Carbon pricing and stock performance: Are carbon prices already more influential than energy prices?

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July 11, 2025

Abstract

This paper assesses the relation between carbon prices and the financial value of United Kingdom companies. It shows that the financial market co-moves with the UK-ETS at least as much as it does to other major energy commodities (i.e., oil, gas and electricity prices), and carbon prices are becoming the single most important energy or environmental variable to consider in determining corporate value. The results indicate that 14.1% of total market capitalisation is exposed to carbon pricing 'risk', 20% or more of the time. The Energy sector has the largest exposure with £251bn (41.51% of this sector) exposed at least 20% of the time. This is equivalent to one-twelfth of the economy's GDP. Within the Energy sector, 13.5% of all observations indicate net-positive relation between carbon pricing and stock returns - these are likely to be associated with low carbon energy sources and technologies. The Financial sector is the second most affected sector with £117bn exposed to carbon pricing at least 20% of the time. Finally, it is shown that information on 'carbon sensitivity' can be utilised to construct investment portfolios wherein carbon sensitive stocks under-perform against the market, while carbon insensitive ('immune') stocks closely track market benchmarks, depending on investment weighting strategy.

***K*eywords** Empirical asset pricing · Emissions trading scheme · Carbon prices · Energy prices · Dynamic model averaging.

1 Introduction

Carbon pricing has become one of the main policy instruments used to achieve national decarbonisation targets by discouraging emission-generating behaviour and promoting a transition to low carbon economic activities. As of April 2024, 75 regional, national, or sub-national carbon pricing schemes have been introduced around the world - 39 carbon taxes and 36 emissions trading systems (ETSs) (The World Bank, 2024). The role of carbon pricing is to charge firms for carbon dioxide emissions, internalise the external costs and risks and ultimately incentivise firms to find ways to minimise their emissions, and can also help better coordinate the actions of the financial institutions (e.g. banks) in allocating capital towards low-carbon solutions (Campiglio, 2016). Among these various roles, we focus on the question of whether carbon pricing is beginning to show effectiveness in supporting decarbonisation efforts by way of altering the value of firms.

Given that the financial sector is vital for coordinating investment in the transition to a low-carbon economy, it is important to identify whether carbon prices are triggering responses in financial markets. Since the introduction of carbon pricing, there have been attempts to identify the impact of carbon prices on firms' value, see for example: Oberndorfer (2009); Veith et al. (2009); Wen et al. (2020); Dechezleprêtre et al. (2023); Millischer et al. (2023); Chu et al. (2024); Tabash et al. (2024).

However, lack of consensus remains concerning the potential impacts of carbon pricing mechanisms on companies' financial performance, so more research is needed on the topic, particularly on the heterogeneity of impacts by industrial sector and firm characteristics. Carbon prices may have a different balance of direct and indirect consequences for stock prices compared with pricing factors like oil. Companies that emit large quantities of carbon may face higher costs or regulatory pressures as carbon pricing mechanisms are implemented. However, the impact on stock prices may vary depending on factors such as the specific regulations in place, a company's ability to adapt to climate change and/or mitigate carbon emissions, and broader market trends. Firms that are better positioned to adapt to climate change may observe no or even a positive association. In other words, there is some tension and uncertainty surrounding the empirical consequences of carbon pricing that can only be assessed through careful empirical analysis. Not all companies are equally affected by carbon prices, so the impact may be more selective across industries and there will be a mix of winners and losers from carbon pricing.

The objective of this paper is to empirically benchmark the association between carbon prices and the stock value of listed companies in the United Kingdom (UK). In so doing, and given the analysis tools deployed, it will contribute a timely assessment on whether and how carbon price fluctuations affect the financial value of companies.

Some studies examine sector-level impacts and present that the positive correlation between carbon price and stock returns is more significant in carbon-intensive industries, such as oil and gas, power and heat, cement and lime, and iron and steel industry. However, they do not provide a comprehensive comparison among industrial sectors or time periods dues to the limited number of sectors analysed Bruggeman and Gonenc (2013); Chan et al. (2013); Scholtens and van der Goot (2014); Zhang and Liu (2019); García et al. (2021); Millischer et al. (2023) or relatively short time series with unusual event such as the unexpected plunge in EU ETS permit prices in 2006 (Bushnell et al., 2013). To bridge this research gap, this paper aims to provide a timely assessment of whether and how carbon price fluctuations affect the financial value of companies and whether these relationships are different by sector and have changed across time. To this end, we empirically benchmark the association between carbon prices and the stock value, using the firm-level data of listed companies in the United Kingdom (UK), covering 11 industrial sectors, between January 2010 and March 2024. We permit rich heterogeneity allowing the association between carbon-pricing and stock values to be assessed individually for each firm. This is important because there will naturally be winners and losers. For example, companies with stranded assets like oil and gas may need to pivot their focus to remain attractive to stakeholders, but may be unable to due to their supply chains. Moreover, we permit dynamics (time-variation) in the estimation process, which is important for carbon pricing in general and for the UK very specifically. In general, the scientific basis of understanding around the impacts of climate change have taken time to refine, hence the importance of pricing the externality has an evolving dimension. At the same time, technologies to support decarbonisation are nascent, and the costs of decarbonising vary considerably. Carbon markets also continue to evolve in many ways, with new markets being introduced, discussions of global pricing and broader systemic transformations.

To be sure that we are estimating the marginal and additive effect of 'pricing the (carbon) externality', we control for fuel commodity prices. This proves illuminating in its own regard, as it helps to establish a key result of this study, which is that carbon pricing already has footprint of impact to the financial system that is at least as extensive as oil. Not only does this serve as an indication that investors are altering their behaviour in response to fluctuations in carbon markets. It can also be seen as a warning flag for the financial system and economy as a whole. Oil prices and oil price shocks have correlated with periods of recession and financial downturn owing to the broad-sweeping consequence and systemic reactions they stimulate (Hamilton, 2013; Kilian and Park, 2009). While we have not seen few (if any) carbon price shock per-se as of yet, such an event is by no means impossible and according to our results would be met with significant system-wide movements in stock prices.

Through our application of time-varying and firm-level analysis, we contribute to the literature with several novel insights that would not be obtained using less flexible econometric frameworks or data aggregations as in previous studies. Our empirical results indicate that almost three-tenths of companies in the stock market are in some fashion 'pricing' carbon - that is, they are affected by carbon prices at least 20% of the time. We add additional insights relative to narratives on the carbon price pass-through effect by empirical evidence that the economic consequences of carbon pricing are tangible, even among firms that are not directly involved in the emissions trading system. The majority of firms (57%) are sensitive to carbon pricing, albeit with varying degrees and nature of exposure across different economic sectors. We approximate the economic relevance of these impacts, and calculate for example that the energy sector has over £250bn (41.51% of this sector) of its market capitalisation influenced by carbon pricing at least 20% of the time. We reveal that company value is affected by carbon price fluctuations at least as often as by oil price variations, the importance of which is not to be understated given the scale of attention that has been given by researchers to oil price effects, and the relative inattention to date given to carbon price effects. In our further analysis investor portfolios are constructed using the estimated ‘carbon-sensitivity of company stock prices as an investment screen, demonstrating the investor salience of such information and helping add validity to the argument that carbon pricing has ‘landed’ as a financial factor.

The remainder of the paper is ordered as follows: Section 2 provides a summary of related literature and general background on carbon pricing in the UK and the European Union (EU) in recent years; Section 3 sets out the empirical framework for this study, including an overview of key data-sources and steps for constructing the variables for estimation; Section 4 provides the main analysis and results; Section 5 evaluates the investor salience of knowledge on stock carbon-price sensitivity, contrasting index performance on carbon sensitive versus carbon insensitive portfolios; Section 6 concludes and discusses key policy implications of the study.

2 Background literature

There are two broad areas of the background that warrant elaborating. First is an overview of the UK’s ETS implementation, including the participation in the EU-ETS. It is assumed that the reader has at least a casual awareness of the fundamental tenets of pricing externalities, and as such this discussion dives more directly into the questions of how the EU-ETS evolved, and the forces behind the recent separation of the UK from the system. Following this, we turn briefly towards reviewing the academic results on the relation between ETS, corporate decarbonisation practices and financial performance.

2.1 Overview of the UK’s ETS implementation

The UK’s ETS implementation can be divided into three stages: i) implementation of voluntary domestic ETS (2002-2004), ii) participation in the EU-ETS (2005-2020), and iii) implementation of mandatory national ETS (2021-present). Since launching the UK Climate Change Programme (CCP) in 2000, the UK government has adopted several policy instruments, including the Climate Change Levy, Climate Change Agreements, and Renewables Obligation, to accelerate cutting national greenhouse gas emissions. The voluntary ETS was also introduced in August 2001 as a pilot under the UK CCP with the aim of helping not only UK companies’ greenhouse gas emission reductions but also learning and preparation for the EU-ETS, which was under active discussion about its implementation. The Department for Environment, Food and Rural Affairs (DEFRA) allocated £215m for incentive funding over five years (2002-2006), and 34 companies and organisations made bids on their future emission reductions in the auction held in March 2002 (NAO, 2004).

Meanwhile, the EU-ETS came into operation in January 2005 as a financing mechanism to support the EU to meet its decarbonisation commitments and targets established under the Kyoto Protocol.[1] Before China’s national ETS started operation in 2021, the EU-ETS was the largest compliance carbon market in the world covering around 38% of the EU’s greenhouse gas emissions. The launch of the EU-ETS represented a significant step in the EU’s efforts to combat climate change by putting a price on carbon emissions and encouraging the transition to a low-carbon economy.

The EU-ETS has undergone four phases (2005-2007, 2008-2012, 2013-2020 and currently 2021-2028), with several amendments and updates to improve its effectiveness and address challenges of the previous phase by expanding sectoral coverage, increasing the linear reduction factor, and decreasing share of free allowances. In Phase I, designed as a pilot, 25 individual EU member states set the number of allowances to allocate in total and to each plant in their territory. The allocation method was primarily through grandfathering free allocation (95%) based on the installation’s historical emissions. Phase II expanded the scope of the EU-ETS geographically and sectorally. The two new member states (Romania and Bulgaria) and three states outside the EU (Iceland, Liechtenstein, and Norway) joined the EU-ETS, and the aviation sector was newly included in the scheme. Also, the total emissions cap was reduced from 2,096 $MtCO_2e$ to 2,049 $MtCO_2e$, and the percentage of allowances auctioned increased from 5% to 10%.

During Phase I and Phase II, the high volatility of carbon prices emerged as a significant challenge. The EU Allowance (EUA) price steadily increased from approximately 7/tCO_2e in early 2005 to 32/tCO_2e in early 2006. However, it sharply fell to nearly zero at the end of Phase I. During Phase II, the EUA price recovered to around 20-25/tCO_2e in the first half of 2008, but the economic recession in 2008 made it plummet again from 28.3/tCO_2e to 8.5/tCO_2e between 2008 and 2009 (Declerq et al., 2011). Moreover, 2 billion allowances went unused in Phase II (Ellerman et al., 2015).

[1] The Kyoto Protocol is an internationally recognised treaty aimed at reducing greenhouse gas emissions, built around binding targets for developed countries to reduce their collective emissions.

Such price volatility was partly due to uncertainties surrounding the system's implementation, the lack of confidence in its effectiveness, and excessive allowances allocated.

Both price volatility and the low price level led to limited emissions reductions compared to initial expectations and made it difficult for companies to plan and invest in emission reduction measures. They triggered debates regarding the shortcomings of the EU-ETS design, and consequently, a series of changes in scheme design were made in Phase III. First, the National Allocation Plans were replaced by EU-wide regulations for allowances and emissions caps. Second, to combat the surplus of allowance supply and reduce price volatility, the auctions of 900 million allowances were postponed to the 2019-2020 period, and the Market Stability Reserve was initiated. Furthermore, an initial proposal to switch to 100% auctioning was developed. However, due to resistance from some member states, it was decided that the share of allowances auctioned would be 40% and reduce free allowances to zero by 2027. The emissions cap (2,084 $MtCO_2e$) was slightly higher than Phase II (2,049 $MtCO_2e$), but it incorporated a linear reduction factor of 1.74%, which would decrease this cap annually.

The UK was one of the five supporter countries (together with Denmark, Ireland, Netherlands, and Sweden) when the EU-ETS was proposed (Skjærseth et al., 2009), and has participated in this scheme until Phase III ended in 2020. As a result of the UK's withdrawal from the EU in 2020, commonly known as Brexit, the UK Emissions Trading Scheme (UK-ETS) replaced the EU-ETS in January 2021. The decision for the UK to leave the EU-ETS was driven by a combination of sovereignty concerns, the desire for policy autonomy, and the opportunity to develop a tailored approach to carbon pricing and emissions reduction efforts in line with UK priorities and objectives.[2] While the EU-ETS included the maritime sector in Phase IV, the UK-ETS still applies to the power generation, energy-intensive industries, offshore oil and gas, and aviation sectors. More than 1,000 installations and approximately 380 aircraft operators are covered by the UK-ETS, and their emissions account for about a quarter of the UK's domestic emissions (UK Government, 2023). Moreover, although auctioning is the primary means of allowance allocation, free allowances are also allowed to reduce the risk of carbon leakage from UK companies.

Figure (1) presents the carbon emissions allowance price, in £'s per tonne, faced in the UK between January 2010 and March 2024. Also included in the plot is the EUA price. The prices faced in the UK are in fact the EU-ETS price spliced with the UK-ETS after it began active trade in 2021. Broadly speaking, up until around 2018, prices were low, with little evidence of meaningful price-discovery in effect. Recent estimates on the social costs of carbon would imply that even prices such as £20 per tonne of CO_2e would be vastly under-pricing the externality effects.

2.2 Insights from firm-level research on ETS and corporate financial performance

ETS's are primarily aimed at addressing adverse consequences from climate change that filter through the real economy by setting quantity restrictions on greenhouse gas emissions for individual emitters and allowing the trading of emissions allowances or permits between emitters. Although the magnitude of impact vary across countries, industrial sectors, and trading periods, firm-level analyses suggest ETS's generally have a positive connection with carbon emissions reductions and decarbonisation efforts of companies, including energy efficiency improvement, low-carbon fuels, and low-carbon patenting (Calel and Dechezleprêtre, 2016; Calel, 2020; Klemetsen et al., 2020; Shen et al., 2020; Cui et al., 2021; Sadayuki and Arimura, 2021; Zheng et al., 2021; Ren et al., 2022; Dechezleprêtre et al., 2023; Colmer et al., 2025).

Despite its decarbonisation objectives, an ETS is ultimately still a financial mechanism which, through the ability to trade, creates opportunities and incentives for speculation and arbitrage. This, in turn, binds ETS with broader financial market interactions. Evidence of this has manifested in stock price co-movement with the implementation of ETS and carbon price uncertainty (Oestreich and Tsiakas, 2015). Studies examining these interactions broadly focus on two features: the relationship between participation in the ETS and a company's financial performance/profitability and the association between carbon price changes and a company's stock price performance.

The nature of relation between ETSs and a participating company's financial performance remains inconclusive. Jaraite and Di Maria (2015) found the EU-ETS did not reduce profitability of participating firms in Lithuania. More recently, Dechezleprêtre et al. (2023) found the EU-ETS increased revenues and fixed assets of regulated firms without significant effects on profits or employment among 31 ETS-regulated countries. Companies regulated by Chinese regional pilot ETSs tended to experience operating cost reductions, profitability and firm value improvements, and stronger stock returns (Chu et al., 2024; Wen et al., 2020). However, not every sector had such a positive relationship. Among the power, cement, and iron and steel sectors in 10 European countries, only the power sector showed a significant positive association between the EU-ETS implementation and the firm's revenue between 2001 and 2009 (Chan et al., 2013).

[2] Brexit, the United Kingdom's withdrawal from the EU, officially occurred on January 31, 2020. It followed a referendum held on June 23, 2016, where 51.9% of voters chose to leave the EU. The decision reflected a desire among some UK citizens and policymakers to regain control over laws, borders, and trade policies independent of EU regulations and institutions.

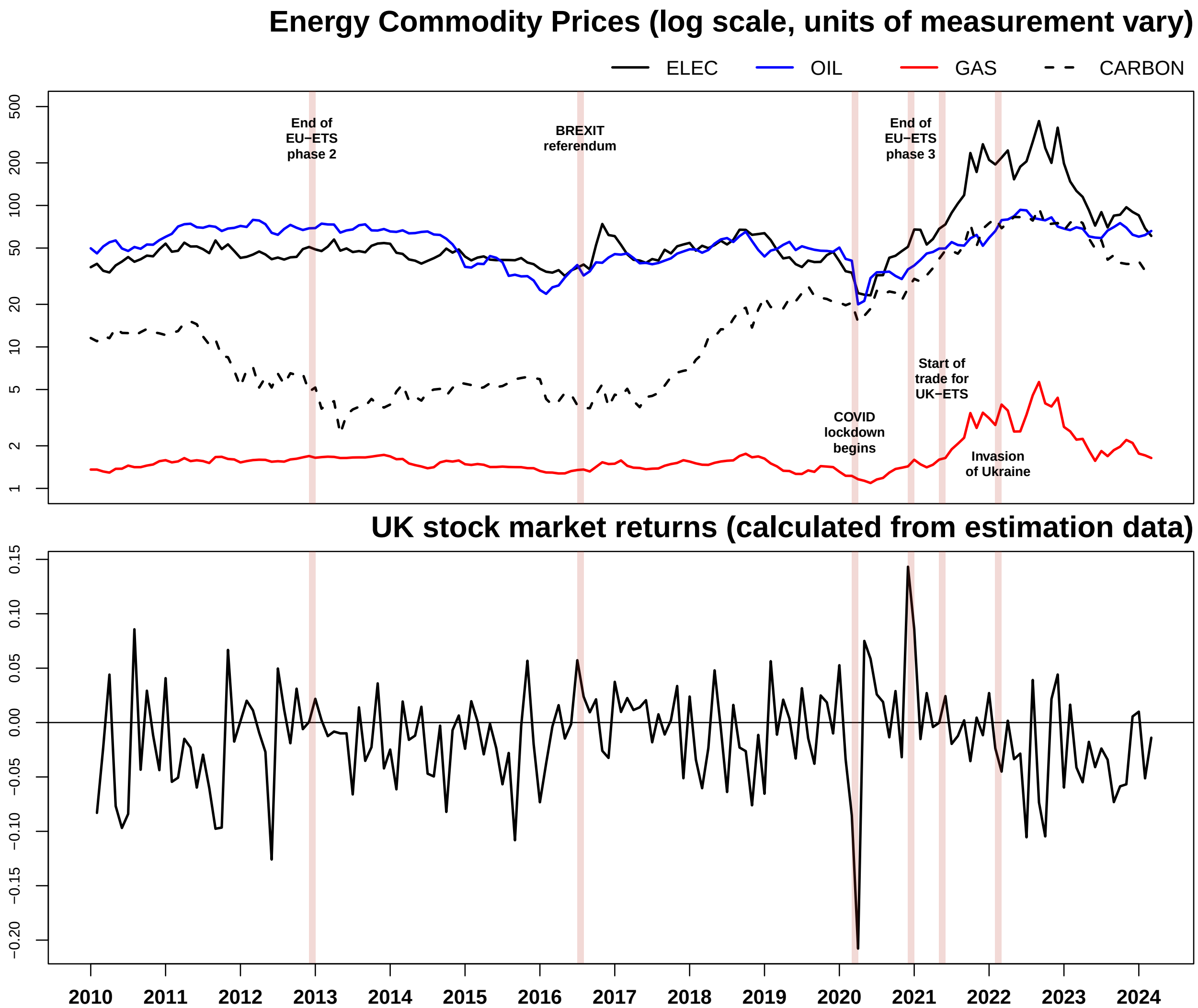

Figure 1: **Time series plots of main estimation variables.**
Note: Summary of monthly commodity prices, and UK listed companies (aggregate) returns, calculated as the log-differences of prices. The top panel shows oil, gas, electricity and carbon prices, using a log-scale for the y-axis, noting that prices for different commodities are measured in different units.

Similarly, results are reported for China's regional ETSs where improved financial performance was found for the power sector - while for other sectors, including chemicals, paper and aviation, the effects of ETSs changed from negative to positive with a 2-4 year lag (Zhang and Liu, 2019).

Several existing studies analyse the significance of carbon price changes while allowing for firm-level heterogeneity of impacts. The direction and amplitude of observed effect vary depending on the country, sector, carbon intensity of firms, and trading period. Oberndorfer (2009) showed EUA prices and stock returns of electricity companies had a negative relationship in Spain during EU-ETS Phase I, whereas a positive relationship was found in Finland, Germany, Italy, Portugal and the UK. More recently, Tabash et al. (2024) suggests EUA prices had positive short- and long-term influences to stock returns in nine Eurozone countries between 2013-2023. However, in the long-term, a 1% increase in EUA prices was met with a 9-17% increase in the financial market value in France, Ireland, and the Netherlands but a 10% decrease in Belgium and Spain.

A positive correlation tends to be observed in carbon-intensive industries (Bruggeman and Gonenc, 2013; Scholtens and van der Goot, 2014), yet within the same sector, it is stronger among companies with low carbon intensity (Bushnell et al., 2013). A number of studies document a positive correlation between EUA prices and the stock returns of electricity companies (Oberndorfer, 2009; Veith et al., 2009; García et al., 2021). However, scrutiny reveals that this positive correlation was driven by electricity companies having low carbon intensity. Tian et al. (2016) and Da Silva et al. (2016) found that stock prices for European power generators using green/renewable energy tended to respond positively to EUA price changes, while the inverse was true for carbon-intensive/non-renewable generators.

Lastly, several studies report different correlations between EUA prices and stock returns over the trading period. Some studies concluded that carbon premium existed in the stock market around the EU-ETS Phase I but dissipated in Phase II, suggesting an increase in EUA prices tended to cause corporate value appreciation in Phase I but induced depreciation in Phase II (Mo et al., 2012; Oestreich and Tsiakas, 2015). On the other hand, some studies argued that the overall co-movements between EUA prices and the stock market were positive in Phase II but became insignificant or negative in the early years of Phase III (Da Silva et al., 2016; Moreno and da Silva, 2016; Tian et al., 2016). By contrast, García et al. (2021) suggested that higher EUA prices led to higher stock prices in the power sector during the EU-ETS Phase III (2013-2017).

Among various previous studies, a paper close in nature to our own is Millischer et al. (2023), who examine the relation between carbon pricing and company stock performance for 338 European firms. The authors utilise weekly stock return and carbon pricing data, together with controlling for other major energy commodity prices including oil, gas, and electricity. The authors introduce carbon intensity, measured in annual frequency, as an interactive term multiplied against carbon prices. The objective of this as highlighted by the authors is that it *"...captures the degree to which stock markets treat firms with different carbon intensities differently."* Their econometric setup is a fixed-effects panel regression design estimated using ordinary least squares, and as such the use of the carbon intensity variable in the manner described provides additional cross-sectional control relating to the size effect of firms. While an interesting approach, two possibly limiting factors are, first, that the variable is measured in a different frequency, meaning it will lack some accuracy and, second, there may be a reasonable likelihood of time-conditional heterskedasticity in the sample given the data are measured in weekly frequency (and with additional results also testing daily data). Our methodology, which will be described in full later, resolves estimations at the firm level hence allows for direct observation of the differences in how stock markets treat firms of different types, and with full heterogeneity. Moreover, the econometric approach deployed includes stochastic volatility controls to ensure any time-conditional heteroskedasticity is adequately controlled for.

On the basis of the reviewed literature, there remains an incomplete understanding of the relationship between carbon pricing mechanisms and companies financial performance. Existing research has pointed itself in the direction of this issue, but has offered fairly limited insights to date on how specific companies are reacting to carbon prices, and whether and how these relationships may have changed across time in-line with different phases of carbon pricing systems and expanded maturity among firms in managing carbon price exposure. In the following section, we describe an empirical framework which can address these potential gaps in understanding (firm heterogeneity, and time-varying effects) while remaining close in spirit to the asset pricing approaches appearing in previous contributions.

3 Empirical framework

In this section, we outline the empirical framework for the paper. Prior to outlining the econometric specification, we conduct a brief exploration on the relation between the variables using an a-theoretic and data-driven directed acyclic graph approach.[3]

3.1 Summary evidence on the relation between carbon pricing and stock values using a Directed Acyclic Graph

Figure (2) presents a directed acyclic graph (DAG) to offer a preliminary assessment of the contemporaneous association between the variables considered in this study. More complete description of the variables used in the study, their construction and data sources is given further below, but in brief they include: changes in stock prices, known as stock returns (R); variables reflecting overall stock market dynamics in terms of market wide returns (RM), the difference in growth rates between high- versus low-growth stocks (HML), and the size distribution between small and big firms (SMB); and information on the changes in prices for carbon ($CARBON$), oil (OIL), gas (GAS) and electricity ($ELEC$).

One benefit of DAGs is that their underlying calculations provide a measure of causal association between variables that differs for example from Granger causality tests which evaluate causality across time periods. As such DAGs are arguably quite well suited to conducting a preliminary assessment of possibly causal association for CAPM type models where it is often assumed that an efficient market hypothesis holds and information within markets is effectively processed immediately, which is defended both on theoretical grounds, and on the basis that the data are measured

[3] We thank an anonymous referee for encouraging us to include this in the paper which adds further validity to the proposed inclusion of carbon pricing as an explanatory variable for stock returns.

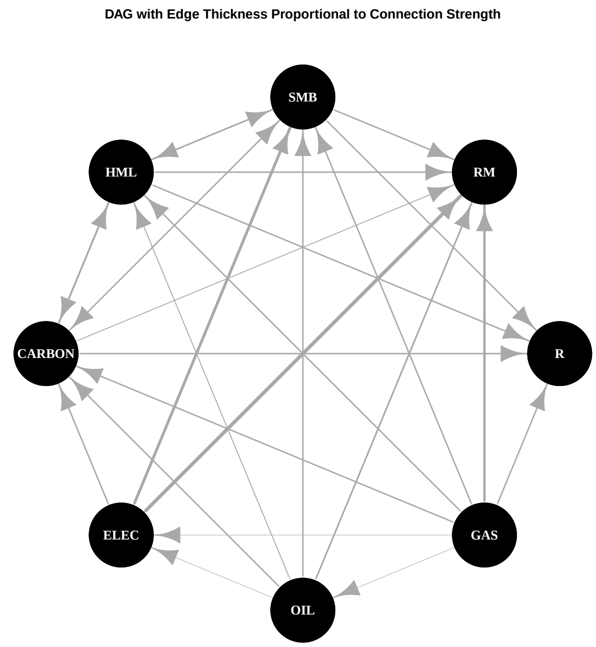

Figure 2: **Directed Acyclic Graph (DAG) illustrating the possibly causal connections between variables under study.**
Lines indicated connected nodes (variables), while line width is scaled to reflect strength of connection, with thicker lines reflecting stronger ties. Directionality of association is indicated by arrowheads, and may be either one way (e.g. as seen from gas to electricity) or bi-directional (e.g. as seen between oil and electricity).

in monthly frequency making it perfectly feasible for example that a carbon price event occurs, and is processed by firms/investors, and outcomes on company stock prices all occur within the same month. A second benefit of DAGs is that they provide an easily interpretable visual representation of the association between variables. However, while useful these tools are more indicative of associations, and serve only as supporting evidence to the subsequent model-based econometric assessment. Notwithstanding this last point, the DAG results add supporting evidence to the conjecture that carbon prices are an important factor towards stock price outcomes.

To elaborate, the DAG in Figure (2), which is evaluated in one-shot for the full sample of data e.g. all periods, and all firms at the same time, reveals several insights. Briefly, interpretation of the plot is that lines between nodes display a connection exists, while arrowheads are used to display the direction of association, and line width is scaled to indicate strength with thicker lines indicating stronger ties between variables. For example, a line exists connecting carbon prices ($CARBON$) to stock returns (R), consistent with our conjecture that it is a factor influencing firms' value, moreover, the arrowhead is consistent with the idea that it is stock returns responding to carbon prices and not the reverse. Interestingly, there is evidence that carbon prices are affected by oil prices (OIL) and gas prices (GAS), and that there is bi-directional influence between carbon prices and electricity prices ($ELEC$).

Yet, the DAG results must necessarily be interpreted with some caution, with some expected connections not found and potentially incompatible with theoretical expectations and evidence from (arguably more sophisticated) statistical modeling. For example, individual firms' returns are not connected with market returns (RM), or oil price returns (OIL), both of which having volumes of empirical support. Hence, it remains ultimately necessary to evaluate the associations within a model-based context.

3.2 Econometric specification

We adopt a 'beauty-contest' empirical design–similar in spirit to that used by Broadstock and Filis (2020)–in which we run separate regressions for each stock in our sample. The advantage of such an approach is that we obtain a granular observation of how carbon pricing is factored into asset pricing outcomes for individual stocks, without losing the ability to aggregate the results and summarise outcomes at the industry and overall market levels. To cater for dynamics in asset pricing relationships observed in previous studies (e.g. Broadstock and Filis (2020); Ang and Chen (2007); Ghysels (1998); Fama and French (1992) *inter alia*), we allow coefficients of the asset pricing model to be time varying.

We employ a multi-factor capital asset pricing model (CAPM) form developed from contribution from Sharpe (1964) and Fama and French (1993, 1996) among many others. Specifically, in line with Millischer et al. (2023), we introduce price returns for key energy indicators as well as the price of carbon. Moreover we allow for potentially asymmetric price responses.[4] The general specification can be expressed thusly:

$$\begin{aligned} \tilde{R}_{it} = \quad & \alpha_{it} + \beta_{it}\tilde{RM}_t + \gamma_{1it}HML_t + \gamma_{2it}SMB_t + \\ & \delta_{it}ELEC_t + \kappa_{it}GAS_t + \gamma_{it}OIL_t + \theta_{it}CARBON_t + \\ & \delta_{it}^{(-)}ELEC_t^{(-)} + \kappa_{it}^{(-)}GAS_t^{(-)} + \gamma_{it}^{(-)}OIL_t^{(-)} + \theta_{it}^{(-)}CARBON_t^{(-)} + u_{it} \end{aligned} \tag{1}$$

In which $\tilde{R}_{it}$ are the 'excess returns' of stock i in period t, adjusted for the risk-free rate of return:

$$\tilde{R}_{it} = R_{it} - RF_t \tag{2}$$

with

$$R_{it} = \ln(P_{it}) - \ln(P_{it-1}) \tag{3}$$

The main market factors (e.g. $\tilde{RM}_t$, HML_t and SMB_t) are usually obtained from Kenneth French's data library[5] when working with US data, however for the UK these factors are not available. We therefore construct these manually based on the stocks included in our final sample. HML_t is a measure of growth structure for the benchmark investment universe, and SMB_t captures information on the distribution of size characteristics of stocks in our benchmark market. The term u_{it} denotes the usual idiosyncratic error term and α_i, β_i, γ_{i1} and γ_{i2} are terms to be estimated.

Estimation data are taken primarily from the LSEG (formerly Refinitiv) Workspace financial data platform, containing stock pricing and trade volume related information, the UK Treasury 10 year bond rate (for the 'risk free' rate of returns), and the near month continuation futures prices for oil, gas, electricity and carbon. The data are in monthly frequency spanning the period 2010:01 to 2024:03. The number of firms surviving the sample screening process is 365, each with 170 months of data, giving a total sample size of 62,050 observations.

For estimation of equation (1) we use the dynamic model averaging (DMA) methodology outlined in Koop and Korobilis (2012), applied separately to each individual stock. This produces company (stock) specific estimates of the time-varying coefficients, hence them being sub-scripted by both i and t.

To help understand what DMA aims to achieve and how it might be interpreted, it is instructive to consider a 'toy' example. Take a simple application in which the excess returns of a firm ($\tilde{R}_{it}$) are a function of just two variables, excess market returns ($RM_t - RF_t$) and carbon price changes ($CARBON_t$), thus we have:

$$\tilde{R}_{it} = f\big((RM_t - RF_t), CARBON_t\big) + u_{it} \tag{4}$$

Subject to testing, there are three possible specifications for the right hand side including the most general form $f\big((RM_t - RF_t), CARBON_t\big)$ as well as the two restricted forms $f\big(CARBON_t\big)$ or $f\big((RM_t - RF_t)\big)$. Typical modeling procedures would seek to choose between these 3 alternatives. DMA on the other hand does not require the imposition of a single preferred model structure. Instead it is assumed that we *cannot* dismiss any particular model, and instead attribute each model its own probability $\pi_t^{(1)}$, $\pi_t^{(2)}$,...$\pi_t^{(k)}$. Assuming linear functional forms we can re-characterise our toy example as:

[4] Concerning the choice to allow for price asymmetry, we note that many previous studies have already demonstrated how economies may react at different speeds to positive and negative energy price shifts. The following for example provide documentary evidence of asymmetric stock price reactions to energy (mainly oil) price movements: Lee and Chiou (2011); Fasanya et al. (2021); Hashmi et al. (2021); Zhang et al. (2022); Rahman (2022) *inter alia*. Bayer and Ke (2018) couch the notion of asymmetry in the context of the rockets and feathers hypothesis and provide an interesting experimental investigation into the causes of such effects in general settings, noting the importance of private information and search costs in explaining sticky final product price movements and consumer expectations.

[5] See: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

$$\tilde{R}_{it} = \begin{array}{l} \pi_t^{(1)} \left(\alpha_{it}^{(1)} + \beta_{it}^{(1)}(RM_t - RF_t) + \theta_{it}^{(1)} CARBON_t + u_{it}^{(1)}\right) + \\ \pi_t^{(2)} \left(\alpha_{it}^{(2)} + \beta_{it}^{(2)}(RM_t - RF_t) + u_{it}^{(2)}\right) + \\ \pi_t^{(3)} \left(\alpha_{it}^{(3)} + \theta_{it}^{(3)} CARBON_t + u_{it}^{(3)}\right) \end{array} \tag{5}$$

From Equation (5) we can extract the time-varying probability that $CARBON$ is included in the set of determinants for excess returns ($\tilde{R}_{it}$) i.e. the inclusion probability for carbon prices which we will denote as $Pr.\left(CARBON\right)_{it}$. This probability is obtained by summing the probabilities $\pi_{it}^{(k)}$ over all models in which the variable $CARBON_t$ is included:

$$Pr.\left(CARBON\right)_{it} = \sum \pi_{it}^{(k)}\Big|_{CARBON_t \in f_{it}^{k}(.)} = \pi_{it}^{(1)} + \pi_{it}^{(3)} \tag{6}$$

Noting for clarity that we place the t subscript for the probability term on the outside of the brackets since the probability itself is time varying. Following Koop and Korobilis (2011), among others, any given variable is considered a significant (important)[6] determinant if its probability exceeds 0.5 e.g. $Pr.\left(CARBON\right)_{it} > 0.5$.

Further, under model averaging, the premise is that the model-averaged coefficient is calculated as the probability-weighted sum over models including the variable in question. Thus in this example we would have:

$$\theta_{it}^{DMA} = \pi_{it}^{(1)} \theta_{it}^{(1)} + \pi_{it}^{(3)}{}_{it}^{(3)} \tag{7}$$

In applying this estimation framework we generate a large database containing estimates of $Pr.\left(CARBON\right)_{i,t}$ and $\delta_{i,t}^{DMA}$ for each of the individual stocks, as well as associated time-varying probabilities and coefficient estimates for all other model components.[7] Thus, while our estimations are resolved at the firm-level, it is impractical to report the results for each individual firm, and we instead present our results on the basis of industry level aggregations. Additional discussion on the econometric procedure can be found in in Koop and Korobilis (2011, 2012), with a closely related exposition also available in Raftery et al. (2010). We note that DMA can be sensitive to the choice of so-called hyperparameters, and therefore to ensure robustness and consistency with previous studies we estimate the models using 121 different hyper-parameter (forgetting factor) combinations for each firm, selecting the configuration that results in the lowest mean square estimation error.

To keep our analysis within reasonable computational parameters and maintain focus on our primary research question we restrict attention to 'classes of specifications', covering the following model options to be added to the baseline CAPM specification (i.e. $\tilde{R}_{i,t} = \alpha_{i,t} + \beta_{i,t}(RM_t - RF_t) + u_{i,t}$):

- Addition of the 3-factor model variables (HML_t and SMB_t)
- Addition of one or more of the energy commodity variables ($ELEC_t$, OIL_t, GAS_t and/or $CARBON_t$)
- Allowing for energy commodity price asymmetry

[6]Related discussion can be found in Drachal (2020) who more clearly separates notions of importance from significance. Here in our work we use these terms interchangeably, yet we recognise that within this study what we refer to as 'significance' should be thought of as 'importance'.

[7]Given I as the total number of firms in our sample, and T as the total number of time periods in the sample, and letting K denote the number of different hyper-parameter combinations considered, the computational burden of working with DMA can be approximated by the number of pieces of information to be stored and used for interpretation:

$$K \times \left[I \times \left(\underbrace{(\text{Number of models} \times T)}_{\text{estimated probabilities}} + \underbrace{(\text{Count of variables in all models} \times T)}_{\text{estimated coefficients}} \right) \right] \tag{8}$$

$$121 \times \left[365 \times \left(\underbrace{(62 \times 170)}_{\text{estimated probabilities}} + \underbrace{(316 \times 170)}_{\text{estimated coefficients}} \right) \right] = 2,838,042,900 \tag{9}$$

The market returns $(RM_t - RF_t)$ are therefore treated as a 'free variable' in the standard model averaging terminology, which essentially means we assume that there is always a basic CAPM structure as a minimum, and we test for various forms of more elaborate multi-factor structures as being preferred alternatives.

4 Analysis and Results

In this section, we report the main results from our analysis. The ordering of the results aims to first present evidence of a clear and systematic relation between carbon pricing and stock returns, illustrating that these effects have material and plausible differences across economic sectors. It will then establish that temporal patterns exist and what they may look like. The final part of this section alludes to the financial materiality connected with 'carbon sensitive stocks' by highlighting the market capitalisation exposed to carbon price related risk. In the subsequent section, the paper will show how information on carbon sensitivity of stocks might be reflected in a portfolio investors returns.

As noted in the methodology section, interpretation of DMA results differs from more conventional estimation techniques. Consistent with previous research we define the reference point for a significant relation between carbon prices and stock returns as being when a stocks returns are 'determined' (i.e. with $Pr.\,(CO_2)_{it} > 0.5$), and consider this as material if it is true for 20% of sample or more. The choice of 20% is somewhat arbitrary, but intended to reflect something more than just intermittent or randomly timed influences from carbon prices to stock returns. It is not a pivotal choice to our main conclusions.

Figure (3) presents a stacked waterfall conveying the relative importance of carbon prices to stock returns, irrespective of time or distribution across economic sectors. The x-axis depicts the percentage of time a stock is determined by carbon prices in 10% bands, while the y-axis indicates the number of stocks in that band. The y-axis tallies up to 365. There are 225 stocks where $CARBON$ is significant between 0-10% of the time, and a further 36 between 10-20% of the time and so forth. From which we can gauge that (365-225-36=)104 firms or 28.49% of stocks are pricing carbon price changes at least 20% of the time.

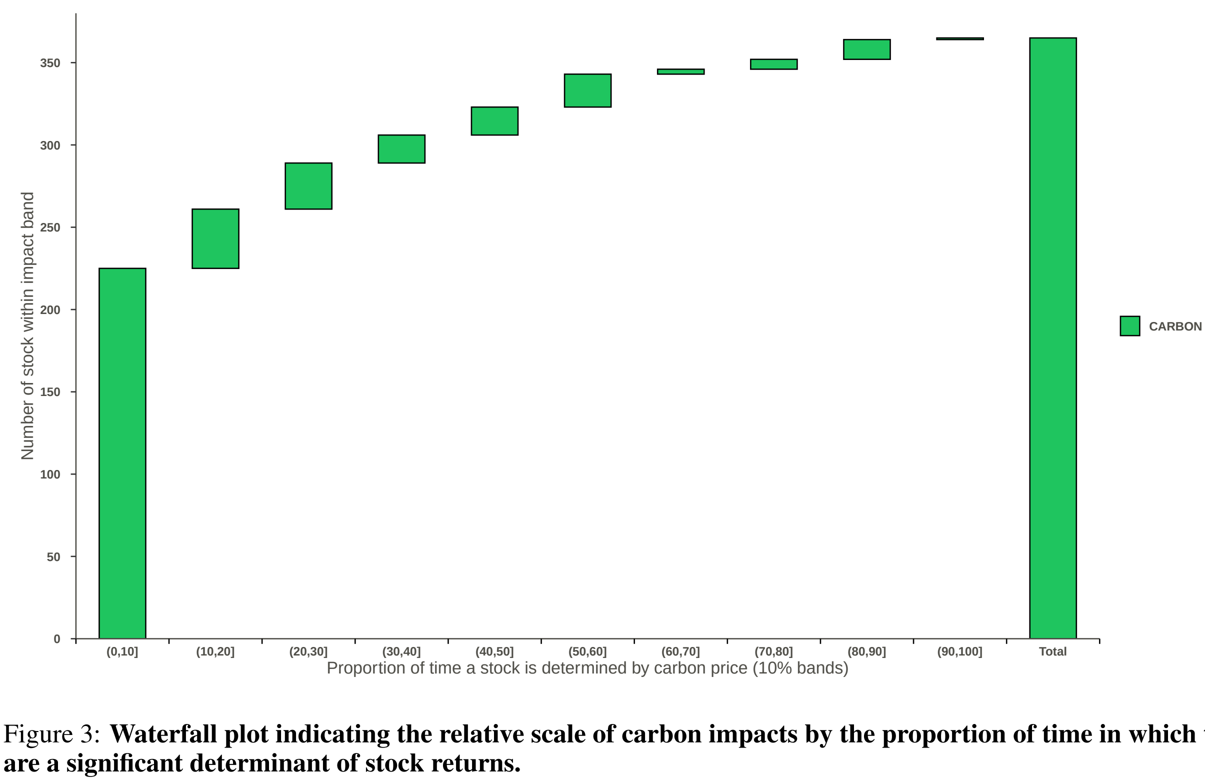

Figure 3: **Waterfall plot indicating the relative scale of carbon impacts by the proportion of time in which they are a significant determinant of stock returns.**

Note: As an example of orientation, the first green box towards the bottom left of the graph indicates that 225 stocks were significantly associated with CO_2 only between 0-10% of the time within the sample period. Looking across the graph we observe for example CO_2 was a significant variable for 36 stocks between 10-20% of the time and so forth.

4.1 Is carbon being priced more or less of the time than fuel commodities?

Figure (4) places the main results within a Venn-diagram (Panel (A)) and Euler-plot (Panel (B)) which illustrate which combinations of carbon and fuel commodity prices which have a significant effect on stock returns. Each element of these plots contains a value indicating how many stocks are affected by the union of overlapping price types at least 20% of the time. We observe that 41 stocks are impacted *only* by $CARBON$ which is greater than the numbers *only* by OIL (29), GAS (13) or $ELEC$ (11). We can however see that there are many permutations highlighting considerable heterogeneity in carbon and fuel price risk exposure across stock returns. For example, there are 15 stocks which are affected by all four, and there are 18 stocks impacted by OIL, GAS and $CARBON$ but not by $ELEC$ and so forth. There are 171 firms (46.8%) that are affected at least 20% of the time by fuel, electricity or carbon prices. Amongst those, carbon prices are materially significant for 104 companies, OIL prices 96, gas prices 75 and electricity prices 57 firms. Thus, carbon prices are being 'priced' more frequently than any individual energy commodity.

The Euler plot in Panel (B) scales the size of ellipses to reflect the relative frequency/importance of a variable, and has the largest ellipsis for $CARBON$. Interestingly, the ellipsis for $CARBON$ is considerably larger than for $ELEC$, which raises important questions over the completeness of carbon price pass through hypotheses which often assume carbon pricing will manifest primarily through electricity prices (i.e. a direct effect through the power generators covered by the ETS), yet the significance of $CARBON$ as a determinant of stock returns in its own right indicates an important indirect channel of effect.

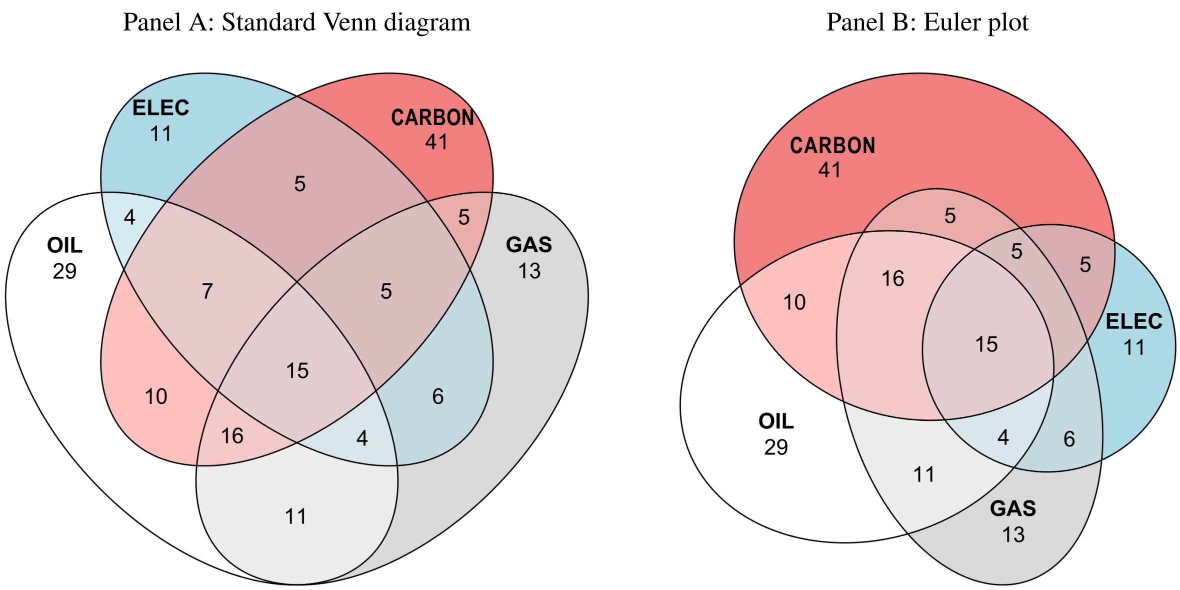

Figure 4: **Venn-diagram (Panel (A)) and Euler-plot (Panel (B)) displaying the number of stocks significantly affected by energy commodity price shocks, of different types, at least 20% of the time.**
Note: These plots are equivalent, except for the relative scaling of areas in the Euler plot which reflect the frequency of observed significance. As an example of interpretation: we observe that 41 stocks are affected only by CARBON; 29 only by OIL; 10 stocks by both OIL and CARBON (and neither of ELEC or GAS).

4.2 The changing role of carbon pricing across time

There are several important events that have occurred within the sample period, including Brexit, the COVID-19 pandemic, the Russian war with Ukraine, and the launch of the UK ETS. The time-varying nature of the econometric procedure allows us to examine whether these or other events coincide with smooth progressive changes (through smoothly time varying parameters) and/or more structural breaks (which can in principle be picked up from the regime switching properties of DMA).

To aid interpretation, we conduct cluster analysis on the recovered probability series $Pr.(CARBON)_{it}$ to search for common stock-probability 'types'. For carbon prices this results in three identified sub-groups for $Pr.(CARBON)_{it}$, which coincidentally reflect groups with low, medium and high probability of significance. Figure (5) plots the average probabilities within each of these three groups. The largest group (cluster 3) is the medium probability group in which the average probability tends to hover around 0.4-0.5, with modest declines following the Brexit referendum and the start of trade in the UK ETS. Stocks within this group are sometimes affected by carbon and sometimes not. The second largest group is the low-probability group containing 139 stocks. For the low-probability group the average probability is around 0.1, and companies in this group are effectively not affected by carbon prices, however it is noteworthy that the average probability for this group appears to have a sustained upward momentum from 2018 onwards, albeit at very low levels. The third group includes the highly affected stocks, with 17 member stocks. Over time the probability within this last group typically ranges between 0.8-1.

In sum, roughly 5% of companies are very likely to be affected by carbon prices most of the time, and the likelihood has increased substantially over the last decade. There is no strict pattern binding the 17 heavily carbon exposed stocks, with them being drawn from a range of business areas including: Homebuilding (NEC), Cruise Lines, Diversified Mining, Airlines (NEC), Direct Marketing, Commuting Services, Iron & Steel (NEC), Apparel & Accessories Retailers (NEC), Forest & Wood Products (NEC), Bio Therapeutic Drugs, Electronic Components, Marine Freight & Logistics (NEC), Wood Products, Special Foods & Wellbeing Products. Additionally, they have a wide spectrum of market capitalisation and employee size. Some are admittedly more dependent than others on hydrocarbon value chains e.g. pharmaceuticals, airlines, cruise lines, marine freight & logistics. Around 57% of firms are likely to be affected by carbon pricing on a frequent basis.

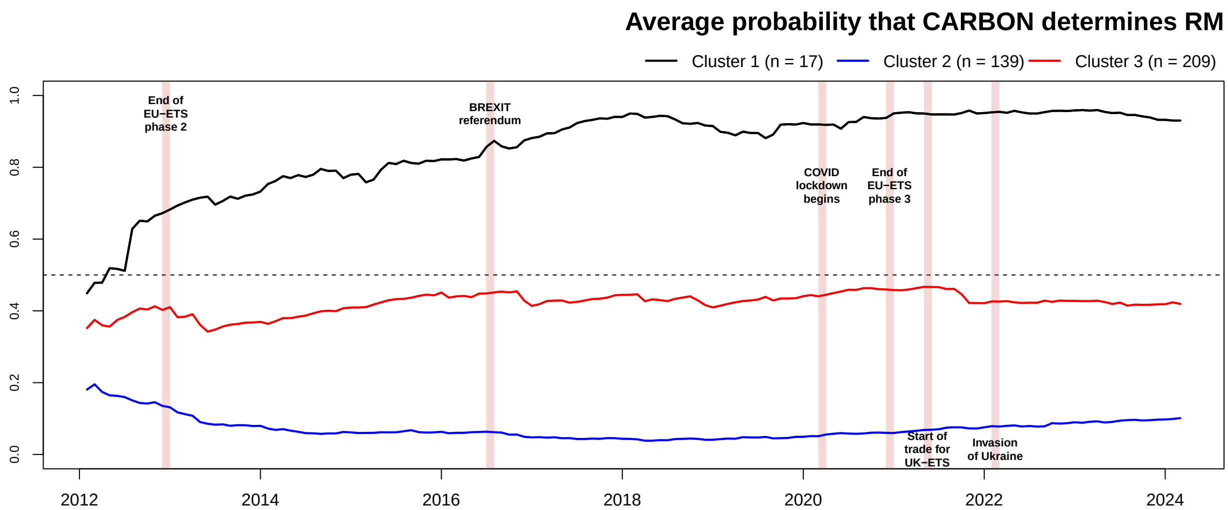

Figure 5: **Time series plots of the probability that carbon price changes are determining stock returns.**
Note: This figure contains plots of group averages for the probability that carbon price changes are determining stock returns. The groups are identified using k-means clustering, revealing three clusters.

4.3 Distribution across sectors

Table (1) aggregates the main results to establish how the relative significance of carbon pricing is distributed across key economic sectors. The Energy sector is the sector most heavily affected by carbon prices, with 52% of stocks in this sector being significantly affected for 20% of the sample period or more. This is consistent with *a-priori* expectations, as the sector participates in the emissions trading system. Other highly impacted sectors include Materials (39.58%), Consumer discretionary (36.36%) and Information Technology (33.33%).

Sectors that are relatively less exposed include Consumer Staples (10.71%), Utilities (11.11%) and Real Estate (11.54%). The low exposure to utilities is consistent with observations and justifications presented in Broadstock and Filis (2020), insomuch as Utilities companies are intimately engaged with energy commodities, as well as the various emissions trading schemes. The elevated importance of these within the core business model of utilities sector participants predicates the need for intelligent cost management and hedging strategies. In turn, this helps rationalise a low probability of exposure among these stocks. A reasonable question to ask at this point is why the same logic may not hold for the Energy sector? One possible explanation is that the relative price of the commodities, and the irreversible nature of the energy transition, gives energy related risks (including carbon prices) a different complexion for an Energy company, which may have stranded assets and frictions to transition. These concerns are not the same for Utilities firms, who have much greater flexibility to transition.

Other less exposed sectors are more straightforward to rationalise. For Consumer Staples, to date there is limited consumer awareness of the energy or environmental footprint embedded within the products falling under this category - which for example includes food, beverages, clothing and various other products consumed on a daily basis. For Real Estate, across the historical sample period there has been relatively little attention given to the embodied emissions, or environmental standards for the built environment.

Table 1: This table gives an overview of the significance of carbon, and energy commodity, price changes to the stock returns of UK listed companies, aggregated by economic sector. The values indicate the percentage of stocks within a given sector, that are impacted/determined by the commodity price, for at least 20% of the sample period or more. For example, we observe that within the energy sector 52% of listed companies returns' are determined by $CARBON$ for at least 20% of the sample period.

Industry	**% stocks impacted $\geq$ 20% of time**				**of which, % impacted asymmetrically**				***Sample info.***	
	ELEC	OIL	GAS	CARBON	ELEC	OIL	GAS	CARBON	Stocks	Obs.
Energy	36.00	64.00	36.00	52.00	4.00	4.00	4.00	4.00	25	4,250
Health Care	20.00	26.67	33.33	26.67	0.00	13.33	6.67	13.33	15	2,550
Financials	8.93	7.14	7.14	21.43	1.79	0.00	0.00	0.00	56	9,520
Consumer Staples	7.14	25.00	7.14	10.71	0.00	3.57	0.00	0.00	28	4,760
Communication Services	15.38	23.08	15.38	23.08	0.00	0.00	0.00	0.00	13	2,210
Materials	29.17	47.92	41.67	39.58	2.08	2.08	0.00	6.25	48	8,160
Consumer Discretionary	9.09	29.55	18.18	36.36	0.00	2.27	0.00	2.27	44	7,480
Industrials	16.88	20.78	19.48	28.57	1.30	0.00	0.00	2.60	77	13,090
Utilities	0.00	11.11	11.11	11.11	0.00	0.00	0.00	0.00	9	1,530
Real Estate	3.85	3.85	7.69	11.54	0.00	0.00	0.00	3.85	26	4,420
Information Technology	16.67	33.33	29.17	33.33	0.00	4.17	0.00	4.17	24	4,080
Full sample	15.62	26.3	20.55	28.49	1.1	1.92	0.55	3.01	365	62,050

Some sectors, such as Healthcare, are exposed more than might be intuitively expected, but can be plausibly explained. Hess et al. (2011) discuss the vulnerability of health care to petroleum supply shifts, highlighting an important chain of dependence. Petroleum supports healthcare in multiple ways, including its role for transportation of staff and those seeking in need of healthcare, and as a feedstock into the various medical supplies and pharmaceuticals that the sector relies upon. From a different perspective Wang et al. (2023) provide evidence of an inverse relationship between health expenditures and life expectancy with energy costs, showing that rising energy costs reduce both health expenditures and life expectancy. Together these results indicate that healthcare-related firms can be negatively exposed due to rising business costs, and negatively (for private healthcare provides) due to budget constraints arising from energy price increases (i.e., with households having to substitute healthcare expenses to compensate rising energy costs, rendering them more susceptible to morbidity).

As introduced in the methodology section, we allow for potentially asymmetric effects in the econometric specification, and the results relating to these are captured in columns 5-8 of Table (1). From the final row it can be observed that the presence of incremental asymmetry is low, but not zero. The estimation procedure is such that asymmetry is retained only when statistically preferred, moreover it is worth recalling that estimations are resolved at the firm level, hence although relatively insignificant across the population, it remains a valid model feature. It is noteworthy that where found, the asymmetry is strongest for $CARBON$, followed by OIL.[8] Given the relative infrequency of asymmetry, we do not separately isolate such effects in the remainder of the results discussion.

4.4 How economically meaningful (financially material) are carbon price shocks?

Having established there is a statistically meaningful frequency of effect that also has plausible distribution across economic sectors, we turn attention towards approximating the economic/financial materiality of historic carbon price changes. The estimated contribution of carbon price changes to stock returns evaluated as:

$$\hat{\theta}_{it}CARBON_t + \hat{\theta}_{it}^{(-)}CARBON_t^{(-)} \tag{10}$$

[8]This does leave open a question of whether asymmetry found in other studies might be capturing what should in fact be time variation or non-linear effects - a discussion point that has anecdotally floated around among practitioners for some time, but would warrant a more dedicated econometric assessment either theoretical or monte-carlo based and is beyond the scope of our study.

Table 2: Summary statistics describing the nature of the affect of carbon prices ($CARBON$) to stock market returns, and the share of market capitlisation exposed to carbon pricing.

Panel A: Estimated contribution of carbon price changes to stock returns evaluated as: $\hat{\theta}_{it}CARBON_t + \hat{\theta}_{it}^{(-)}CARBON_t^{(-)}$. Summary statistics are given for the minimum, median, mean and maximum values as well as the first and third quartiles, Q_1 and Q_3 respectively.

Industry	Min	Q_1	Median	Mean	Q_3	Max	Stocks	Obs.
Energy	-0.7089	-0.0098	0.0012	0.0034	0.0153	1.0092	25	4,250
Health Care	-0.3005	-0.0158	-0.0001	-0.0073	0.0062	0.2177	15	2,550
Financials	-0.3500	-0.0030	0.0000	0.0006	0.0044	0.3727	56	9,520
Consumer Staples	-0.5365	-0.0062	-0.0001	-0.0022	0.0024	0.1303	28	4,760
Communication Services	-0.1664	-0.0026	0.0000	-0.0001	0.0035	0.1372	13	2,210
Materials	-0.2916	-0.0066	0.0001	0.0023	0.0106	0.6562	48	8,160
Consumer Discretionary	-0.2334	-0.0038	0.0000	0.0006	0.0036	0.3102	44	7,480
Industrials	-0.2331	-0.0038	0.0000	0.0003	0.0049	0.1666	77	13,090
Utilities	-0.0643	-0.0006	0.0003	0.0055	0.0091	0.1047	9	1,530
Real Estate	-0.1154	-0.0073	-0.0008	-0.0059	0.0004	0.0693	26	4,420
Information Technology	-0.1048	-0.0023	0.0008	0.0052	0.0087	0.2862	24	4,080
Total	-0.7089	-0.0047	0.0000	0.0009	0.0061	1.0092	365	62,050

Panel B: Share of sample for which estimated impacts of $CARBON$ are: insignificant ($\% = 0$); positive ($\% > 0$); negative ($\% < 0$); of stocks impacted by carbon at least 20%, 50% or 80% of time periods, τ_{20}, τ_{50} and τ_{80} respectively.

Industry	$\% = 0$	$\% > 0$	$\% < 0$	τ_{20}	τ_{50}	τ_{80}	Stocks	Obs.
Energy	75.39	13.55	11.06	52.00	16.00	4.00	25	4,250
Health Care	84.00	7.84	8.16	26.67	13.33	6.67	15	2,550
Financials	87.41	6.20	6.40	21.43	10.71	0.00	56	9,520
Consumer Staples	90.57	4.37	5.06	10.71	7.14	3.57	28	4,760
Communication Services	84.43	7.92	7.65	23.08	15.38	7.69	13	2,210
Materials	74.08	13.43	12.49	39.58	25.00	8.33	48	8,160
Consumer Discretionary	80.39	9.71	9.91	36.36	11.36	9.09	44	7,480
Industrials	85.19	7.34	7.47	28.57	9.09	0.00	77	13,090
Utilities	94.64	3.27	2.09	11.11	0.00	0.00	9	1,530
Real Estate	94.32	1.88	3.80	11.54	0.00	0.00	26	4,420
Information Technology	81.79	10.91	7.30	33.33	8.33	4.17	24	4,080
Total	83.81	8.24	7.95	28.49	11.51	3.56	365	62,050

Panel C: Summary of market capitlisation (MCAP) as of March 31^{st} 2024 for firms in sample by sector, and for subsamples of stocks impacted by carbon at least 20% or 50% of the time, MCAP_{20} and MCAP_{50} respectively.

Industry	MCAP (UK£bn)	MCAP_{20} (UK£bn)	MCAP_{50} (UK£bn)	MCAP_{20} (share)	MCAP_{50} (share)		Stocks	Obs.
Energy	604.20	250.83	1.15	41.51	0.19		25	4,250
Health Care	312.19	6.36	0.62	2.04	0.20		15	2,550
Financials	634.93	116.57	7.25	18.36	1.14		56	9,520
Consumer Staples	495.36	28.98	2.64	5.85	0.53		28	4,760
Communication Services	86.61	1.71	1.38	1.97	1.59		13	2,210
Materials	258.27	14.80	11.21	5.73	4.34		48	8,160
Consumer Discretionary	219.77	24.81	11.95	11.29	5.44		44	7,480
Industrials	331.03	87.94	36.70	26.57	11.09		77	13,090
Utilities	106.10	2.95	0.00	2.78	0.00		9	1,530
Real Estate	53.88	2.69	0.00	4.99	0.00		26	4,420
Information Technology	760.50	6.13	0.52	0.81	0.07		24	4,080
Total	3090.27	435.03	58.74	14.08	1.90		365	62,050

Noting from the earlier description of the econometric procedure that the DMA coefficients $\hat{\theta}_{it}$ and $\hat{\theta}_{it}^{(-)}$ are already probability weighted, hence each may in principle become numerically zero (or very close to), when carbon prices are not a significant determinant of stock returns. Table (2) uses this information to help describe the materiality of carbon pricing from several complementary perspectives:

- Panel (A) provides a summary description of the nature of carbon pricing to stock returns, conveying minima, maxima mean, median and lower and upper quartile values on the estimated contribution ($\hat{\theta}_{it}CARBON_t + \hat{\theta}_{it}^{(-)}CARBON_t^{(-)}$) by sector.
- Panel (B) complements Panel (A) and indicates the share of sample for which estimated contributions of $CARBON$ are: insignificant ($\% = 0$); positive ($\% > 0$); negative ($\% < 0$); of stocks explained by carbon at least 20%, 50% or 80% of time periods, τ_{20}, τ_{50} and τ_{80} respectively. Specifically, the first three columns are signs on the effect (the coefficient multiplied against the $CARBON$ data), and between them sum to 100. These are taken across all firms and all periods with the primary objective being to get a sense of the net affect to companies returns i.e. it ignores the relative distribution across firms. The following three columns (4 to 6) are effectively offering up the information about the distribution across firms, by indicating something about the proportion of firms exposed by what proportion of time.
- Panel (C) summarises of market capitlisation (MCAP) as of March 31^{st} 2024 for firms in sample by sector, and for subsamples of stocks significantly explained by carbon at least 20% or 50% of the time, MCAP_{20} and MCAP_{50} respectively.

From Table (2), Panel (A), we discern that the nature of carbon pricing intuitively includes a diversity of positive and negative effects. At the median, it can be seen that the expected exposure of stock returns to carbon pricing at any given time will be small in magnitude, and even zero for the Financials, Communications services, Consumer Discretionary and Industrials sectors. This is not to say that there is no role, but that for stocks in these sectors which are exposed, the balance between positive and negative effects is fairly evenly distributed, thereby canceling each other out when aggregating. The absolute values of the maxima are larger than the minima, with the largest of each being within the Energy sector. Other sectors experiencing relatively large negative effects include Consumer Staples, Financials and Health Care. Larger positive effects are observed also in the Financials, Materials, Consumer Discretionary and Information Technology sectors.

Panel (B) Table (2) requires interpreting in two parts. The first three columns provide a more immediate summary of the sign of effect by sector. Taking Energy as an example, across all stocks and all time periods, there is no significant exposure to carbon pricing 75.39% of the time. For the remaining observations, 13.55% of observations are consistent with a net-positive effect of carbon pricing to stock returns, while 11.06% of observations lead to a net-negative effect. The Information Technology sector is another sector where carbon price effects are more frequently positive to stock returns than negative. In contrast, for Real Estate the effects are more likely to be negative (3.80%) than positive (1.88%). For the Real Estate sector, column 4 indicates that carbon prices are a significant determinant of 11.54% companies stock returns for at least 20% of periods in the sample - we refer to this as the τ_{20} number, with τ_{50} and τ_{80} defined analogously for different proportions of time exposed. While 11.54% of stocks are signficantly explained 20% of the time, none for 50% or more of the time. In contrast, for the Energy sector, 52% of stocks are significantly affected 20% of the time or more, while 16% of stocks for 50% of the time or more. Taken together these numbers allude to a relatively high concentration of exposure, and also further indicates the heterogeneity of impact, which each provide supporting rationale for the need to conduct firm level estimations so as to avoid aggregation biases and canceling out effects.

The final panel from Table (2), namely Panel (C), summarises the aggregate value of MCAP exposed to carbon pricing within each sector, alluding to the overall economic significance of carbon pricing. The largest sector by MCAP is Information Technology at £760.50bn. From Panel (B) we know that 33.33% of stocks in this sector are significantly explained by carbon prices for 20% of the time, the aggregate MCAP of the affected stocks sums to just £6.13bn, accounting for 0.81% of MCAP within this sector. Perhaps unsurprisingly, given the primary sectors covered by emissions trading schemes, the Energy sector has the largest exposed level of MCAP, at £250.83bn (41.51% of this sector), although the value of MCAP exposed to carbon pricing 50% of the time or more is vastly smaller at just £1.15bn (0.19% of this sector). The sector with the largest enduring impact of carbon pricing is the Industrials sector, where 11.09% of the sector's MCAP is exposed to carbon pricing 50% of the time or more, which equates to £36.70bn.

The Financial sector is the second most affected sector by MCAP, with £116.57bn exposed to carbon pricing 20% of the time or more. This correlates with a well understood practice of financial speculation and/or financial hedging in relation to commodities - the so-called commoditisation effect. From this we have additional evidence that the range of effects from carbon pricing to stock returns will in effect be made up of some real-economic effects (such as Energy sector firms being participants of emissions trading schemes) and revised expectation of the financial valuation of stocks indirectly for example as a result of carbon-price pass through effects (financial effects) or due to speculative actions resulting from the commoditisation of carbon.

As a complementary point of reference, Figure (6) presents an empirical cumulative distribution plot of the estimated contribution of carbon prices to stock returns i.e.:

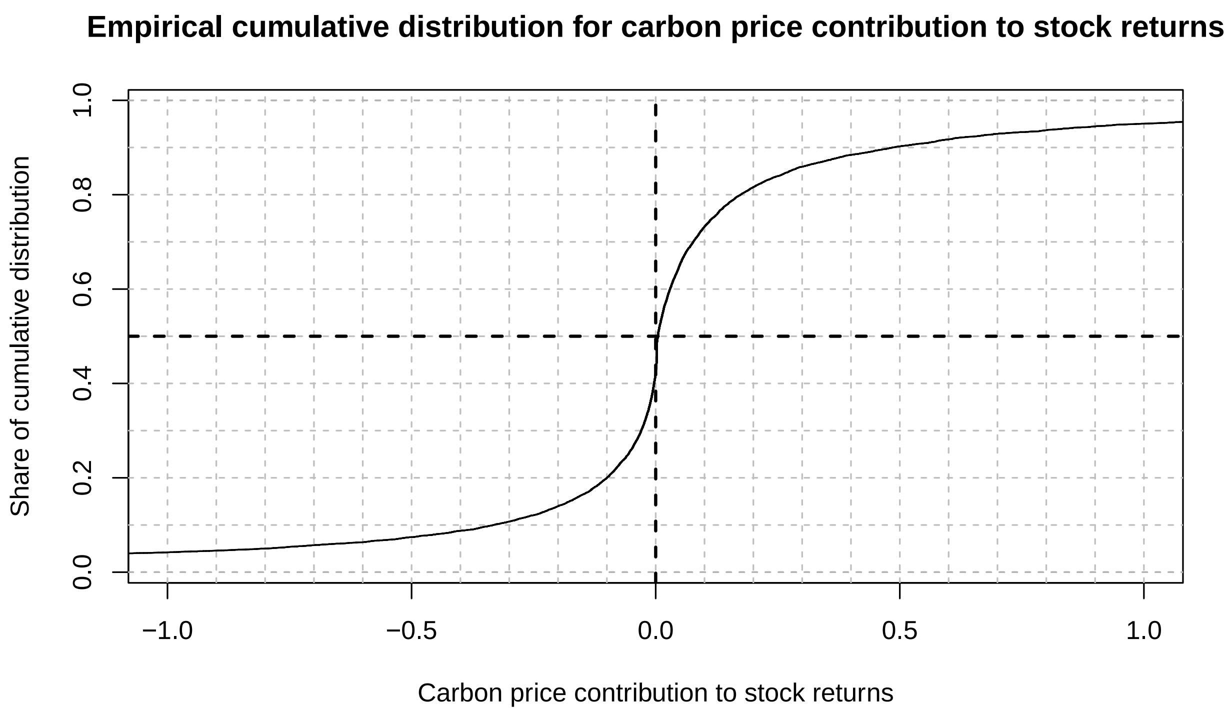

Figure 6: **Empirical cumulative distribution for the contribution of carbon pricing to stock returns.**
Note: The contribution is calculates as $\left(\hat{\theta}_{it}CARBON_t + \hat{\theta}_{it}^{(-)}CARBON_t^{(-)}\right)$ *and is evaluated relative to the observed returns for a firm* $\left(\tilde{R}_{i,t}\right)$*. Note that the division means that positive numbers reflect situations under which the contribution of carbon prices move in the same direction as observed returns, and negative numbers occur when the two are of different signs. Only observations where the carbon price contribution is non-zero are included in the plot.*

$$\frac{\hat{\theta}_{it}CARBON_t + \hat{\theta}_{it}^{(-)}CARBON_t^{(-)}}{\tilde{R}_{i,t}} \tag{11}$$

With this expression, numbers close to one will occur if the the contribution from carbon prices is of the same size and sign of the observed level of returns for the same period (i.e. when they are both positive, the expression will be positive, and, if they are both negative, the expression will also return a positive number). Values less than one (in absolute terms) mean that the contribution is smaller than the observed returns, while larger values indicate the opposite. If the ratio is negative then the contribution and the observed returns are operating in different directions. From Figure (6), we can observe generally similar patterns in the positive and negative regions, albeit with slightly higher mass above zero indicating that stock price changes are likely to be reinforced by carbon price contributions (i.e. they share the same sign). At this point, it is worth highlighting that the plot focuses only on observations with non-zero contributions from carbon pricing.

5 Additional analysis: Event study on daily (abnormal) stock returns around the announcement of an independent UK-ETS

To this point, the paper has demonstrated a non-trivial co-relation between carbon prices and stock returns. There is additional interest in understanding whether there is an identifiable causal association to add further overall validity to the analysis. We therefore complement the main results with a traditional event study, built around a price shock that serves as a natural experiment. Specifically we take the ‘event’ as the official announcement that a UK-ETS will be launched, which occurred on June 1^{st} 2020. While there was some prior government consultation on options for carbon pricing in the UK following Brexit, the announcement on June 1^{st} marked a policy confirmation shock introducing specific design details for the first time (e.g. cap level, market rules) which made this a legitimate information shock directly related to carbon pricing. Hence the event marked a reasonable juncture affecting the expectations of carbon allowance scarcity and future prices.

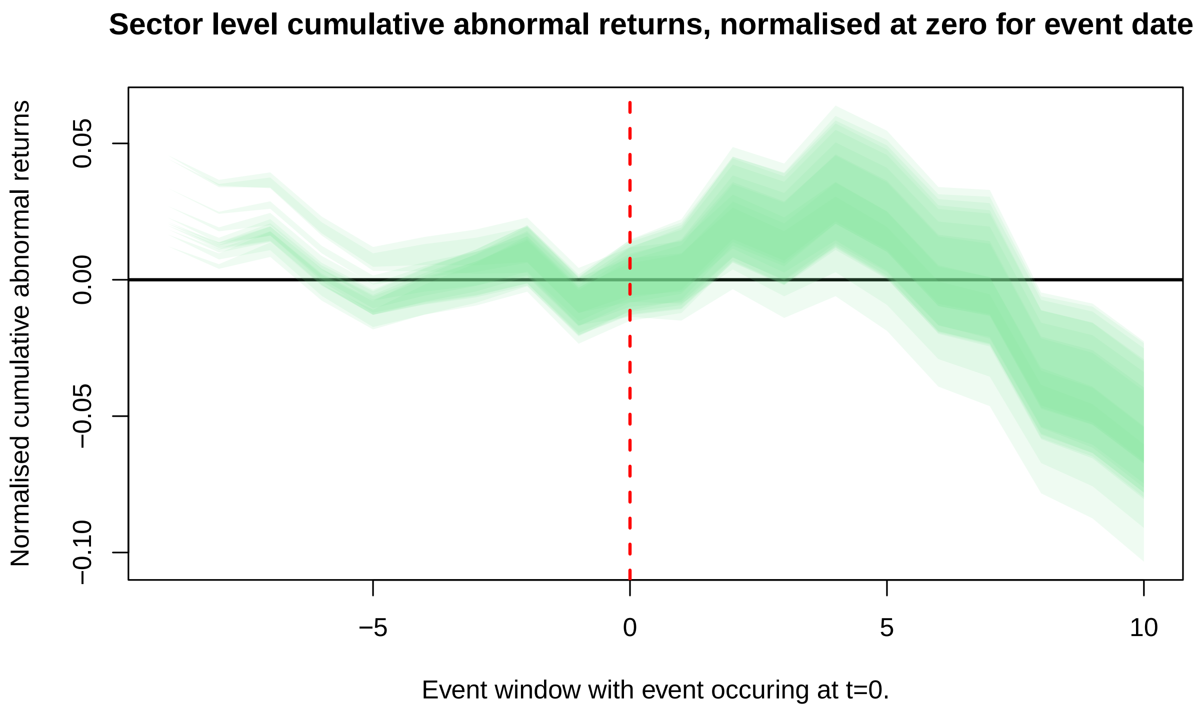

Figure 7: **Event study summary results.**
Note: This figure reports event study results for analysis describing daily cumulative abnormal daily returns before and after the announcement on 1st June 2020, that a separate UK emissions trading scheme will be introduced. The plot overlays bootstrap distributions evaluated for individual sectors, moreover the series are normalized around the event date for ease of interpretation. While the individual sectors are not labeled, it is clear that the same underlying trend exists across all sectors, with discernible pre- and post-event differences, and final cumulative abnormal returns that are negative at the end of the 10 day window for all sectors.

Within the parameters of the sample, this is the most natural choice of event representing a shift in the overall market mechanism that will undoubtedly create room for carbon price uncertainty. Yet we concede that this is also an event occurring at a relatively early phase of the covid pandemic. Although mindful of this attribute, the event study remains informative on at least two important grounds: first is that the effects of Covid are economy wide, and will be conditioned for in the event study in the calculation of abnormal returns; second is that for the event study we use daily frequency data allowing us to keep the event window sufficiently narrow that the early disruptions from the first few weeks and months of Covid will not be included. Nonetheless we consider our results here indicative and not definitive for these reasons.

The event study design is as follows:

- The event in question (t_0) is the announcement that a separate UK-ETS will come into effect - the launch was not immediate, but the announcement event will leave market participants clear that a different carbon price mechanism will apply to them i.e. a 'shock' to the pricing mechanism.
- For each firm in the sample, a simple measure of abnormal returns (AR) is obtained by running a standard CAPM using ordinary least squares for all data up to and including 2019, i.e. based on historic firm-specific market betas:

$$\tilde{R}_{i,t} = \alpha_i + \beta_i(RM_t - RF_t) + u_{i,t} \tag{12}$$

The historic betas are used to predict normal returns for the event window based on actual RM values, and abnormal returns are obtained as the difference between actual returns and the predicted normal returns. The event window is set at 10 trading days.

- The abnormal returns are accumulated to obtain firm specific cumulative abnormal returns (CAR), which are the main series used in determining whether the event in question created a discontinuity of sorts on firms 'unexpected' (i.e. after conditioning for normal returns based on overall market conditions) stock valuation. A discontinuity would be represented by a clear shift in the level or trajectory of CAR at around t_0, though possibly with delay depending on the time required to process the event. In addition, the event may trigger temporary or more permanent shifts, hence observing the 'return to stationarity' of CAR, or absence of it, is of interest.

Varying approaches can be used to conduct the final evaluations. Here we draw upon the bootstrap summary approach used in Patnaik and Shah (2010), allowing for a non-parametric depiction of the impact of the event on CAR within the event window. To ease interpretation, the CAR terms are recentered at 0 for the event date (t_0). The results are summarized at the industry classification level, to permit for better understanding of the differentiated impacts that may exist in different sectors. For the present application this proves sufficiently illuminating, and while other complementary/alternative summaries could be conceived, the implications of the event study do not warrant further testing.

As noted earlier, we caution our interpretation of the event study against the pragmatic understanding that this event occurred within the middle of a historically unprecedented global pandemic. What we can learn is that there is supporting evidence that the UK-ETS caused a decline in company returns. While there is some observed variance of this decline across sectors, that variation is nonetheless quite modest.

6 Investor salience: returns on carbon sensitive versus carbon insensitive portfolios

To complement the main findings we conduct a thought exercise in which we assume an investor knew, from the start of our sample, which stocks are most sensitive to carbon pricing, and which are not (i.e. can predict 'carbon immunity'), and uses this information to construct investment portfolios. We refer to this investor as an 'oracle' investor insofar as they are awarded perfect forward looking knowledge, at least with regard to stock carbon sensitivity. The purpose of this exercise is to establish whether knowledge of carbon sensitivity carries incremental information that may be useful to the investor community though also serves as a test of sorts around the economic value of being carbon sensitive or engaged with carbon pricing in a way that connects to firm value. We note that the findings in this section can be seen as being connected with an emerging strand of literature on the 'carbon-alpha hypothesis', which posits that *"...financial markets underprice carbon risk to the point that conscientious investors attain favorable outcomes through low-carbon choices."* as discussed in Kim and Eom (2023) among others. However it at the same times differentiates from that literature in so far as our inquiry here is not sign dependent i.e. does not contrast between firms that respond positively or negatively, and instead is more focused in whether a stock responds at all.

The steps taken to construct these portfolios are as follows:

- Carbon sensitivity is identified based on the likelihood that a given stock is exposed to some effect from carbon pricing. This is obtained for stock i as the time-average of the probability that $CARBON$ is a determinant of stock returns:
$$\frac{1}{N}\sum_{t} Pr.\left(CARBON\right)_{it}$$
- This series is ranked from highest value to lowest value.
- Carbon sensitive stocks are defined as the top 20 stocks in the rank ordered list.
- Carbon insensitive stocks are defined as the bottom 20 stocks in the rank ordered list.
- Equal weighted portfolios are developed by investing in equal proportions across the identified stocks in any given category e.g. for the equal-weighted carbon sensitive portfolio, assuming a principle investment of 1, then we invest 0.05(=1/20) of the principle into each of the 20 carbon sensitive stocks.
- Recalling that we assign our 'oracle' investor with perfect foresight on carbon sensitivity, we assume that the investor did this at the start of our sample, then bought and held these stocks (with equal weight) until the end of the sample. [9]

[9] We appreciate that this toy example is quite unrealistic when compared against real-word investment practices, but is nonetheless instructive in demonstrating the potential value from understanding carbon sensitivity.

- The initial value of the portfolio holding is indexed at 100, largely for ease of interpretation, and its performance tracked across time.
- The process is repeated for carbon insensitive stocks, enabling a more complete comparison and understanding of a carbon sensitivity avoidance based investment strategy.
- In addition to an equal-weighting strategy, we also constructing value weighted portfolios, in which stocks are purchased with relative quantities defined by their market capitlisation e.g. if carbon sensitive stock #1 has twice the market capitalisation of carbon sensitive stock #2, it will have twice as large an investment weight within the portfolio. For these assignments, we base the market capitalisation on the end of sample values (March 31^{st} 2024), hence assuming this as additional information provided to the oracle investor.

From Figure (8), we can observe that across the full sample period, the carbon insensitive (immune) portfolios achieve greater financial returns then carbon sensitive portfolios, albeit with differing dynamic relations depending on investment weighting scheme.[10] Under the MCAP investment weighting approach, the two portfolios track fairly closely between 2010-2015, but in the period from 2015-2020, the carbon sensitive portfolio outperforms both the insensitive portfolio, and the overall market benchmark, by quite a substantial margin. Between 2020-2024, any previous gains are eroded, and the portfolio closes out at 142.33, reflecting a 42.33% return on investment. This contrasts with 111.00% return on investment from the carbon insensitive portfolio, although both of these fall shy of the value-weighted market benchmark. The lower panel of this figure shows the equal weighted portfolios in which there is a much more robust separation and the insensitive portfolio outperforms the sensitive portfolio for close to the complete sample.

It is important to remember that these are 'toy-example' illustrations designed to allude to the potential financial salience or materiality that might be obtained from being aware of stock carbon sensitivity. Many alternative choices on portfolio construction could be conceived, and here we apply a fairly intuitive screening procedure. One could certainly question or contest the assumptions made, and replace them with more thoroughly considered choices. Yet this does not detract from the conclusions we can gather from the exercise, which is that without a great deal of effort in investigation, it is possible to unpack an additional layer of evidence that carbon pricing correlates with companies financial performance, and that these relationships bear evidence of systematic structure that investors may be able to leverage.

[10]We note that the carbon insensitive portfolio includes a 5% investment allocation share in the Energy sector, this is into Hargreaves Services PLC, which "is a diversified group delivering services to the Environmental, Industrial and Property sectors." (https://www.hsgplc.co.uk/about-us/)

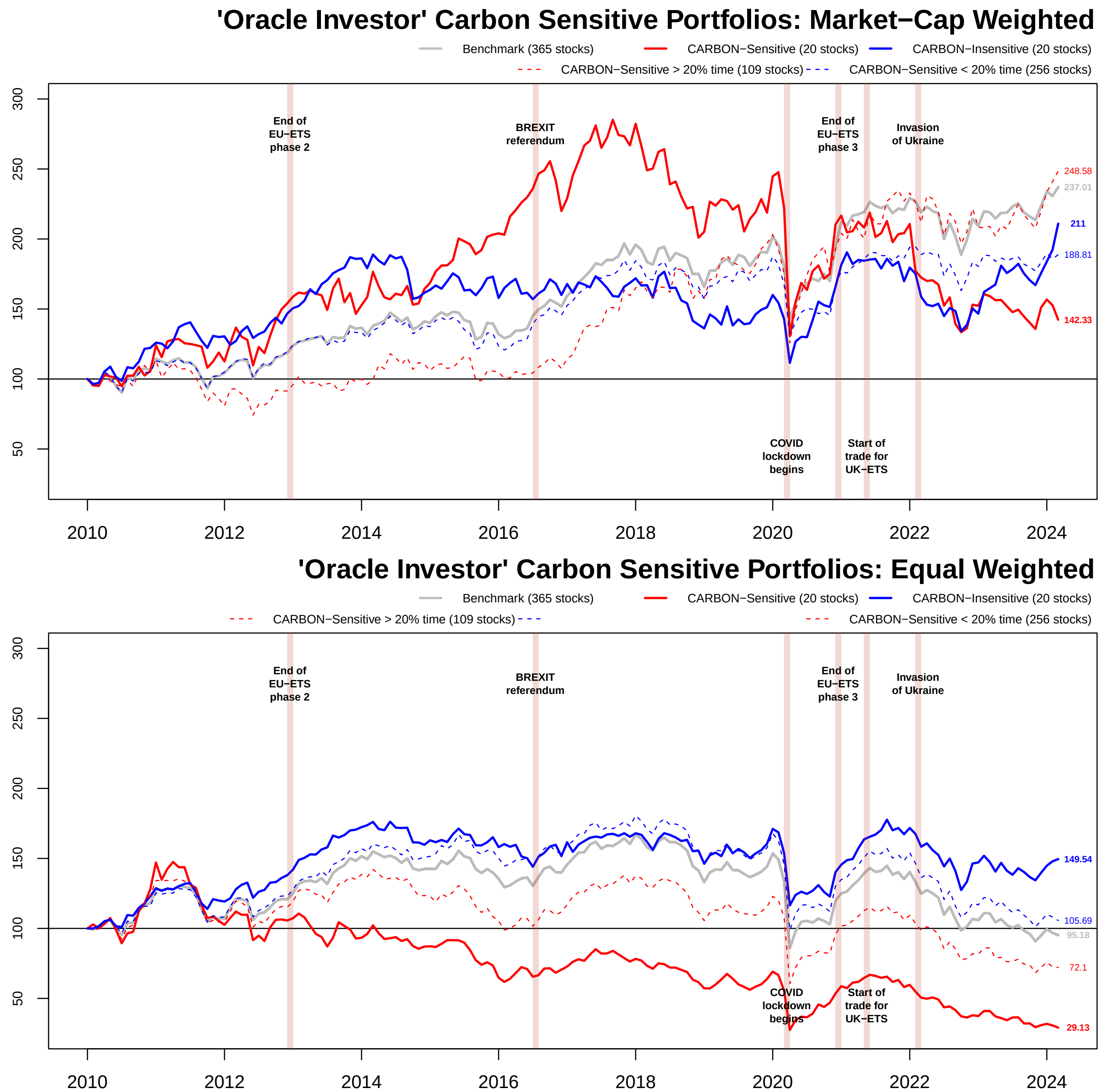

Figure 8: **Buy-and-hold financial portfolios based on carbon sensitivity of stocks.**
Note: Description of the portfolio construction procedure is provided in the main text. Sectoral composition of carbon sensitive stocks: Materials 35%; Consumer Discretionary 20%; Health Care 10%; Industrials 10%; Communication Services 5%; Consumer Staples 5%; Financials 5%; Information Technology 5%; Real Estate 5%. Sectoral composition of carbon insensitive stocks: Consumer Staples 35%; Consumer Discretionary 15%; Financials 10%; Information Technology 10%; Real Estate 10%; Energy 5%; Industrials 5%; Materials 5%; Utilities 5%.

7 Conclusions and policy implications

This paper aimed to identify the importance of carbon prices in the economy - by estimating the frequency that carbon price fluctuations affect the financial value of companies and the scale of these fluctuations. It also sought to compare the frequency with those for specific energy prices, including oil, natural gas and electricity. To provide evidence, this paper investigates the UK stock returns for 365 companies over more than fourteen years.

The results indicate that almost three-tenths of the variation in listed companies financial value are significantly explained by carbon prices at least 20% of the time. This is at least as often as by oil price variations. Firms are also more affected by carbon prices than electricity prices - which given the potential for electricity suppliers to pass-through increases in carbon prices via higher power prices, suggests that carbon prices are more pervasive than electricity prices. Despite concerns about the negative role of oil and other energy prices on the economy, economists need to be aware of the critical role carbon prices are now playing in the economy. In fact, carbon prices are becoming the single most important energy or environmental variable to consider in determining corporate value - at least, in the UK.

Looking at the evolution of results through time, around 5% of companies have become highly vulnerable to carbon prices over the last decade. These are predominantly energy sector firms and it is surmised that the nature of their investments and core activities limits their flexibility to adapt to the low carbon transition. This inflexibility implies they are buffeted by fluctuations in carbon markets.

Looking across sectors, the evidence confirms that the Energy sector was most affected. Consumer Staples, Real Estate and Health Care also experienced relatively more frequent negative effects. By contrast, Industrials, Materials, Consumer Discretionary and Information Technology sectors observed more frequent positive effects. Converting these impacts into market capitalisation reveals that the energy sector has the largest amount of assets affected - over £250bn (41.51% of this sector) at least 20% of the time. The Financial sector was also a highly affected sector, more than £116bn significantly exposed to carbon pricing 20% of the time or more. The Industrial sector was the third largest sector with assets of nearly £88bn affected by carbon pricing. For other sectors, the market capitalisation affected was below £30bn.

Carbon prices have become a cornerstone of climate policy in many economies around the world, it is important to assess whether markets are responding. The results of this paper confirm that carbon prices' signaling over the external costs of economic activity is being received by firms and the incentives are re-structuring firm behaviour. It is possible to imagine that twenty-first century global markets will be as sensitive to carbon price fluctuations as they were to oil prices in the second half of the twentieth century. Just as these oil price vulnerabilities led to a transition away from oil in many markets, it is probable to expect that carbon prices will be instrumental in driving markets away from high-emitting activities.

Given that a majority of companies (57%) are significantly exposed to carbon pricing, and over 14% of total market capitalisation is affected, policymakers should recognise that carbon markets are already influencing firm-level financial decisions, particularly in the energy and financial sectors, and adjust regulatory strategies accordingly. These policies could include ensuring long-term price stability, gradually tightening emissions caps, and expanding coverage to reduce uncertainty and reinforce low-carbon investment signals. Governments could also play a role in supporting corporate adaptation through targeted subsidies, transition finance, or mandatory carbon disclosure standards to improve market transparency and resilience - especially for sectors like Energy, Financials and Real Estate, which the analysis shows are most frequently and materially affected, and may face structural limits in adapting swiftly to carbon price shocks. Thus, governments have a critical role in regulating and managing financial markets to prevent systemic disruptions during the transition to low-carbon energy, and to ensure that firms can become increasingly resilient and ultimately immune to carbon-related shocks.

Throughout this work we have focused our attention on the importance of carbon pricing, but there are a suite of supporting mechanisms that need also to be kept in view in transitioning to low or net-zero economies. Campiglio (2016) for example discuss the importance of introducing non-price based signals as complements to pricing mechanisms in order to support banking related activities. Future research in this area might seek to bridge a more concrete connection between public awareness of, and behavioural perceptions towards, climate related risks and solutions such as carbon pricing.

While our study offers a novel perspective upon an important and timely issue, it is not without its limitations or shortcomings, some of which being more deserving than others for attention in future research. For example, we document the UK experience on the separation form the EU ETS, but of equally valid interest would be the EU experience on the UK separation.

Another area for future research to consider would be that of delineating carbon price-pass through effects. Within the scope of our study we argue that the price pass through hypothesis is incomplete, since there are measurable and economically meaningful co-movements between carbon prices and stock returns both among firms that are participants in the ETS, as well as other indirect effects for firms and sectors which are not - hence the general equilibrium effects are greater than a pure carbon price pass through hypothesis would permit. Yet the more traditional notion of price pass through is not dismissed, and understanding how for listed firms the decision to pass on carbon prices they face by way of modified menu pricing for their products may subsequently impact stock valuation is interesting to consider. Doing so, however, requires considerably richer data than we have available for this study, including product catalogues, and pricing revisions, as a pre-requisite for identifying firms that do implement price pass-through versus those that do not. Finally, giving more attention to the causal association between carbon pricing and stock values would be an area of interest. As part of this study a directed acyclic graph and event study were used to help motivate the existence of an association, and we are mindful that each point towards potentially causal connections. Yet within the scope of the present study, and the context of the available data, these are indicative but not definitive evidence points. With more data and/or application to different geographies there would be opportunities to give a more concrete assessment of the causal ties between these variables.

Of additional importance might be to consider the managerial insights, challenges and opportunities faced by specific firms in their efforts to incorporate and/or react to carbon pricing mechanisms they either voluntarily adopt or are exposed to. Doing so would require more intensive exploration of data where such information may be captured, such as within the text of company reports. Doing so may help reveal effective preparedness strategies pre- and post-implementation of carbon pricing mechanisms that are likely to be applicable to a range of market conditions across different country contexts.

Indeed, future research should explore how industries respond to the impact of carbon pricing. Certainly, this paper suggests that the emissions trading scheme has been creating incentives for firms to introduce carbon mitigation measures. These measures would include investing in energy efficiency solutions (e.g., upgrading equipment, improving insulation and optimizing industrial processes) and, where possible, switching to low carbon technologies (e.g., electrifying using renewable power or carbon capture). Perhaps to assist these investments and switches, firms may seek to develop internal carbon pricing (e.g., internal fee, shadow price or implicit carbon price) to ensure that the company is making decisions that align with government policy of internalising external costs. Companies could also actively participate in carbon markets to optimise the timing of allowance purchases and to consider carbon hedging strategies, which could involve investing in forward contracts and futures or options to hedge against price volatility and market uncertainty. These measures could substantially reduce the corporate vulnerability to carbon prices. With this in mind, we can anticipate that the more saliently and frequently a firm's value is changed by carbon prices, the more likely a firm is to introduce carbon mitigation measures. Thus, the hypothesis of this research avenue is that, over time, as they adopt such measures, more firms will become increasingly insensitive to carbon prices, shifting the economy onto a low carbon pathway.

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