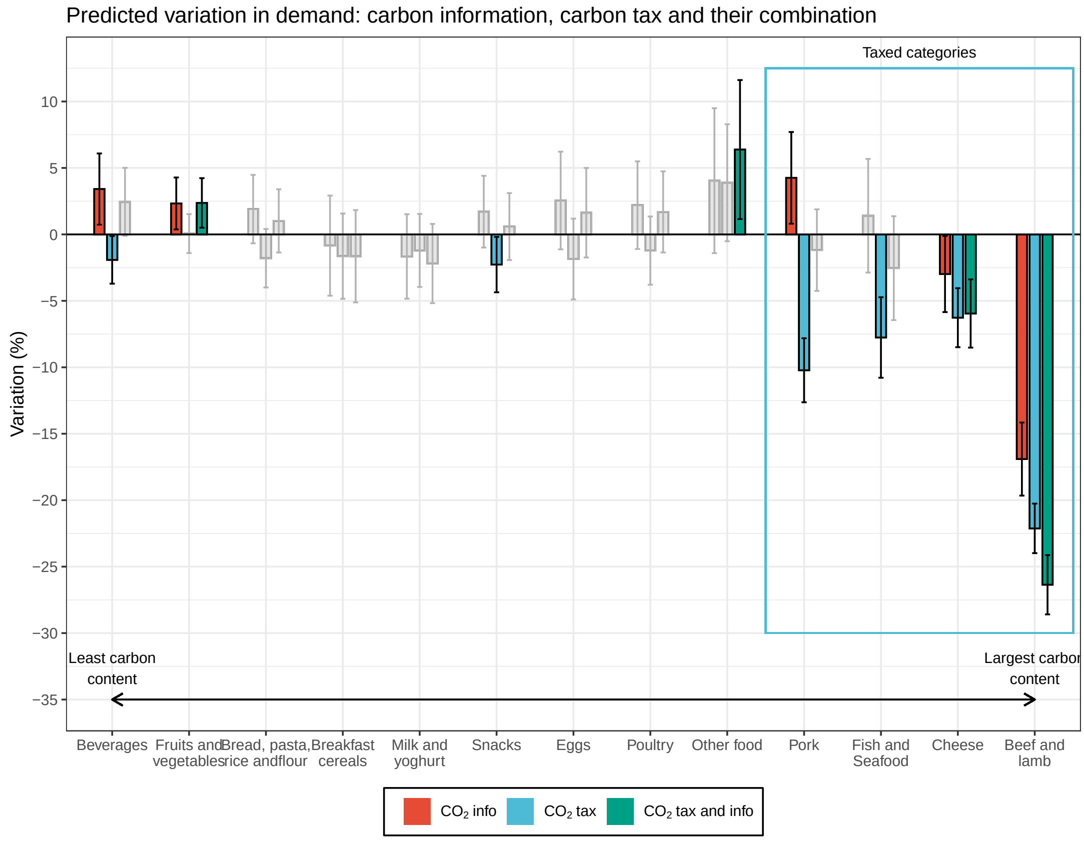
This figure shows the estimated Marshallian elasticities. The error bars report the 90% confidence interval.

(Carbon taxation); (3) a tax, combined with carbon labelling (Carbon labelling and tax). Figure 4 reports the changes in food purchase patterns under the different scenarios. With the introduction of carbon labelling, the demand for carbon intensive products would shift towards less carbon intensive products. Among the former products, beef and lamb markedly decrease (-17%), together with cheese (-3%), and it is substituted by pork meat (+4%), which albeit being relatively high in carbon content it remains lower than other red meats. At the same time, the demand for beverages (+3%), and Fruits and Vegetables (+2%) increases; predicted changes for the other categories are not statistically different from zero. With a price increase due to a carbon tax, all taxed goods (namely, beef and lamb, cheese, fish and seafood, and pork) see a decrease in demand. In order to compensate the loss in purchase power, also the demand for two untaxed products decreases, i.e., for beverages and snacks.

In order to look at the combined effect of carbon labelling and carbon tax, we simulate a £27.78/CO_2e ton tax rate, which is the rate that achieves the same emission reduction as in the carbon tax scenario. We find a small increase in the demand for fruits and vegetables (+2%) and for other food (+6%), which includes meat substitutes, as well as ready meals and plant-based milk; among the taxed goods we find a decrease in the demand for beef and lamb (-26%), which is the largest among the scenarios investigated, despite the tax rate not being the highest applied, and for cheese (-6%), which is the second category in decreasing order of carbon intensity.

Through the change in demand, these policies affect both the carbon content of the average household's

Figure 4: Variation in quantities across different policy scenarios



This figure reports the predicted variation in demanded quantities of the average household under different scenarios. The variation is expressed as a percentage of the demand in the baseline scenario. *CO_2 info* refers to the introduction of carbon labelling. *CO_2 tax* indicates the introduction of a tax on products with a carbon intensity above average (i.e., beef and lamb, cheese, pork, and fish and seafood). The error bars report the 90% confidence interval and grey bars are not statistically significant.

Table 5: The impact on carbon footprint and welfare of policies

	Baseline	Carbon labelling	Carbon tax	Carbon labelling and tax
Carbon price	0.0	0.00	60.00	27.78
CO_2e ton	2.30	2.17	2.07	2.07
Change (%)	0.0	-5.77	-10.20	-10.20
Welfare cost				
CV (-)	0.0	0.00	-71.40	-30.43
Welfare benefit				
Tax revenues	0.0	0.00	63.25	28.72
Averted CO_2e	0.0	7.98	14.11	14.11
Net welfare change	0.0	7.98	5.96	12.41

This table reports the estimated yearly CO_2e content and welfare impact of different policies for a member of the average household. Under *Baseline* no policy is introduced; *Carbon labelling* is the scenario where carbon labelling is introduced; *Carbon tax* indicates the introduction of a tax with a rate of £60 per CO_2e ton, on items with a carbon content above average (i.e., Beef and lamb, Cheese, Pork, and Fish and seafood). *Carbon labelling and tax* indicates the introduction of carbon labelling together with a tax calibrated such that the overall CO_2e decrease is the same as in the Carbon tax scenario. The first column indicates a particular outcome: *Carbon price* indicates the introduced tax rate in terms of £/CO_2e ton; CO_2e ton indicates the carbon footprint of at home food consumption; *Change (%)* indicates the variation in carbon content with respect to the baseline; *CV* indicates the Compensating Variation associated with the increase in price (it is reported with the negative sign in order to indicate the loss in welfare); *Tax revenues* are the estimated revenues from a tax, obtained as the difference between the baseline price, the new price and the quantity predicted; *Avoided CO_2e* is the difference in GHG content multiplied by the tax rate; *Net welfare change* reports the difference between benefits and costs.

food basket and its welfare, as reported in Table 5. Starting from the baseline food consumption, we estimated that the emission associated with food purchases is 2.30 tons of CO_2e , for each member of a household per year. With the introduction of carbon labelling, this figure decreases to 2.17 tons, or -5.8%[10]. A £60/CO_2e ton carbon tax is more effective in reducing emissions (-10.2%). Combining the tax with carbon labels, a lower tax rate (27.78/CO_2e ton) is sufficient to achieve the same reduction in emissions as in the tax only scenario: notably, the carbon price is less than half of the original tax rate. However, from a policy-maker perspective, it is relevant to consider both benefits of a policy (namely, avoided GHG emissions and tax revenues) and its costs, i.e., the loss in consumer welfare due to an increase in price. In order to include avoided emissions in the welfare estimation, we multiply the GHG emission reduction by the £60/ton tax rate. In the first scenario, the introduction of labelling leads to a benefit of £7.98 per person per year through the decrease in GHG. A carbon tax has larger benefits, divided between tax revenues (£63.25 per year) and a larger carbon reduction (-235 kg of CO_2e , £14.11 in monetary terms), but a large loss in consumer welfare, which in terms of Compensating Variation amounts to £71.40 per person per year (almost 5% of expenditure in at-home food). The net welfare change in the carbon tax scenario remains positive (+£5.96), but lower than the carbon labelling scenario. In the third scenario, the synergy between labels and taxation allows the reduction of the tax rate to achieve the same emission reduction as in the carbon tax scenario. The CV[11] amounts to £30.43 (around 2% of related expenditures), while welfare benefits are £28.72 from tax levy and £14.11 from emission avoidance; the net change is £12.41, which is almost 60% larger than the result of Carbon labelling policy scenario and more than double than the benefit of a tax alone.

[10]This result is slightly more conservative with findings in Lohmann et al. (2022) (4.3% reduction in average CO_2e emissions per meal), Muller et al. (2019) (8.6% decrease in the content of the food basket in an online supermarket), and Potter et al. (2022) (between 8.6% and 14.8% decrease in food-related emissions). Lanz et al. (2018) in a field experiment estimate that providing information about GHG content is equivalent to a change in relative prices ranging from £30.69 to £165.15 per CO_2e , depending on the product.

[11]Since the CV is a measure of the welfare effect of a price change, in this scenario we estimate the CV with the Carbon labelling scenario as the baseline.

4.3 Heterogeneity across different households

In Section 4.2 we looked at the impact of the different policies under ivnestigation on the average household. However, consumers differ widely in the content of their diet: for instance, a substantial share of the UK population avoids particular products for climate or ethical reasons[12] . Since the policies discussed above are more likely to affect certain food categories than others, it is important to look at how households with a consumption pattern that differs from the average are affected.

For this reason, first we look at the effect on households that have different types of diet and that therefore already consume a lower quantity of carbon intensive products, or one larger than the average. We focus on 5 types of household: households with a large quantity per capita of meat consumption (High meat), households with a low quantity per capita of meat consumption (Low meat), households that consume fish but not other animal meat (Pescatarian), households that do not consume fish nor meat (Vegetarian), and households that do not consume any product of animal origin (Vegan).

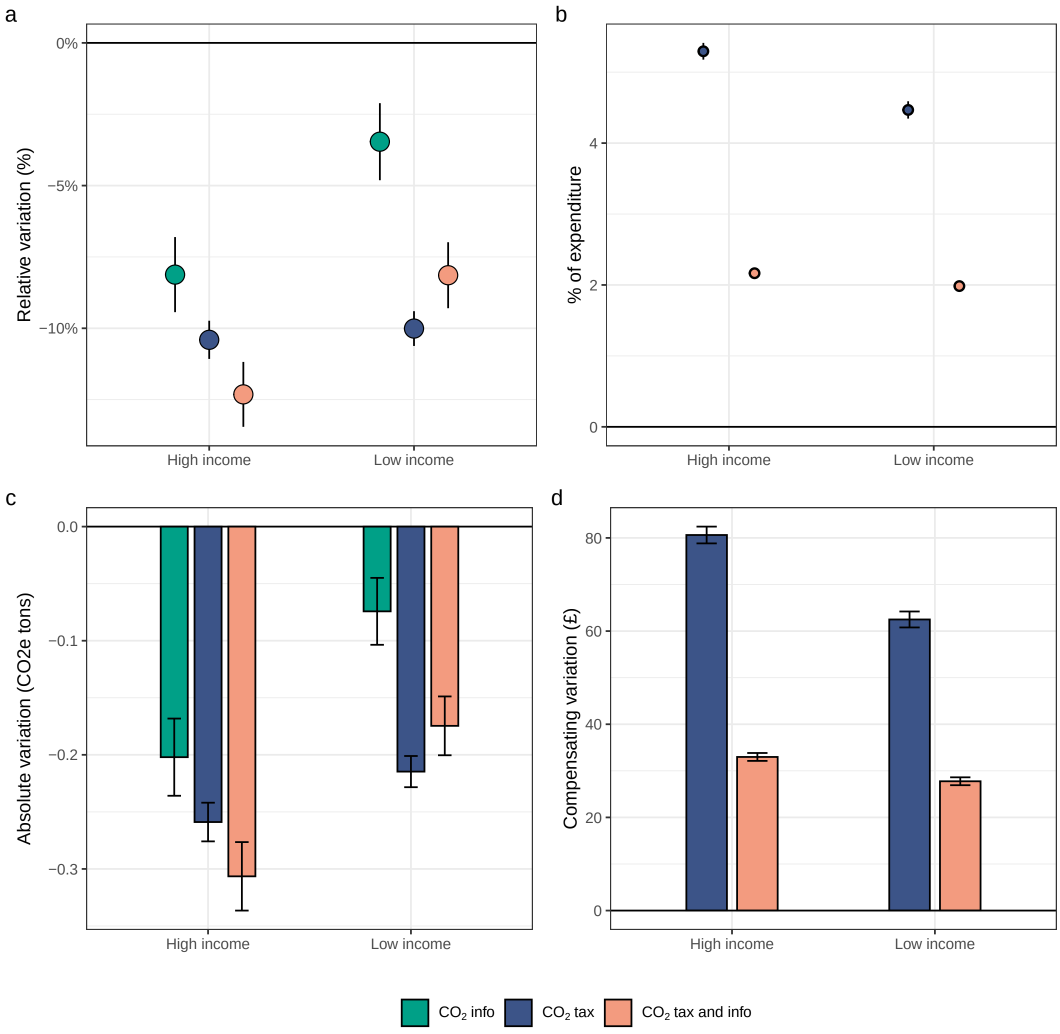
Table 6: Scenario simulation for different households

		CO_2e change (%)			CV (£ p.c)	
Group	Baseline CO_2e ton	CO_2e info	CO_2e tax	CO_2e tax and info	CO_2e tax	CO_2e tax and info
Average	2.30	-5.77	-10.20	-10.20	3.70	1.58
High meat	3.75	-6.62	-12.55	-12.12	6.81	2.91
Low meat	1.39	-3.75	-7.26	-6.96	1.63	0.71
Pescatarian	1.28	0.30	-1.19	-0.26	0.59	0.27
Vegetarian	1.05	0.43	-1.20	-0.15	0.37	0.18
Vegan	0.86	0.24	0.69	0.59	0.00	0.00
Low income	2.14	-3.46	-10.01	-8.14	62.49	27.76
High income	2.49	-8.12	-10.40	-12.32	80.63	32.98

The first column of Table 6 shows the carbon content per household member for each dietary profile. High meat households are associated with the largest carbon emissions (3.75 CO_2e tons per year), which is more than 60% larger than the footprint of the average household and more than double the footprint of other kinds of diets. Carbon labelling has a larger impact on households with high meat consumption rate than for those with low meat consumption rates, both in relative and absolute terms (Figure 6, panels a and c). This finding suggests that despite having a more carbon intensive diet, households, which consume high levels of meat, take into consideration environmental issues and are willing to decrease

[12]"In the UK, 25% of the public described themselves as "still eating but cutting down on meat, dairy and animal products". A further 5% already identify as vegetarian, 3% say they are pescatarian and 2% vegan" from https://www.food.gov.uk/our-work/chapter-1-the-nations-plate-our-diet-and-food-choices-today#what-are-we-eating-today. In our data, we find that 5% of households are vegetarian, 2% pescatarian and less than 1% vegan: obviously, by looking at households we consider it to follow a certain diet only if all members follow it.

Figure 5: Impact of different policies on carbon content of food for households with different income

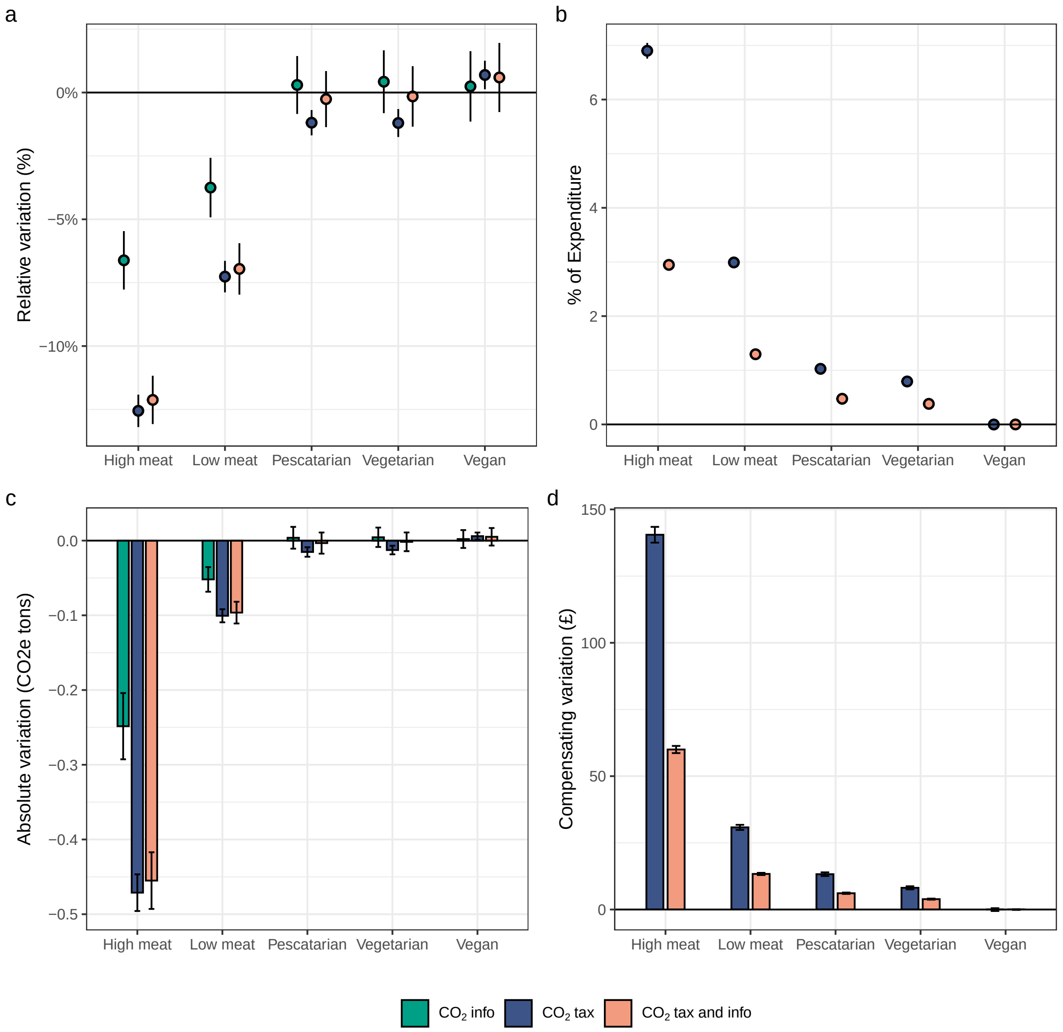


the consumption of more carbon intensive goods. The relative decrease for households with low meat consumption is smaller but statistically different from zero, indicating that any moral licensing effect is limited. On the other hand, the effect for pescatarian, vegetarian and vegan households is not statistically significant, suggesting that they do not substitute, as a result of the carbon labelling, between more carbon intensive food categories and less intensive ones to a substantial degree[13]. Carbon taxation remains more effective, in terms of reducing emissions, for all household types, and in particular for those consuming high levels of meat (-13%) and low levels of meat (-7%). The welfare effect of a carbon tax applying the £60 per ton of CO_2e results in a negative CV value of more than £140 per household member per year in the case of households consuming high levels of meat, and around one fifth of this figure for households consuming low levels of meat. Compared to the total at-home food expenditure, the welfare impact of a pure carbon tax ranges from almost 7% of the total food expenditure for high-meat consuming households, almost 3% for low-meat consumers, 1% of pescatarian households, less than 1% and 0% respectively for vegetarian and vegan households (Figure 6, panel b). Relative to a tax alone, the combination of the tax and labelling leads to a similar emission reduction for high-meat and low-meat consuming households. However, when combining the policies, the CV amounts to respectively around £60 for households with a large consumption of meat and £13 for households that consume a limited amount of meat, about 40% of the welfare loss for a full tax.

We also look at the impact of emission mitigation policies at different levels of income. Previous research has shown that taxes on food tend to be regressive (Klenert et al., 2023). Table 6 reports how carbon information and/or carbon taxes affect households according to their level of income. In the baseline, yearly CO2e emissions per capita from food increase with income, ranging from 2.14 tons for low-income households to 2.49 for higher income households, implying about a 16% difference. Interestingly, the reduction in emissions with carbon labelling is larger for high-income households (-8%) relative to low-income households (-3%). Similarly, a carbon tax has a slightly larger impact in absolute terms for richer households (Figure 5, panels a and c). The combined emission reduction from carbon tax and carbon labelling is larger than that of a tax alone for high income, but lower for low-income households. These results suggest that different policy tools have heterogeneous impacts at different income levels. On the other hand, the welfare loss is larger for high-income households (£81 in the carbon taxation scenario and £33 in the scenario with a combination of policies) than for low-income households (£63 in the carbon tax scenario and £28 combined policies scenario), but not very dissimilar. In relative terms, however, welfare losses are not very dissimilar between high and low income households: they are equivalent to about 5% increase in expenditure in the case of a carbon tax and to about 2% increase in the expenditure for the combined tax and labelling. This means that,

[13]Note that we look at changes between categories, rather than within. Further emission reduction might be possible by switching from brands with a higher footprint to ones with a lower one, despite offering a similar product.

Figure 6: Impact of different policies on carbon content of food for households with different diets



carbon taxation remains regressive, i.e. it impacts proportionally more the low, relative to high, income households.

5 Robustness tests

Some limitations of our work deserve further discussion: in this section we argue that nonetheless they do not invalidate our results. The first aspect is the nature of our data, namely that they are experimental and not observational. This might have induced respondents not to react as if they were in a real supermarket. Three aspect suggest that this should not be the case. First, in stated preference experiments, one of the standard ways to limit the scope for hypothetical bias is to a present a realistic setting to respondents (Haghani et al., 2021): our simulated online supermarket, with a large and representative choice of available products, should result familiar to respondents. We indeed compare the demand for food in the baseline with observational data (Appendix B), finding that our data are very close to secondary data in terms of quantities, expenditure and estimated emissions. We also show in a robustness test (Appendix D) that our baseline results in terms of consumer welfare, measured through CV, are consistent even when employing elasticities estimated in studies using observational data in the UK .

The second potential limitation is that carbon labelling is a hypothetical policy. While by definition there is no available information about the effect of this measure on real supermarket purchases on a large scale, we can compare our result in terms of emission reduction with the existing literature, which includes both choice experiments (Muller et al., 2019; Potter et al., 2022) and field experiments (Lohmann et al., 2022). We find an effect for the average household that is similar in magnitude and comprised in the range of those reported in the cited studies.

Third, we look only at at-home consumption and not at food for consumption outside. According to the Office for National Statistics, in the UK expenditure for the average household for at-home food and beverages was about 64% of the total in 2019. However, the energy intake from food eaten outside the home accounts for only about 10% of the total. Therefore, at-home food consumption accounts for the largest share of food-based emissions for consumers.

Fourth, we assume a high level of pass-through of the tax: as Klenert et al. (2023) note, this is a common assumption in this kind of study, but it is supported to some extent by empirical evidence in the domain of energy prices (Andersson, 2019; Ganapati et al., 2020; Harju et al., 2022) and health taxes on sugar sweetened beverages (Andreyeva et al., 2022).

Fifth, our experimental design does not allow us to understand if changes in demand are persistent over time or mostly transitory. However, the literature on the taxation of sugar sweetened beverages suggests that the shift in consumption lasts at least a number of months (Lee et al., 2019; Rogers et al., 2023). The literature about information provision policies finds some evidence in the same direction. An evaluation of the 5-per-day information campaign in the UK finds a persistent effect after 4 years (Capacci & Mazzocchi, 2011). Additionally, Lohmann et al. (2022) estimate the impact of carbon labelling in a university canteen over a 7-week intervention. Thorndike et al. (2014) find that following the introduction of labelling the healthiness of cafeteria items the sale of unhealthy items remains decreased after two years. Jalil et al. (2023) find that providing information about the environmental and health benefits of reducing meat consumption results in a change in diet that persisted after 3 years.

6 Conclusions

The food sector accounts for a relevant share of global GHG emissions and it retains a large mitigation potential (IPCC, 2022). The debate about how to improve its environmental sustainability is ongoing and different options are available. A carbon tax, i.e., directly pricing the carbon content of food products, would induce adjustments in consumers choices and upstream firms' decisions, thus internalizing the GHG externalities (Baranzini et al., 2017) at least in part. In general, the application in the past of carbon taxes has been found to be effective (Köppl & Schratzenstaller, 2023), but they may face public opposition (Carattini et al., 2018): importantly, in the case of the food sector taxes risk to be regressive as low-income households devote a larger share of their expenditures to food (Klenert et al., 2023). In comparison with taxation, carbon labelling has the advantage of facing less opposition (Pechey et al., 2022) and be less costly to implement (e.g., Jalil et al., 2023). On the other hand, as Taufique et al. (2022) report, their impact tends to be small. Nonetheless, these measures are increasingly advocated for reducing the footprint of food consumption, especially in rich countries (European Commission, 2023; Willett et al., 2019). The introduction of a combination of different policy instruments can thus alleviate their limitations.

In this work we explore the combination of a hard policy (a carbon tax) and a soft policy (carbon labelling). We show that this policy mix can yield the same emission reduction of a carbon tax alone, with the introduction of less than half of the tax rate of a carbon tax alone. As public acceptance of a carbon tax has been shown to decrease with the tax rate (Carattini et al., 2018), it is not straightforward that policy-makers might be able to implement it: the combination of the two policies could then make it feasible, without renouncing to more ambitious emission reduction goals. Encouragingly, we find that even households with a larger carbon footprint, due to a diet relatively more abundant in animal products, react strongly to both information provision and price signals. This result supports the finding that most consumers care about their carbon footprint, but either lack the knowledge about carbon content or the information is not salient during grocery shopping (Camilleri et al., 2019). Thus, carbon information can help individuals with pro-environmental preferences to assess and decrease their carbon footprint, while the tax provides the monetary incentives for all. In addition, we find that high-income households decrease their GHG footprint significantly more than low-income ones with carbon labelling. As the fairness of the transition to a low-carbon economy remains a key issue, this finding shows that the policy mix might allow a distribution of burdens that is more equitable than that resulting from a tax alone.

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7 Appendix

A Additional tables

Table A1: Composition of food categories

Beef and lamb	Beef mince or diced; Beef steaks; Beef roasting joints; Processed beef; Raw lamb chops; Raw lamb leg or shoulder; Processed lamb;
Beverages	Breakfast Tea; Instant coffee; Sugary soft drinks; Diet soft drinks; Sugary (fruit) juices & squash; No added sugar (fruit) juices & squash; Beer & cider; Wine; Spirits;
Bread/pasta/rice/flour	Bread; Pasta; Rice; Flour;
Breakfast cereals	Muesli, porridge, bran- & cornflakes; Sugary breakfast cereals or granola;
Cheese	Hard cheese; Soft & spreadable cheese; Butter; Cream;
Eggs	Eggs;
Fish/Seafood	Raw fish & seafood; Processed fish & seafood; Smoked salmon;
Fruits/vegetables	Oranges & clementines; Apples & pears; Bananas; Grapes; Strawberries; Peaches, nectarines, plums; Pineapple; Fresh lettuce; Fresh tomatoes; Fresh carrots; Fresh potatoes; Onions; Cauliflower, Cabbage, Broccoli; Tomato products; Canned pulses; Dried & frozen pulses; Chips & fries;
Milk/yoghurt	Whole milk; Skimmed & semi-skimmed milk; Low fat/low sugar yoghurt; Yoghurt (not diet);
Pork	Pork loin, chops, mince; Pork joints; Pork sausages & bacon; Ham;
Poultry	Poultry breast & boneless thighs; Whole chicken; Processed poultry;
Snacks	Chocolate; Biscuits; Ice cream (1L); Ice cream (450ml); Cake; Nuts & dry fruit; Crisps; Savoury snacks;
Other food	Plant-based milk; Meat alternatives; Meat-based ready meals; Fish-based ready meals; Pizza; Vegetarian/vegan ready meals;

This table reports which items make up each of the 13 food categories used in this study, from the 72 single items in the original survey.

Table A2: CO_2e content per unit in the baseline and other survey scenarios

Category	Baseline	Carbon labelling	Unlabelled tax	Carbon tax
Fruits/vegetables	0.58	0.57	0.57	0.57
Bread/pasta/rice/flour	1.28	1.26	1.28	1.26
Breakfast cereals	1.30	1.30	1.30	1.30
Milk/yogurt	2.31	2.30	2.31	2.30
Cheese	3.29	3.26	3.26	3.23
Eggs	1.66	1.66	1.66	1.66
Beef and lamb	31.65	31.80	30.95	31.24
Pork	4.69	4.86	4.71	4.79
Poultry	5.66	5.66	5.77	5.68
Fish/Seafood	3.30	3.30	3.29	3.29
Snacks	0.74	0.73	0.74	0.73
Beverages	0.85	0.85	0.83	0.85
Other food	3.09	3.00	2.98	2.91

Table A3: Summary statistics

Item	Share (%)	Quantity (kg)	Censored (%)	CO_2e (kg)	Price (£ per kg)
Apples & pears	1.89	0.64	26.55	0.26	2.02
Bananas	0.66	0.52	17.71	0.41	0.81
Beef mince or diced	2.97	0.36	27.16	21.77	6.23
Beef roasting joints	2.00	0.22	69.10	13.56	8.62
Beef steaks	2.42	0.16	53.91	9.37	13.47
Beer & cider	3.08	0.97	58.50	1.16	2.59
Biscuits	1.90	0.32	23.57	0.45	4.25
Bread	2.24	1.11	6.68	1.44	1.36
Breakfast tea	1.12	0.10	30.60	0.01	8.31
Butter	1.43	0.19	17.32	1.78	5.50
Cake	0.77	0.13	52.71	0.32	4.66
Canned pulses	1.35	0.72	14.88	1.52	1.33
Cauliflower, Cabbage, Broccoli	1.16	0.64	27.44	0.26	1.28
Chips & fries	1.19	0.63	27.44	2.46	1.42
Chocolate	2.21	0.18	28.51	0.92	8.62
Cream	0.22	0.05	78.37	0.13	3.62
Crisps	1.64	0.18	19.11	0.79	6.59
Diet soft drinks	0.97	1.37	56.97	0.41	0.54
Dried & frozen pulses	1.36	0.27	30.96	0.30	3.68
Eggs	1.82	0.08	8.84	0.34	15.45
Fish-based ready meals	0.72	0.11	74.68	0.84	5.15
Flour	0.26	0.31	45.22	0.41	0.65
Fresh carrots	0.58	0.74	20.92	0.96	0.55
Fresh lettuce	0.83	0.31	37.25	0.55	1.93
Fresh potatoes	1.19	0.97	12.18	0.48	0.87
Fresh tomatoes	1.72	0.45	21.48	0.31	2.63
Grapes	1.74	0.33	37.43	0.47	3.77
Ham	2.01	0.16	36.82	1.75	9.14
Hard cheese	2.77	0.29	12.46	4.81	6.76
Ice cream (1L)	1.04	0.25	56.89	0.51	3.44
Ice cream (450ml)	0.50	0.12	64.23	0.25	3.40
Instant coffee	1.70	0.07	35.16	0.04	17.39
Low fat/low sugar yoghurt	1.31	0.37	53.99	1.01	2.61
Meat-based ready meals	1.61	0.22	63.75	2.64	5.13
Meat alternatives	1.29	0.14	72.28	0.30	6.26
Muesli, porridge, bran- & cornflakes	1.27	0.30	26.04	0.77	3.01
No added sugar (fruit) juices & squash	1.15	0.85	43.77	0.85	0.97
Nuts & dry fruit	1.19	0.11	52.33	0.11	8.18
Onions	0.39	0.31	18.24	0.12	0.87
Oranges & clementines	1.29	0.46	36.20	0.14	1.93
Pasta	0.65	0.40	15.46	0.52	1.18
Peaches, nectarines, plums	0.36	0.12	71.67	0.08	2.42
Pineapple	0.26	0.27	76.76	0.19	0.79
Pizza	1.61	0.26	32.41	3.14	4.53

Plant-based milk	0.64	0.37	76.54	0.33	1.20
Pork joints	1.22	0.25	75.41	2.67	4.32
Pork loin, chops, mince	0.98	0.15	59.75	1.58	5.08
Pork sausages & bacon	2.40	0.28	27.72	2.97	6.45
Poultry breast & boneless thighs	3.56	0.46	28.56	3.48	5.61
Processed beef	1.61	0.16	53.48	9.62	8.31
Processed fish & seafood	1.60	0.18	41.94	2.02	6.53
Processed lamb	0.23	0.03	90.32	1.13	8.27
Processed poultry	1.23	0.13	64.66	0.98	7.73
Raw fish & seafood	2.47	0.14	52.61	1.56	13.08
Raw lamb chops	0.78	0.06	76.38	2.36	11.43
Raw lamb leg or shoulder	0.77	0.09	81.99	3.59	8.39
Rice	1.25	0.47	28.76	1.74	1.99
Savoury snacks	1.53	0.16	46.96	0.73	7.18
Skimmed & semi-skimmed milk	1.84	2.24	30.57	6.04	0.55
Smoked salmon	0.61	0.02	76.41	0.15	26.50
Soft & spreadable cheese	0.81	0.09	50.39	1.16	6.58
Spirits	3.11	0.16	72.71	0.54	17.55
Strawberries	1.63	0.17	52.38	0.24	7.45
Sugary (fruit) juices & squash	0.46	0.35	71.72	0.35	1.09
Sugary breakfast cereals or granola	0.98	0.22	50.01	0.58	3.50
Sugary soft drinks	1.25	1.07	61.55	0.32	0.95
Tomato products	0.66	0.47	26.78	0.99	0.99
Vegetarian/vegan ready meals	0.71	0.10	80.94	0.78	5.16
Whole chicken	1.57	0.51	48.05	3.81	2.49
Whole milk	0.87	1.10	63.18	2.97	0.56
Wine	4.25	0.52	56.15	0.83	6.71
Yoghurt (not diet)	1.16	0.31	56.08	0.84	2.69

This table contains the descriptive statistics for prices and goods in our sample. *Share* reports the average budget share for each food category (as a percentage), while *Quantity* reports the average quantity in kg. *Censored* indicates the percentage of observations that are equal to zero. CO_2e indicates the average CO_2e content (in kg) for the demanded quantities. *Price* reports the average price per kg/l in the baseline scenario.

Table A4: Summary statistics: demographic variables

Variable	Share (%)
Region	
London	11.13
England	73.40
Scotland	7.77
Wales	4.87
Northern Ireland	2.83
Occupation	
Managerial	49.55
Manual	24.36
Unemployed	8.00
Retired	16.20
Student in higher education	1.89
Ethnicity	
White	90.88
Asian or Asian British	4.89
Black, African, Caribbean or Black British	1.55
Mixed	1.86
Any other ethnic group	0.31
Prefer not to say	0.51

This table reports the shares of the respondents according to their region, occupation and ethnicity.

Table A5: Variation in expenditure between scenarios

Dependent Variable:	log(expenditure)
Model:	(1)
Variables	
Survey scenario: Carbon labelling	-0.0184***
	(0.0023)
Survey scenario: Unlabelled tax	0.0199***
	(0.0042)
Survey scenario: Carbon tax	-0.0022
	(0.0036)
Fixed-effects	
Respondent	Yes
Fit statistics	
Observations	6,563
R^2	0.98644
Within R^2	0.01830

Clustered (Respondent) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

This table reports the results of a linear regression where the dependent variable is the logarithm of the expenditure in food. The independent variables are dummies for each survey scenario and treatment. Fixed effect for respondents are included.

Table A6: Marshallian (uncompensated) elasticities

	Fruits and vegetables	Bread, pasta, rice, flour	Breakfast cereals	Milk and yoghurt yoghurt	Cheese	Eggs	Beef and lamb	Pork	Poultry	Fish and seafood	Snacks	Beverages	Other food
Fruits/vegetables	-0.199***	-0.005	-0.023	-0.094***	0.002	-0.023	0.064*	-0.033	-0.046	0.094***	-0.033	-0.137**	-0.11**
	(0.074)	(0.0231)	(0.0194)	(0.0345)	(0.0313)	(0.0159)	(0.0334)	(0.0363)	(0.037)	(0.0361)	(0.0436)	(0.0548)	(0.0515)
Bread/pasta/rice/flour	0.035	-0.165**	-0.09**	-0.056	0.058	0.085**	0.038	-0.033	-0.012	0.044	-0.102	0.206**	-0.248***
	(0.0961)	(0.0737)	(0.0395)	(0.0723)	(0.0624)	(0.0386)	(0.0526)	(0.0613)	(0.0698)	(0.0583)	(0.0728)	(0.0832)	(0.0848)
Breakfast cereals	-0.167	-0.156**	-0.397***	-0.12	-0.041	-0.038	0.008	-0.022	-0.003	0.024	0.05	0.29**	-0.141
	(0.1275)	(0.0623)	(0.0718)	(0.0927)	(0.0821)	(0.043)	(0.0752)	(0.0855)	(0.0885)	(0.0831)	(0.1024)	(0.1208)	(0.1232)
Milk/yoghurt	-0.285**	-0.052	-0.055	-0.062	-0.088	-0.044	0.11*	-0.108	0.071	-0.012	0.065	-0.102	0.082
	(0.1125)	(0.0566)	(0.0461)	(0.1089)	(0.0711)	(0.0391)	(0.0647)	(0.0753)	(0.0775)	(0.0706)	(0.089)	(0.1001)	(0.1031)
Cheese	-0.04	0.02	-0.023	-0.102	-0.281***	0.002	-0.104*	0.025	-0.05	0.067	-0.211***	-0.1	-0.037
	(0.0978)	(0.0463)	(0.0389)	(0.0674)	(0.0883)	(0.0325)	(0.0622)	(0.0662)	(0.0702)	(0.0648)	(0.0799)	(0.0899)	(0.0941)
Eggs	-0.103	0.198**	-0.038	-0.1	0.049	-0.262***	0.067	-0.009	0.008	0.025	-0.165	0.17	0.128
	(0.146)	(0.0839)	(0.0597)	(0.1093)	(0.0955)	(0.0947)	(0.0741)	(0.0905)	(0.0979)	(0.0855)	(0.1077)	(0.1161)	(0.1217)
Beef and lamb	-0.116**	-0.048**	-0.023	-0.013	-0.101***	-0.019	-0.806***	-0.253***	0.005	-0.136***	-0.123***	-0.226***	0.089*
	(0.0541)	(0.0198)	(0.0176)	(0.0306)	(0.0309)	(0.0126)	(0.0557)	(0.0373)	(0.0348)	(0.0383)	(0.0452)	(0.0659)	(0.0532)
Pork	-0.105	-0.037	-0.009	-0.094	0.026	-0.015	-0.299***	-0.08	-0.099	-0.025	0.068	0.121	-0.186**
	(0.0912)	(0.0364)	(0.0322)	(0.0571)	(0.0526)	(0.0246)	(0.0599)	(0.0878)	(0.062)	(0.0647)	(0.0764)	(0.1006)	(0.0912)
Poultry	-0.126	-0.021	0	0.049	-0.031	-0.009	0.128**	-0.097	-0.301***	-0.346***	0.076	-0.054	0.095
	(0.0971)	(0.0431)	(0.0351)	(0.0616)	(0.0582)	(0.0278)	(0.0585)	(0.0646)	(0.091)	(0.0647)	(0.0797)	(0.0937)	(0.0936)
Fish/Seafood	0.097	-0.022	-0.009	-0.065	0.023	-0.018	-0.253***	-0.086	-0.45***	-0.458***	-0.052	-0.19	-0.14
	(0.1084)	(0.0412)	(0.0369)	(0.0635)	(0.0611)	(0.0275)	(0.074)	(0.0771)	(0.074)	(0.1066)	(0.0919)	(0.1182)	(0.1055)
Snacks	-0.113	-0.066**	0.007	0.009	-0.113***	-0.046**	-0.032	0.032	0.029	0.013	-0.214**	-0.23***	-0.18**
	(0.0709)	(0.0282)	(0.0249)	(0.0442)	(0.0414)	(0.019)	(0.0469)	(0.0489)	(0.0494)	(0.0502)	(0.0838)	(0.0793)	(0.0709)
Beverages	-0.358***	-0.021	0.014	-0.099***	-0.085***	-0.015	-0.144***	-0.028	-0.097***	-0.067*	-0.234***	-0.649***	-0.081
	(0.0529)	(0.0185)	(0.0169)	(0.0285)	(0.027)	(0.0117)	(0.0387)	(0.0374)	(0.0336)	(0.0371)	(0.0457)	(0.0834)	(0.0515)

This table contains the estimated Marshallian elasticities for the average household (see text). Standard errors in parentheses.
*,**, and *** respectively refer to statistical significance at the 10, 5, and 1 percent levels.

Table A7: Hicksian (compensated) elasticities

	Fruits and vegetables	Bread, pasta, rice, flour	Breakfast cereals	Milk and yoghurt yoghurt	Cheese	Eggs	Beef and lamb	Pork	Poultry	Fish and seafood	Snacks	Beverages	Other food
Fruits/vegetables	-0.0743	0.0238	-0.0071	-0.0586*	0.0398	-0.0109	0.1391*	0.0121	-0.002	0.1275*	0.0422	-0.0073	-0.067
	(0.0735)	(0.023)	(0.0194)	(0.0345)	(0.0313)	(0.0159)	(0.0335)	(0.0362)	(0.037)	(0.0361)	(0.0435)	(0.0544)	(0.0516)
Bread/pasta/rice/flour	0.1563	-0.1367*	-0.0743*	-0.0216	0.0948	0.0968*	0.1105*	0.0106	0.031	0.0757	-0.0291	0.332*	-0.2063*
	(0.0958)	(0.0736)	(0.0395)	(0.0722)	(0.0622)	(0.0386)	(0.0527)	(0.0613)	(0.0697)	(0.0583)	(0.0727)	(0.0826)	(0.0846)
Breakfast cereals	-0.0464	-0.1278*	-0.3816*	-0.0858	-0.0039	-0.0262	0.0809	0.0219	0.0402	0.0559	0.1228	0.4166*	-0.0995
	(0.127)	(0.0622)	(0.0717)	(0.0927)	(0.082)	(0.043)	(0.0753)	(0.0854)	(0.0884)	(0.083)	(0.1021)	(0.1202)	(0.1231)
Milk/yoghurt	-0.1678	-0.0244	-0.0399	-0.0289	-0.0523	-0.0331	0.1811*	-0.0653	0.1127	0.0189	0.1351	0.0206	0.1225
	(0.1118)	(0.0565)	(0.0461)	(0.1088)	(0.071)	(0.039)	(0.0645)	(0.0752)	(0.0775)	(0.0706)	(0.0889)	(0.0993)	(0.1031)
Cheese	0.107	0.0543	-0.0039	-0.0604	-0.2366*	0.0161	-0.0149	0.0782	0.0019	0.1061	-0.1228	0.0538	0.0139
	(0.0973)	(0.0461)	(0.0389)	(0.0675)	(0.0881)	(0.0325)	(0.0622)	(0.0661)	(0.0701)	(0.0647)	(0.0797)	(0.0894)	(0.094)
Eggs	0.0077	0.2237*	-0.0233	-0.0684	0.0826	-0.2513*	0.1338*	0.0307	0.0469	0.0546	-0.0978	0.2855*	0.1667
	(0.1455)	(0.0838)	(0.0597)	(0.1092)	(0.0955)	(0.0947)	(0.0742)	(0.0905)	(0.0978)	(0.0855)	(0.1075)	(0.1151)	(0.1216)
Beef and lamb	0.1264*	0.0084	0.0083	0.0551*	-0.0278	0.004	-0.6593*	-0.1651*	0.0907*	-0.0715*	0.0231	0.0267	0.1724*
	(0.0534)	(0.0198)	(0.0177)	(0.0306)	(0.031)	(0.0126)	(0.0559)	(0.0373)	(0.0348)	(0.0384)	(0.0453)	(0.0652)	(0.0534)
Pork	0.0787	0.0055	0.0144	-0.0417	0.0813	0.0027	-0.1881*	-0.0132	-0.0341	0.0234	0.1783*	0.3125*	-0.1221
	(0.0904)	(0.0363)	(0.0322)	(0.057)	(0.0526)	(0.0246)	(0.0599)	(0.0877)	(0.0619)	(0.0647)	(0.076)	(0.1002)	(0.0911)
Poultry	0.0399	0.0175	0.0213	0.0958	0.0192	0.0072	0.2278*	-0.0371	-0.2421*	-0.3022*	0.1753*	0.1195	0.1522
	(0.0962)	(0.0431)	(0.035)	(0.0615)	(0.0582)	(0.0278)	(0.0581)	(0.0645)	(0.0908)	(0.0647)	(0.0793)	(0.0929)	(0.0935)
Fish/Seafood	0.2937*	0.0244	0.0159	-0.0094	0.0824	0.0012	-0.1339*	-0.0147	-0.3803*	-0.4057*	0.0665	0.0158	-0.0721
	(0.1071)	(0.041)	(0.0368)	(0.0634)	(0.061)	(0.0274)	(0.0734)	(0.0769)	(0.0737)	(0.1064)	(0.0914)	(0.1174)	(0.1055)
Snacks	0.0634	-0.0251	0.0296	0.059	-0.0599	-0.0287	0.0746	0.0955*	0.0913*	0.0596	-0.1084	-0.0458	-0.1186*
	(0.0702)	(0.0281)	(0.0249)	(0.0441)	(0.0413)	(0.019)	(0.0465)	(0.0488)	(0.0492)	(0.0501)	(0.0834)	(0.0788)	(0.0708)
Beverages	-0.0878*	0.042*	0.0484*	-0.0233	-0.0033	0.0106	0.0187	0.0693*	-0.001	0.005	-0.0721	-0.3669*	0.012
	(0.052)	(0.0183)	(0.0168)	(0.0281)	(0.0268)	(0.0116)	(0.0383)	(0.0369)	(0.0333)	(0.0368)	(0.0452)	(0.0824)	(0.0512)

This table contains the estimated Hicksian elasticities for the average household (see text). Standard errors in parentheses.
*,**, and *** respectively refer to statistical significance at the 10, 5, and 1 percent levels.

Table A8: Predicted food quantities (in kg): baseline, carbon information and carbon tax scenarios

Category	Baseline	Carbon labelling	Carbon tax	Carbon labelling and tax
Fruits/vegetables	8.18	8.37	8.18	8.37
Bread/pasta/rice/flour	2.30	2.34	2.26	2.32
Breakfast cereals	0.54	0.53	0.53	0.53
Milk/yoghurt	4.16	4.09	4.11	4.06
Cheese	0.62	0.60	0.58	0.58
Eggs	0.08	0.09	0.08	0.08
Beef and lamb	0.82	0.68	0.64	0.60
Pork	0.76	0.79	0.68	0.75
Poultry	1.07	1.09	1.06	1.09
Fish/Seafood	0.33	0.34	0.31	0.33
Snacks	1.41	1.44	1.38	1.42
Beverages	5.44	5.62	5.33	5.57
Other food	1.14	1.19	1.19	1.22

This table contains the predicted food demand of the average household, expressed in kg per week. The column labels indicate the scenario for which quantities are estimated: under *Baseline* no policy is introduced; *Carbon labelling* is the scenario in which carbon labelling is introduced; *Carbon tax* indicates the introduction of a proportional tax with a rate of £60 per CO_2e ton on items with a carbon intensity above average (i.e., Beef and lamb, Cheese, Pork, and Fish and seafood). *Carbon labelling and tax* indicates the combination of carbon taxation and carbon labelling.

Table A9: Predicted food shares (in %): baseline, carbon information and carbon tax scenarios

Category	Baseline	CO_2e info	CO_2e tax	CO_2e info and tax
Fruits/vegetables	17.78	18.20	17.80	18.21
Bread/pasta/rice/flour	4.17	4.25	4.09	4.21
Breakfast cereals	2.29	2.27	2.25	2.25
Milk/yoghurt	5.02	4.94	4.96	4.91
Cheese	5.40	5.24	5.67	5.36
Eggs	1.72	1.76	1.69	1.75
Beef and lamb	10.75	8.93	11.29	9.19
Pork	6.43	6.70	6.35	6.65
Poultry	6.30	6.44	6.22	6.41
Fish/Seafood	4.72	4.78	4.63	4.73
Snacks	10.70	10.88	10.46	10.76
Beverages	18.57	19.20	18.22	19.03
Other food	6.15	6.40	6.39	6.54

This table contains the predicted food purchase shares of the average household, expressed as percentages of total expenditure in at-home food. The column labels indicate the scenario for which quantities are estimated: under *Baseline* no policy is introduced; *Carbon labelling* is the scenario in which carbon labelling is introduced; *Carbon tax* indicates the introduction of a proportional tax with a rate of £60 per CO_2e ton on items with a carbon intensity above average (i.e., Beef and lamb, Cheese, Pork, and Fish and seafood). *Carbon labelling and tax* indicates the combination of carbon taxation and carbon labelling.

A Additional Figures

Figure A1: Engel curves

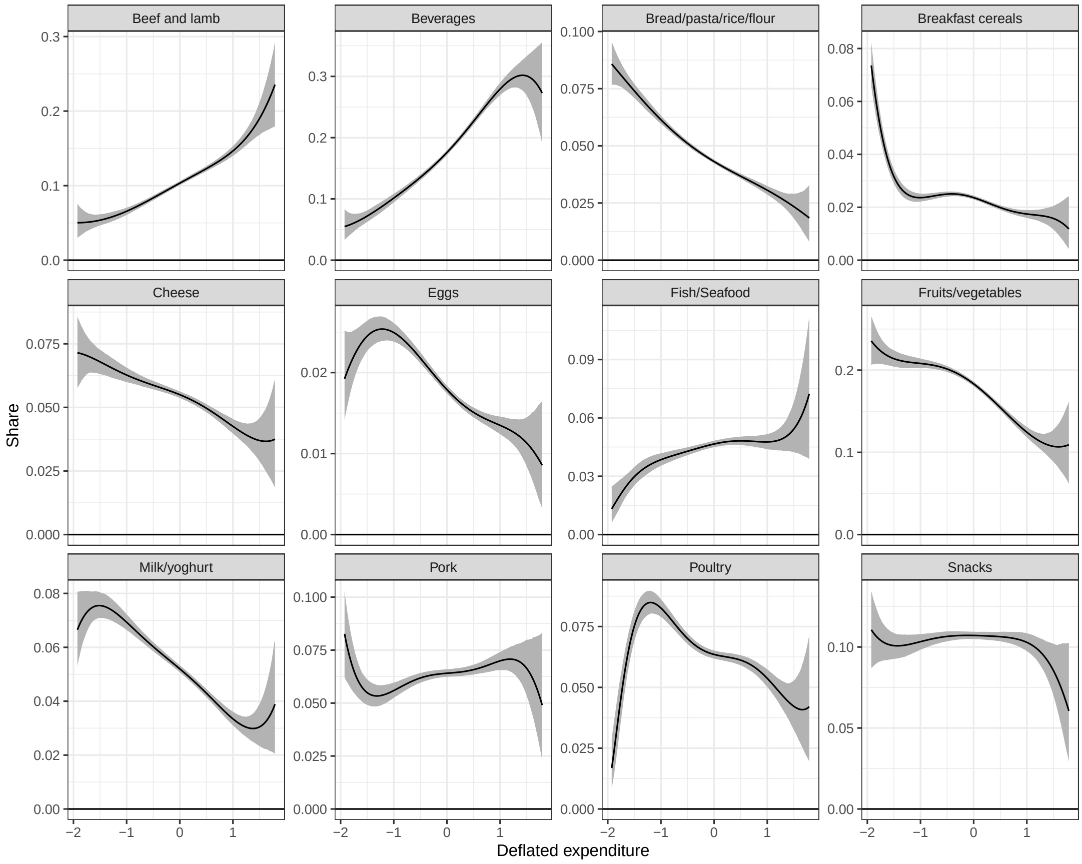
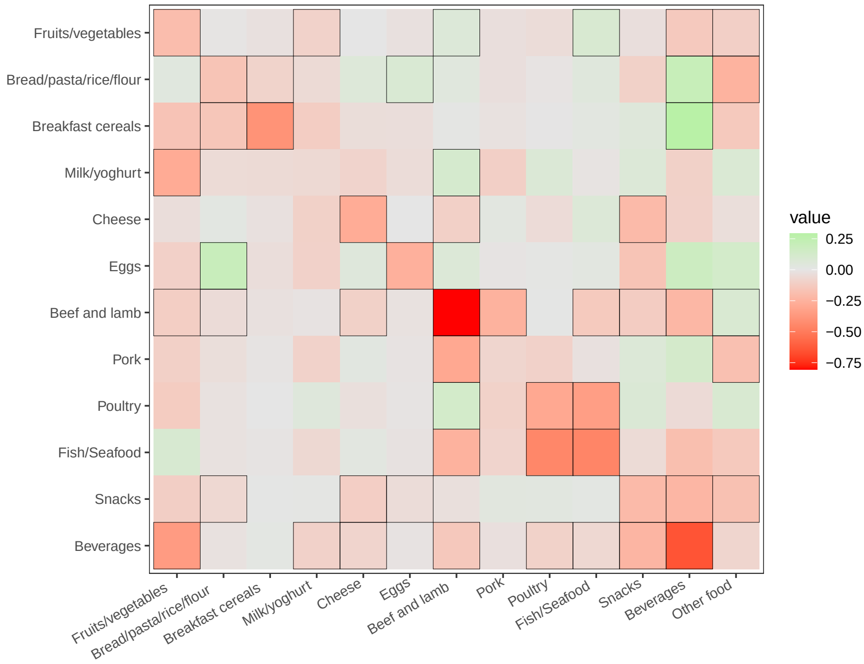


Figure A2: Marshallian elasticities

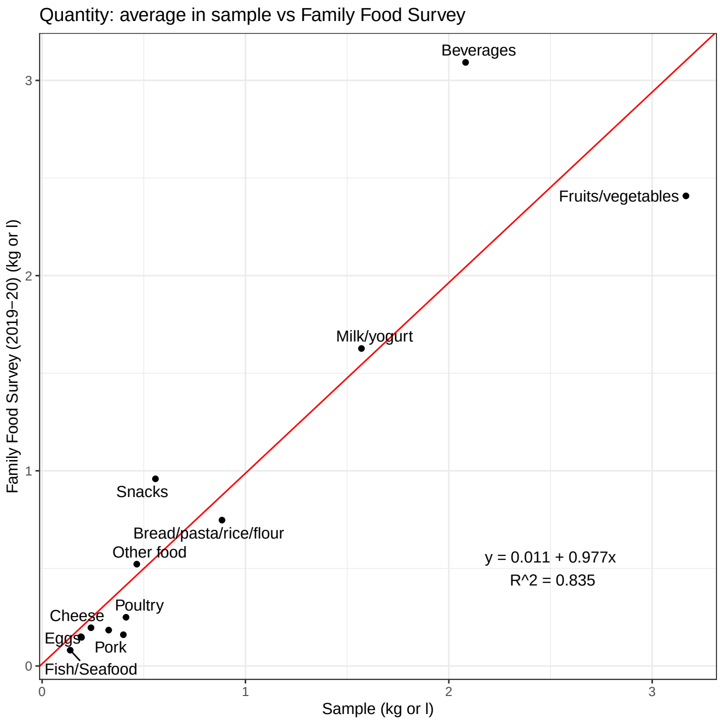


This figure shows the estimated own- and cross-price Marshallian elasticities for the average household in matrix form. Green cells indicate substitute goods, while red ones indicate complementary goods. Cells with a solid border indicate elasticities significant at the 90% level.

B Data validation

We compare our dataset with the Family Food Survey FYE 2022 (2019–20 wave), derived from the Family Food Module of the Living Costs and Food Survey and from the National Food Survey, published by the Department for Environment, Food & Rural Affairs of the UK government[14]. We match the categories in our sample with those in the Family Food Survey. Quantities are expressed as averages per person per week. We match the categories in our sample with those in the Family Food Survey. Quantities are expressed as averages per person per week.

Figure B1: Comparison of weekly average quantities per person between the Family Food Survey (2019–20) and our sample



This figure reports the average weekly consumption of food in kg or litre per person as reported in the Family Food Survey (2019–20) or in our sample. The red line indicates the result of a linear regression.

Figure B1 shows a scatterplot with the values in our dataset, plotted against those of the Family Food Survey, and the corresponding linear regression. The intercept of the regression line is not significantly different from 0, while the slope is close to 1 ($\beta = 0.977$), with an R^2 of 0.835 (Table B1). A Wilcoxon rank sum test does not reject the hypothesis that the food categories have same ordering in the two samples ($p = 0.579$).

According to the Office for National Statistics, the average weekly expenditure in food and alcoholic drinks of UK households was £73.00 in 2019–20[15]. As a comparison, the average expenditure in the

[14] https://www.gov.uk/government/statistical-data-sets/family-food-datasets; consulted on 18/01/2024.

[15] https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/expenditure/datasets/familyspendingworkbook1detailedexpenditureandtrends; consulted on 25/01/2024.

baseline in our dataset is £75.65.

We also compare the CO_2e content of food purchases determined by respondents' choices in the survey. The average in our dataset is 2.68 tons per person per year (baseline scenario), which is in line the estimate of 2.7 CO_2e tons in Rippin et al. (2021) and Berners-Lee et al. (2012).

Table B1: Regression of weekly average quantities per person

Dependent Variable:	$Q_{\text{Family Food Survey}}$
Model:	(1)
Variables	
(Intercept)	0.011
	(0.157)
Q_{Sample}	0.977***
	(0.131)
Fit statistics	
Observations	13
R^2	0.835

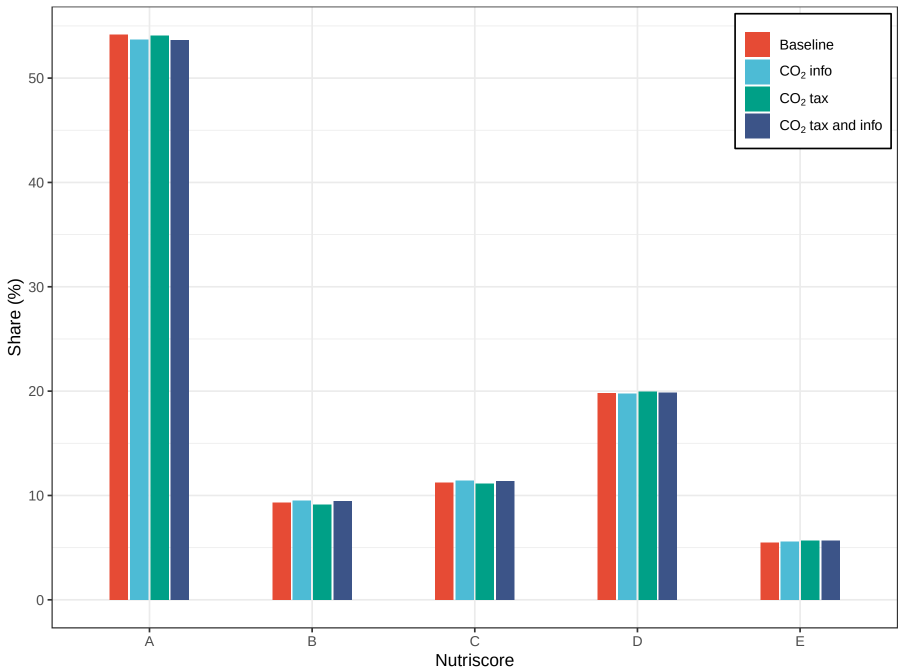
IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

C Nutritional impacts under different scenarios

In order to understand the impact of a shift in consumption on the nutritional profile of food intake, we consider the variation in Nutriscore categories. Nutriscore combines different aspects of the nutritional content of food into a single score ranging from A to E, where products with a score of A are the most balanced and should have a larger share of the diet.

Since we are using aggregate food categories, we compute for each category the share assigned to each score weighted by consumption per capita (in kg) in the baseline. Assuming that the combination of products does not change within a category, we use this Nutriscore profile to predict the score of a change in consumption in a scenario. The results of this exercise for the average household are shown in Figure C1. Variation in Nutriscore shares are below 1 percentage point, suggesting that changes in diet under policy scenarios do not substantially affect the nutritional profile as measured by this indicator.

Figure C1: Share of food consumption by Nutriscore



This figure reports the predicted change in the nutritional profile of the diet of average household under different policies. Each bar represents in a given scenario what percentage of products in a diet (in units) belongs to a particular score. Therefore, the bars sum to 100% (by scenario). Nutriscore ranks food products in terms of nutritional quality from highest (A) to lowest (E).

D Robustness with different elasticities

We estimate the Compensating Variation using the elasticities found in Tiffin et al. (2011) and Kehlbacher et al. (2016), who both estimate price elasticities for food items of UK households. Since the EASI demand model computes the CV from its parameters and not from its elasticities (Equation 13), we need to derive parameters γ and ζ. Price elasticities are a function of these parameters and for this reason we numerically estimate these parameters by minimizing function $f(\boldsymbol{\theta})$ where $\boldsymbol{\theta} = (\hat{\gamma}_{1,1}, ..., \hat{\gamma}_{12,12}, \hat{\zeta}_{1,1}, ..., \hat{\zeta}_{12,12})$

$$f(\boldsymbol{\theta}) = \sum_r \sum_s (e^*_{rs} - \hat{e}^2_{rs}) \tag{24}$$

where e^*_{rs} are the elasticities in either Tiffin et al. (2011) and Kehlbacher et al. (2016), aggregated as described below in order to match our categories, and $\hat{e}^*_{rs}$ are the elasticities computed at each iteration by changing parameters $\hat{\gamma}$ and $\hat{\zeta}$. We use the function 'optim' from the 'stats' package in R. We choose as starting values both our estimated parameter, and a vector of 0's, as well as bounded between $-|\max(\hat{\gamma}, \hat{\zeta})|$ and $|\max(\hat{\gamma}, \hat{\zeta})|$; estimates converge to similar parameters (Figure D1).

These parameters are then used to estimate the Compensating Variation:

$$\Delta \hat{\log} C = \log C(\mathbf{p_1}, u_0) - \log C(\mathbf{p_0}, u_0) \tag{25}$$

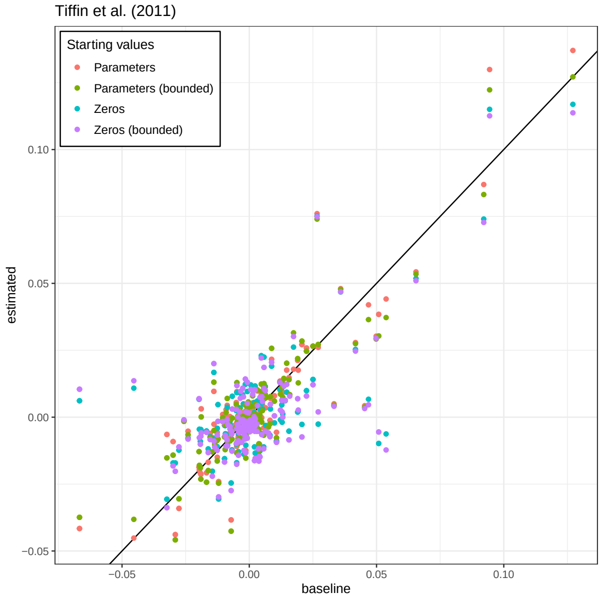
$$\Delta \hat{\log} C = \sum_i w_i (\log p_i^1 - \log p_i^0) + \frac{1}{2} \sum_k \sum_j (\hat{\gamma}_{kj} + \hat{\zeta}_{kj} \tilde{y})(\log p_k^1 - \log p_k^0)(\log p_j^1 - \log p_j^0) \tag{26}$$

$$\hat{CV} = \exp(\Delta \hat{\log} C) \times C(\mathbf{p_0}, u_0) \tag{27}$$

Elasticities in both Tiffin et al. (2011) and Kehlbacher et al. (2016) are at a more granular level than our food categories. In order to derive the elasticities at the same level of aggregation, we match the finer categories in Tiffin et al. (2011) and Kehlbacher et al. (2016) with ours and average them.

The results are reported in Table D1, in terms of £ per person per year, for the average household. In our estimation, we find a CV of £71.40. The figure becomes slightly larger when employing the parameters derived from the elasticities of Tiffin et al. (2011) and Kehlbacher et al. (2016), ranging from £72.17 to £75.85; in relative terms the derived CV are larger than our estimation by between 1% and 6%.

Figure D1: Comparison between our estimated parameters and those derived from the elasticities in Tiffin et al. (2011) and Kehlbacher et al. (2016)



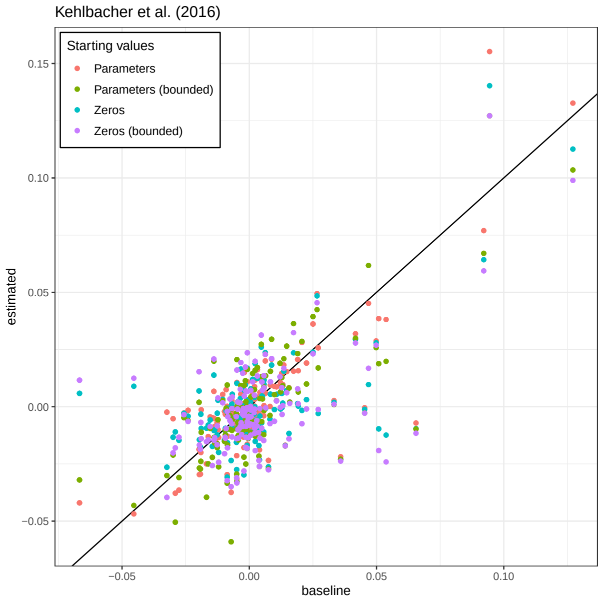


Table D1: Comparison of the CV, estimated from our parameters or from the elasticities in Tiffin et al. (2011) and Kehlbacher et al. (2016)

	CV (£)		$\Delta\hat{\log C}$	
Starting values	Tiffin et al. (2011)	Kehlbacher et al. (2016)	Tiffin et al. (2011)	Kehlbacher et al. (2016)
From parameters	75.85	73.77	0.051	0.050
From parameters (bounded)	75.43	72.42	0.051	0.049
From zero	74.91	72.81	0.050	0.049
From zero (bounded)	74.77	72.17	0.050	0.049
Our estimates	71.40		0.048	

E Robustness with full and reduced sample

We estimate the demand system using the full sample, or only observations collected in the first scenario of the survey, in order to compare with our main results. Table E1 presents the results of this exercise: using different samples of our dataset leads to slightly different results, but in line with our estimate.

Table E1: Comparison of the CV, estimated on different samples

	CV (£)	$\Delta \hat{\log C}$
Cleaned sample	71.40	0.048
Full sample	72.42	0.049
Scenario 1 only	75.88	0.051

Conclusions

The aim of this thesis was to contribute to the collective effort of dealing with the issue of climate change: specifically, by advancing, with all due caveats and in a minimal part, our understanding of the impacts of climate change on the behaviour of firms and consumers. We can consider impacts in a broader way, ranging from direct impacts, such as the vulnerability of agricultural firms explored in the first chapter, to the effect of climate policies, including their effectiveness and related costs, which are studied in the second and third chapter. Despite departing from the common issue of climate change, the chapters vary in setting and this reflects the opportunities I encountered during my Ph.D. career to work with more senior researchers. On the other hand, they share the quantitive approach and rigorous use of advanced econometric techniques.

The first chapter studies the impact of rising temperatures on agricultural firms in Italy, and how these cope by investing in countermeasures. We find that higher temperatures decrease output in an economically significant measure. Thus, a warming climate represents a risk that is at the same time an incentive to invest in protective measures against future impacts. In fact, a temperature shock that is an abnormal increase in very high temperatures in a given year, is associated with investment in tangible assets for those farms that witness it. In addition, we find that these shocks are associated with the uptake of irrigation systems. In a reduced form model, we estimate the effect that these exogenous shocks have in reducing the vulnerability in subsequent years to higher temperatures and we find that is it almost halved. These finding suggest that at least those firms, that in the production process directly depend on climate as it determines weather, are acknowledging future climate impacts as a pressing issue. At the same time, however, adaptation efforts might not be able to counterbalance fully these impacts and hence from a policy-maker perspective they should be complemented by mitigation policies: the following chapters explore these aspects.

The second chapter investigates the role of current climate policies in leading firms to decarbonize through the bank lending channel. In financial markets, the effect of climate change is transmitted broadly through physical risk, i.e., direct adverse impacts such as those investigated in the previous chapter, and transition risk, which indicate the potential loss in profitability due to the carbon footprint of the business of model of firms, which may suffer from new policies, changes in demand, or new competing green technologies. We investigate to what extent this risk is priced by lenders in the international syndicated loan market. We proxy exposure to transition risk by the emission intensity and patenting in mitigation technologies, and how it interacts with two types of mitigation policies: carbon taxation and green technology support policies. Our findings indicate that firms with a better environmental performance face a lower cost of borrowing, but only in the presence of stringent climate policies, which indicates that the policy-maker has a determining role in aligning the economic incentives for the decarbonisation. In turn, this effect may induce a sizeable reallocation of investment from brown to green firms as climate policies become more stringent. A further result is that the availability and quality of information about the environmental sustainability of firms is key in allowing investors to price the transition risk. Environmental, Social and Governance scores, albeit widely used as proxies of environmental performance, in our results do not have an impact that increases with stricter policy, suggesting that they are not used to measure the transition risk of companies but rather more to satisfy environmental preferences and portfolio management strategies.

The third chapter shifts the focus from firms onto consumers, in order to investigate how to design policies to internalize the pollution externality of their food consumption as the food sector is an important source of GHG emissions. Exploiting a survey-based randomized controlled experiment on a representative sample of UK households, we look at how carbon taxation and carbon labelling affect demand for food products during grocery shopping. Our results indicate that these policies are effective in significantly decreasing the carbon content of the food basket, but they suffer from distinct limitations when introduced alone: while carbon labelling does not entail an increase in prices, its effect might fall short of decarbonization goals; on the other hand, a carbon tax causes a loss in consumer welfare. Studying the combination of the two policies, we find that they have they same result in terms of avoided emissions as in the scenario of the single carbon tax, but with about half of the corresponding tax rate. Our findings support the argument that policy mixes can alleviate the limitations of single policies: thus, in order to make the food sector more sustainable, different measures should be introduced in a concerted way.