Greenium, Oil Cycles and Carbon Policy*

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Abstract

This paper investigates the asset pricing effects of carbon policy shocks in Europe. Previous studies treat brown stocks as homogeneous and document green stocks outperform brown. The standard approach neglects critical heterogeneity within brown assets. In particular, the returns of fossil energy firms are mainly driven by the price of oil rather than carbon regulation, creating a divergence from other brown firms. I also show that the effects of carbon policy are non linear, and they crucially depend on the oil cycles (bull vs bear regimes): oil bull scenarios make carbon regulation much more effective compared to bear scenarios, in which the green outperformance seems to disappear. These findings highlight the pivotal role of oil in shaping the asset pricing effects of climate policy, both through the oil-driven behavior of fossil energy firms and the broader influence of oil market regimes.

Keywords: Carbon Policy Shocks, Firm Heterogeneity, Climate Finance, Greenium, Oil, State Dependency

JEL Codes: E60, G11, G12, Q43, Q54

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1 Introduction

The pricing of carbon transition risk is a central question in economics. In this context, the academic literature examines the return from investing in firms that are more climate-friendly (green) compared to those that are less climate-friendly (brown). Theoretically, brown firms are more exposed to policy risk during the transition period and should earn higher expected returns (carbon premium hypothesis). On the other hand, the ESG industry predicts the so-called *greenium* (green premium), since green firms can provide better risk-adjusted returns to investors.

More specifically, the European market is an interesting laboratory to assess whether climate policies actually benefit green firms and hurt brown ones. Indeed, the European Union is a pioneer in the effort to reducing carbon emissions. In 2005, the EU set a cap on emissions and established the EU Emissions Trading System (ETS) which was the first international emissions trading scheme in the world. The effectiveness of such Cap-and-trade system requires directing financial resources towards the low-carbon economy. Previous studies show that carbon regulation in Europe is actually able to hurt stock returns of carbon-intensive firms (Berthold et al. (2023), and Hengge et al. (2023) among others).

In this paper, I extend the existing literature by providing new empirical evidence on the asset pricing effects of carbon policy shocks. I show that the overall effects on more climate-friendly vs less climate-friendly companies mask a large degree of heterogeneity and vary within oil-related sectors and states. This challenges the common assumption in the literature that treats brown firms as homogeneous. In reality, a substantial share of carbon-intensive firms operate in the oil and gas sector, where stock returns are strongly correlated with oil price fluctuations. Figure 1 shows a regression of the monthly Euro Stoxx Oil & Gas return on the monthly oil return, highlighting the strong positive correlation between the two series. Appendix A.5 further supports this idea with cumulative return plots.
This correlation suggests that the commonly used brown-minus-green (BMG) spread does not isolate the effects of carbon policy shocks, as it is also significantly exposed to oil price shocks. Therefore, I follow the approach of Shi and Zhang (2024) and decompose the BMG

spread into two components: (i) the ex fossil energy spread (the return differential between brown firms excluding fossil energy and green firms), and (ii) the fossil energy spread (the return differential between fossil energy firms and other brown firms). These two components allow to examine the potential contribution of oil shocks to the BMG spread return.

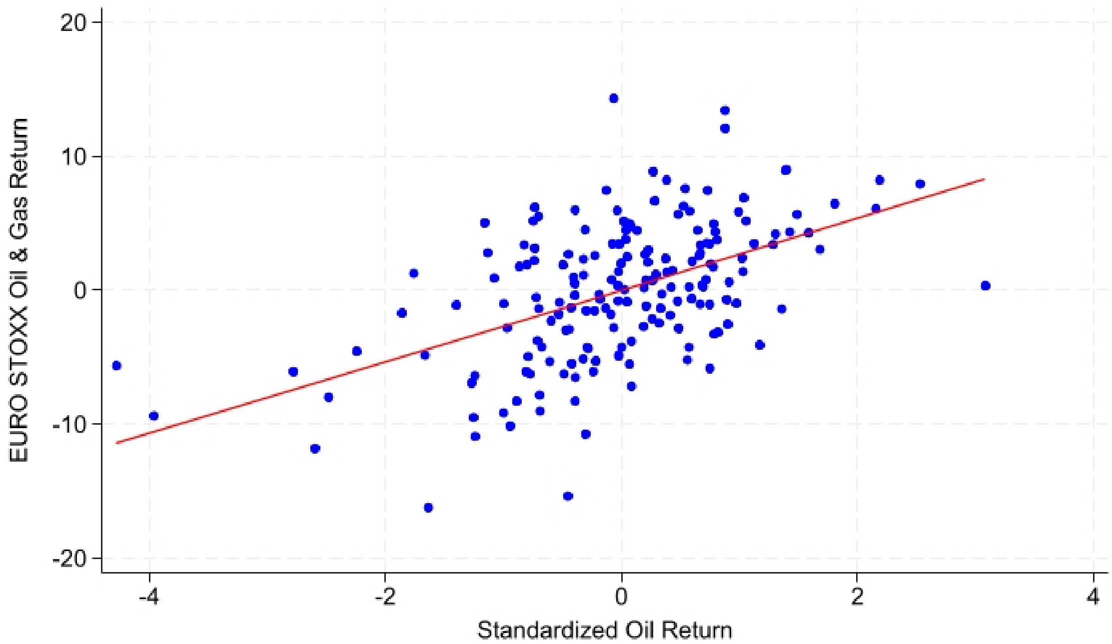

Figure 1: The figure plots the monthly return of the Euro Stoxx Oil & Gas Index against the standardized monthly return of oil. Sample period: January 2005 to December 2019.

The first contribution from this decomposition is that not all carbon returns are alike: the ex fossil energy spread decreases after carbon policy shocks as expected, in line with the literature. However, the fossil energy spread increases, meaning that fossil energy firms do not respond to carbon policy shocks as other brown firms, since they mainly reflect oil price variation.

The second contribution of the paper regards the non linear effects of carbon pricing policies. In particular, I show that the response of stock returns after carbon policy shocks vary depending on the specific oil cycles: bull vs bear regimes. Oil bull (bear) scenarios are identified endogenously via Markov-switching regression. Equity returns tend to suffer significantly more during oil bull periods (especially one year after the shock) compared to bear regimes, in which the equity response is more muted. Moreover, green firms tend to outperform brown during oil bull regimes compared to oil bear, in which the greenium disappears and brown firms may even benefit from the lower oil price.

To measure exogenous changes in the carbon price, I use the carbon policy shocks series recently developed by Känzig (2023). He identifies 126 regulatory events that influenced the supply of emission allowances in the EU ETS. The series of carbon policy surprises is then computed from the change in the carbon futures price in a tight window around the regulatory news. This surprise series serves as an instrumental variable, allowing for the estimation of the dynamic causal effects of a carbon policy shock on the economy.

My analysis consists of portfolio-level local projections à la Jordà (2005) with the carbon policy shocks series. The portfolio-based method is an established practice from empirical asset pricing (see for example Fama and French (1993)). I sort firms into green or brown portfolios based on reported emissions data and appropriate publication lags, and compute the two components of the BMG spread return. In particular, I measure firm-level greenness with the intensity of carbon emissions since such measure is the most used in the climate finance literature. The sample includes 587 unique stocks from the main 8 euro area countries: France, Germany, Italy, Spain, Austria, Belgium, Netherlands, and Finland.

As robustness test, I also estimate panel local projections at firm level, finding similar results compared to the portfolio-based local projections, confirming the main findings and providing additional confidence in the estimated heterogeneous responses across firm types.

My findings suggest the need for caution when analyzing brown vs green performance since the fossil energy sector follows oil price variation rather than carbon policy shocks, and such oil cycles (bull vs bear) are key to unpacking the effects of the carbon policy. Overall, this paper highlights the necessity of accounting for oil dynamics when assessing the impact of climate policy on asset prices.

Following an overview of the related literature (Section 2), the paper is structured as follows: Section 3 describes the data sources. Section 4 reports the results from the linear local projections, and the state-dependent local projections with oil bull and bear regimes. Section 5 shows the robustness of both the linear and the state-dependent cases with panel data. Section 6 concludes.

2 Related literature

This paper contributes to three key strands of literature. First, I add industry heterogeneity to the growing climate finance studies on the relationship between environmental practices of firms and financial performance.

The influential studies by Bolton and Kacperczyk (2021) and Bolton and Kacperczyk (2023) provide evidence in favor of the carbon premium, with brown stocks outperforming green ones, consistent with Delmas et al. (2015) and Busch et al. (2022). This evidence is based on panel regressions in which measures of financial performance, such as stock returns, are regressed on measures of greenness. Another example is Görgen et al. (2020), who regress their custom brown minus green score and find a positive coefficient.

Different works have instead investigated this issue with traditional empirical methods in asset pricing, based on portfolio sorts. Following this approach, Pástor et al. (2022) show that green stocks in the US have on average outperfomed brown. Such greenium is found also by Bauer et al. (2022) and Zhang (2025). Shi and Zhang (2024) is the first paper that underlines the importance of oil shocks in shaping the ex ante greenium (cost of capital gap between brown and green firms) in the US and internationally. Monasterolo and De Angelis (2020) develop an empirical analysis of the low-carbon and carbon-intensive indexes for the EU, US and global stock markets. They test if financial markets are pricing the Paris Agreement (PA) by rewarding (penalizing) low-carbon (carbon-intensive) indexes. They find that the overall performance of the low-carbon indexes has increased after the PA due to a reduction in their level of systematic risk. Borghesi et al. (2022) examine the behavior of green and brown portfolios around green policy-related announcements made by major

European governments in 2020 via a standard event study analysis and the use of returns of stocks listed in the STOXX 100 All Europe Index. Their results indicate the presence of positive cumulative abnormal returns both in the green and brown sectors, with a stronger effect in the former sector. Focusing on the european market, Benchora and Galanti (2024) study the returns of firms partecipating in the EU ETS and find evidence on the greenium based on carbon measures with a relatively short sample of firms. Ardia et al. (2023) show that green stocks tend to outperform brown stocks in response to unexpected increases in climate change concerns, measured from newspaper articles.

Second, I contribute to the literature on the impact of climate policy on the economy and financial markets. Using a novel dataset containing stock prices and carbon intensities of 338 European publicly traded companies between 2013 and 2021, Millischer et al. (2023) find a negative relationship between stock performance and carbon intensity. Using data on more than 2000 publicly listed European companies, Hengge et al. (2023) show that carbon pricing shocks lead to negative abnormal returns, which increase with a firm's carbon intensity. A similar result comes from Berthold et al. (2023) through firm-level panel local projections. Donadelli et al. (2022) develop a calibrated macro-finance model to show that is extremely difficult to quantify carbon premia based on relatively short sample periods. Mangiante (2024) studies the heterogeneous impact of carbon pricing on European regions and document that poorer regions are more exposed to these shocks.

Third, I contribute to a large and growing literature on the state-dependent effects of macroeconomic and policy shocks. Auerbach and Gorodnichenko (2012) and Ramey and Zubairy (2018), among others, investigate the effects of fiscal policy shocks during good and bad times and find mixed evidence. Here I follow their specification with oil bull and bear periods identified via Markov-switching regression (see for example Hamilton (1989), Kim et al. (1998)).

3 Data

I obtained firm-level accounting, equity return, and carbon emissions data from Refinitiv: accounting data are from the Refinitiv's Worldscope database, equity returns are from Datastream, and environmental performance (carbon emissions) from the ESG database. In my empirical analysis I include 587 unique companies listed in the following 8 euro area countries: France, Germany, Italy, Spain, Austria, Belgium, Netherlands, and Finland.

An important methodological consideration is whether to focus on total emissions or emission intensity. The appropriate choice depends on the research question at hand. In this paper, I focus on emission intensity, since it is more suitable for capturing the relationship between policy shocks and stock returns, as discussed by Hengge et al. (2023). The database reports the sum of scope 1 (direct) and scope 2 (indirect) total greenhouse gas (GHG) emissions in tons of CO_2 equivalents. Following other climate finance studies I leave out scope 3 emissions, because these indirect emissions from upstream and downstream activities of the reporting firm are very large in magnitude and difficult to estimate. Then, I scale the level of emissions by firm-size, following a procedure that is widely used in empirical works in climate finance. Specifically, I define emission intensity as the ratio between total emissions and sales.

To compute monthly stock returns, I use the closing price in euro for each stock in my sample and I compute the monthly stock return as follows:

$$R_{i,t} = ln(P_{i,t}) - ln(P_{i,t-1}),$$

where t is end-of-the month closing price. To construct the value weighted portfolios, I also use monthly observations of market cap. Table 1 reports summary statistics of emissions data together with market cap for firms over the sample period from 2005 to 2019. The choice of this sample is driven by the availability of emissions data and the carbon policy shocks series provided by Känzig (2023), which stops in 2019 to avoid large shocks due to the Covid-19 pandemic.

Table 1: Summary Statistics. Sample period: January 2005 to December 2019.

	Mean	SD	Q25	Median	Q75	Obs.
Emission Intensity	0.30	0.86	0.01	0.04	0.16	53,760
Log Emissions Level	12.31	2.64	10.63	12.19	14.07	53,688
Log Market Cap	8.51	1.38	7.61	8.45	9.44	53.760

I define firms to be in the fossil energy sector if the Refinitiv Business Sector is *Energy - Fossil Fuels*. A closer look at emission intensities across sectors reveals that utilities is the most carbon-intensive, followed by mineral resources, fossil fuels, chemicals, and applied resources (Figure 2).

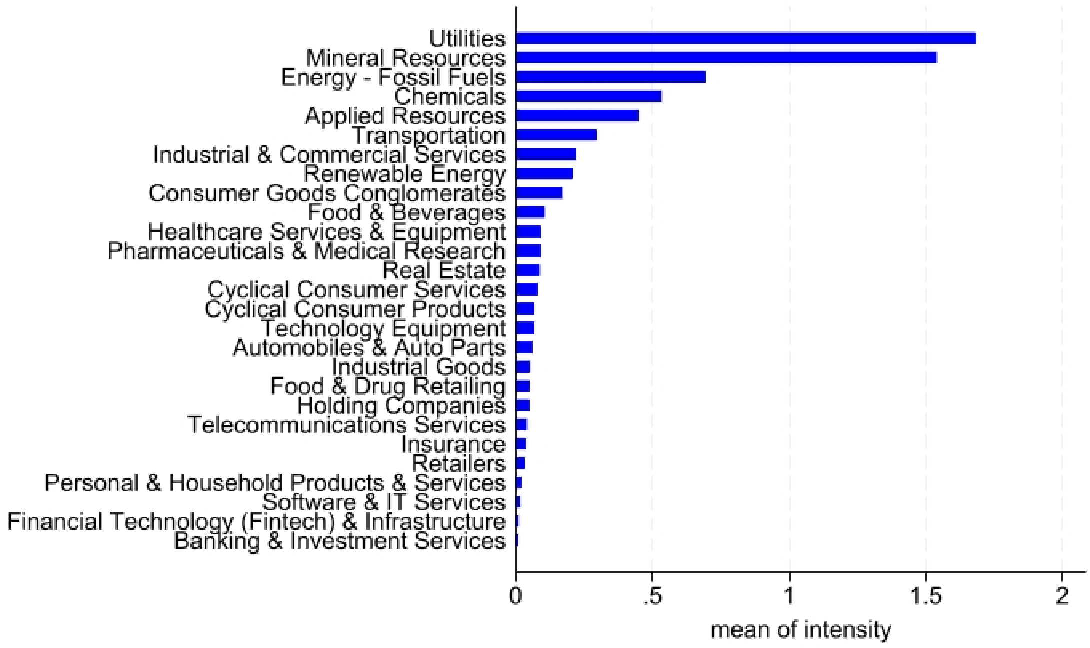

Figure 2: Emission intensity across sectors. The figure shows the mean scope 1 plus scope 2 emission intensity across sectors.

To illustrate the coverage of firms in my data, Figure 3 plots the number of firms in the sample. At the beginning of the sample (2005), the number of available firms is 180 and increases to a level around 600 in 2019. This increase reflects a greater tendency of firms to report emissions and the improved coverage of the Refinitiv database. Additional statistics on the number of firms by country and sector are in Appendix A.2.

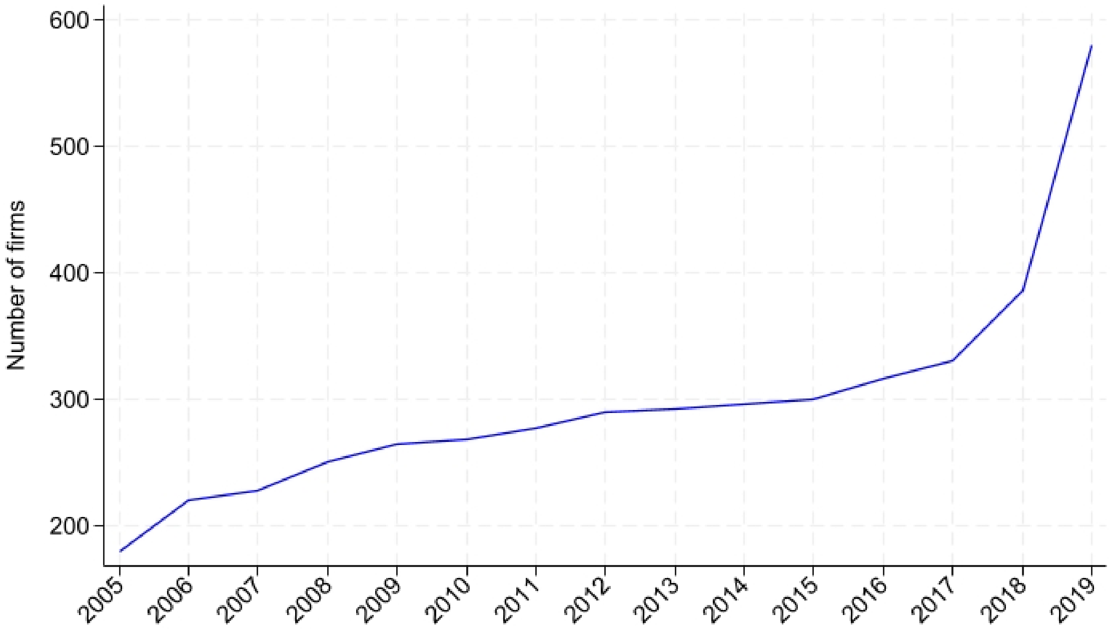

Figure 3: Number of firms (using 1-year publication lag).

I construct the real price of oil by adjusting the nominal price of Brent Crude Oil using the Harmonized Consumer Price Index (HICP) for the euro area. In order to define oil bull and bear regimes, I apply a Markov-switching regression (Hamilton (1989)) to the monthly return of oil as follows:

$$oil_t = \mu_{s_t} + \epsilon_t, \tag{3.1}$$

with $s_t \in \{Bear, Bull\}$ that follow a Markov process, and ϵ_t is a white noise error with switching variances σ_{s_t}. The regression's results are in Appendix A.1. The mean return in bear periods is -0.54, while the mean return in bull is around 0.13. The standard deviation of oil returns is twice as high during oil bear periods compared to bull periods, as expected, due to increased volatility typically associated with market downturns. The filtered probabilities to be in each oil state are represented in Figure 4. The filtering is performed on previous periods and the current period.

The carbon policy shocks are computed as in Känzig (2023). Here I briefly summarize his approach but I refer to the original paper for a detailed description. The author exploits the fact that the European carbon market, established in 2005, operates under the cap and trade principle. This means that a cap is set on the overall amount of certain greenhouse

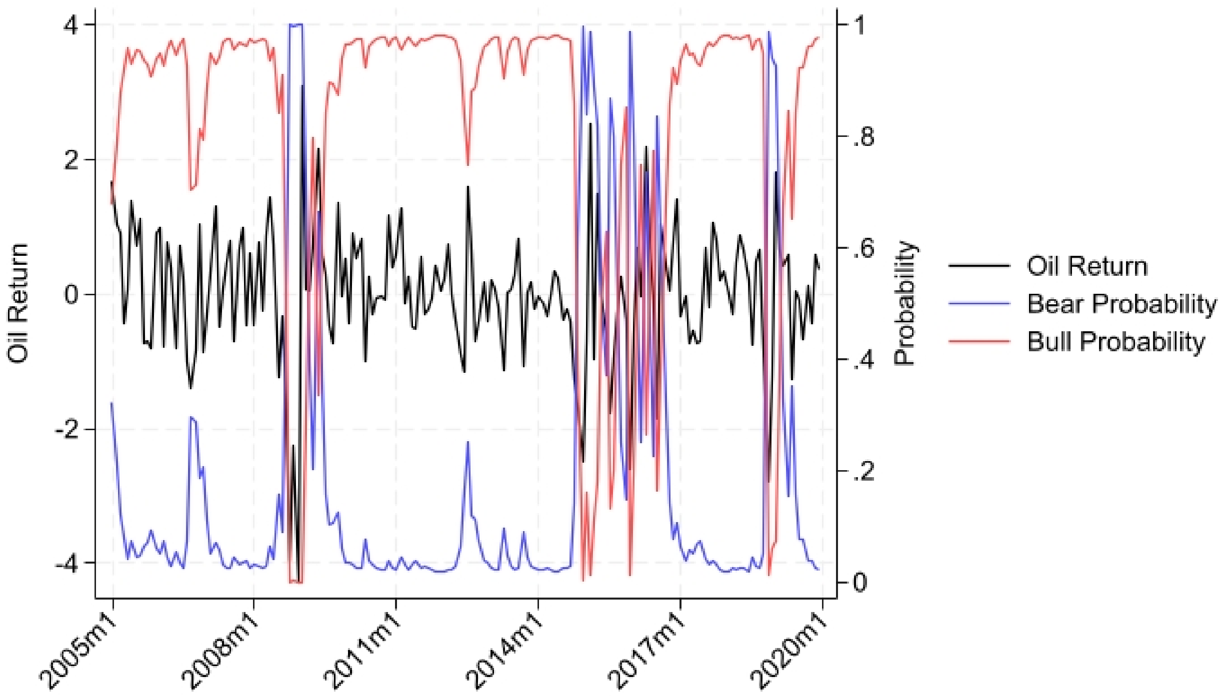

Figure 4: The figure plots the standardized oil return (%), together with the filtered probabilities to be in oil bull (red) or oil bear (blue) scenarios.

gases that can be emitted. Within the cap, emission allowances are auctioned off and traded in different organized markets. Each year the cap decreases ensuring that total emissions fall. Känzig (2023) identifies 126 events during the period between 2005 and 2019 concerning the overall cap in the European Union Emissions Trading System (EU ETS), the free allocation of allowances, the auctioning of allowances as well as the use of international credits. He then defines carbon policy surprises from the changes in the futures price of the EU emission allowances (EUA) around the day of regulatory events. The daily surprises are then aggregated into a monthly series by summing over the daily surprises in a given month. In months without any regulatory events, the series takes zero value. The resulting carbon policy surprise series is shown in Figure 5.

The carbon policy surprise series can be considered only a partial measure of the shock of interest. Indeed, it may not capture all relevant instances of regulatory news in the carbon market and could be subject to measurement errors. Therefore, to isolate the carbon policy shocks, Känzig (2023) uses the surprises as an external instrument in a proxy-VAR model with eight variables: the energy component of the HICP, total GHG emissions, the headline

HICP, industrial production, the unemployment rate, the policy rate, the Euro Stoxx Index, as well as the real effective exchange rate.

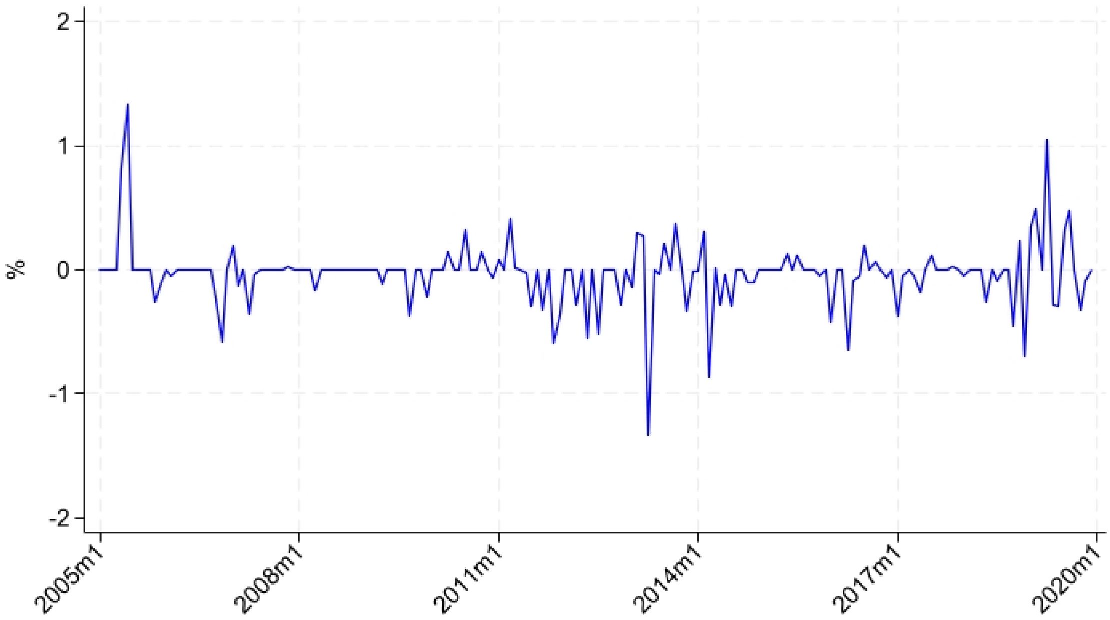

Figure 5: The carbon policy surprise series, constructed by dividing the daily change in the price of EUA futures contract around regulatory policy events by the wholesale energy price.

4 Portfolio returns and carbon policy shocks

4.1 Empirical methodology

My empirical approach is to analyze portfolios constructed of green and brown firms that are defined by their relative emission intensity. For this exercise to be informative, it is important to classify firms and measure their performance in a way that is consistent with what investors could have achieved in real time. To this end, I classify firms into portfolios based on lagged environmental data that was available at that time.

ESG data are available on an annual basis. Therefore, at the beginning of each year I build new green and brown portfolios using environmental data from the previous year. Specifically, the value weighted portfolios are constructed using contemporaneous market data as of the beginning of January and environmental data from the previous year. Then, portfolio returns are calculated for the subsequent twelve months until the beginning of the new year, when a new sorting process takes place. In other words, returns at year t are matched to environmental data from year t-1. For example, the portfolio sorts used for the returns in each month from January 2008 to December 2008 are based on environmental data for 2007.

I sort firms into tercile portfolios and then classify the top tercile as brown firms and the bottom tercile as green peers. Figure 6 presents the sector representation in the value weighted brown portfolio. Consistent with the firm-level intensity distribution, the brownest sector is Utilities followed by Energy, and Basic Materials. These three sectors account alone for more than half of the value weighted brown portfolio. Such sectoral distribution appears slightly different within the equally weighted brown portfolio (Figure 7). In this case, the largest fraction of firms in the brown portfolio is composed by Basic Materials (28.21%), followed by Utilities, Industrials, and Energy. Quite interestingly, in the equally weighted brown portfolio the energy sector represents a smaller share than in the value weighted counterpart. This is likely due to the smaller number of firms in the energy sector, despite their typically higher market capitalization. Appendix A.3 describes the sectoral distribution within green portfolios, with the Financial sector that dominates the composition of both, the value weighted and the equally weighted portfolios.

Previous studies have considered the brown sectors as homogeneous, while actually the fossil energy sector is particularly vulnerable to oil fluctuations. Therefore, I follow Shi and Zhang (2024) and decompose the brown minus green spread into the following two components:

1) **Ex fossil energy spread**, which represents the spread between the top tercile brown firms (excluding fossil fuels) and the bottom tercile green firms.

2) **Fossil energy spread**, which is the spread between fossil energy firms and other non fossil energy brown firms.

Appendix A.4 shows the time series evolution of the fossil energy spread and the ex fossil energy spread across the sample. These two series display distinct dynamics over the 15-

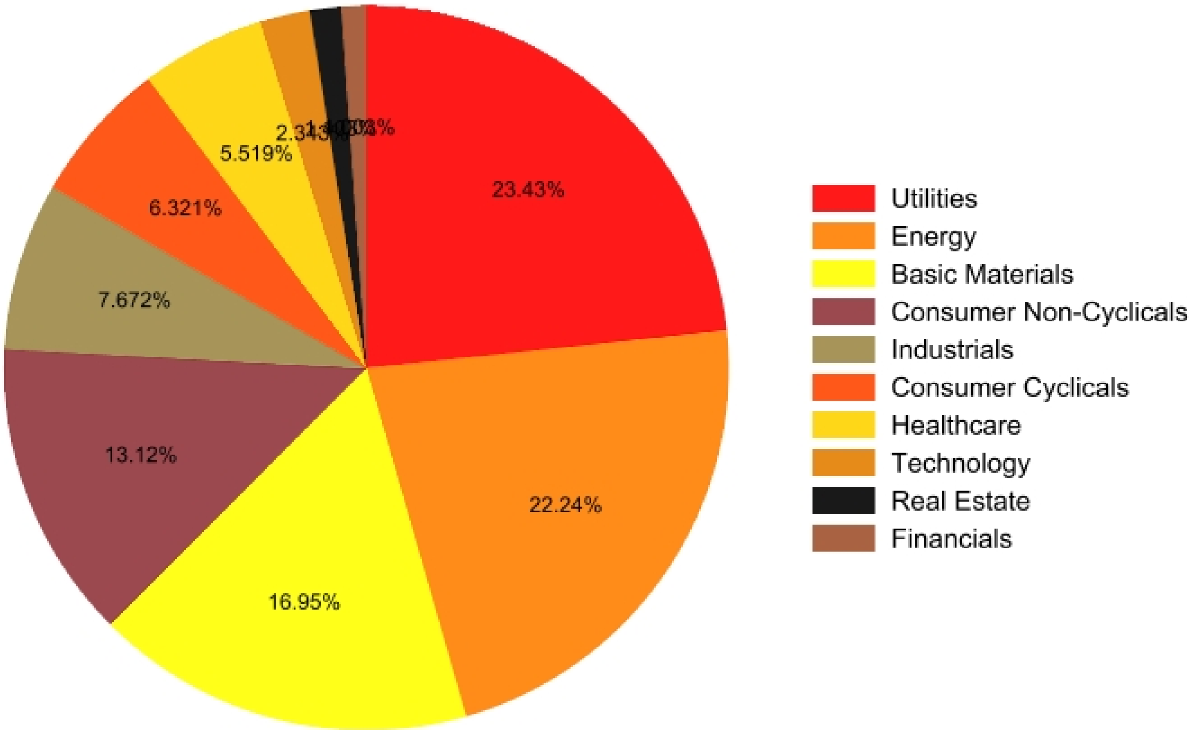

Figure 6: Average brown portfolio weight by sector. The weights reflect the proportional representation of each sector within the value weighted brown portfolio.

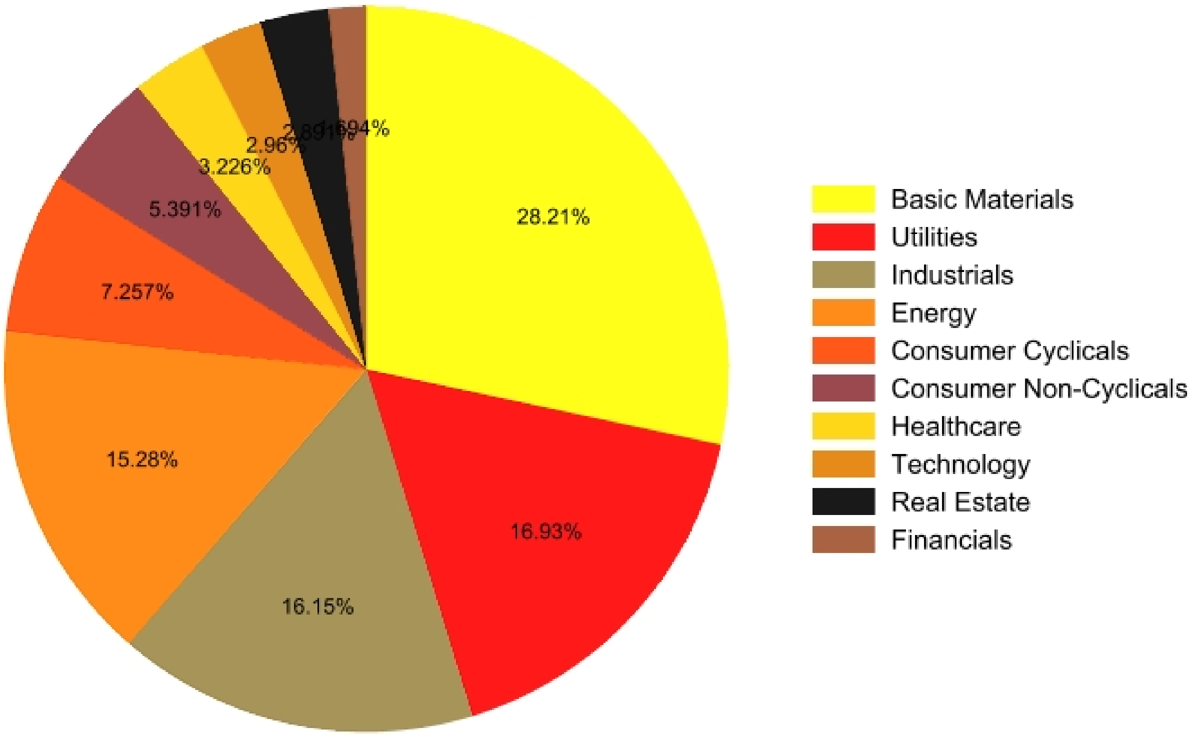

Figure 7: Average brown portfolio weight by sector. The weights reflect the proportional representation of each sector within the equally weighted brown portfolio.

years period and display a negative correlation of -0.37 for the value weighted portfolios, and -0.28 for the equally weighted.

Before moving to the dynamic effects of carbon policy shocks on the two components of the brown minus green spread, I test the effects of the carbon policy shocks on the green, the brown, and the market portfolio. Then, I examine the relative performance of ex fossil energy spread and fossil energy spread. Finally, I exploit the non linear effects of carbon policy shocks under different oil regimes.

4.2 Linear local projections

I first establish a linear benchmark to assess the effects of one standard deviation carbon policy shock. To do this, I perform local projections as in Jordà (2005). Specifically, the specification takes the following form:

$$z_{t+h} = \alpha_h + \beta_h CPS_t + \gamma_h oil_t + \phi_h(L) y_t + \epsilon_{t+h}, \tag{4.1}$$

where z_t is the variable of interest (portfolio returns), CPS_t is the standardized carbon policy shocks series, oil_t is the standardized return of oil, and I control for six lags of portfolio returns (the vector y_t).

As a sanity check, I first run the specification in 4.1 for the market, the green, and the brown portfolio. Figure 8 shows the results for the value weighted portfolios (Market, Green, Brown), while Figure 10 shows the results of the same specification for the equally weighted portfolios (Market, Green, Brown).

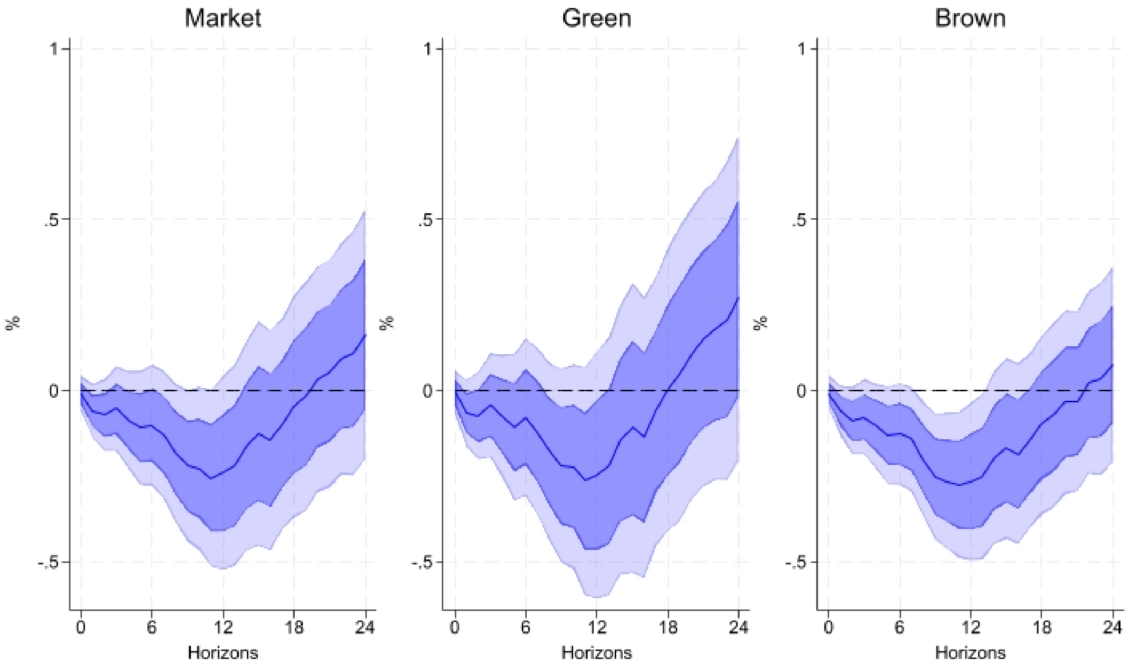

Figure 8: Impulse response of value weighted portfolio returns (β_h) from equation 4.1 for horizon $h \in \{0, 1, 2...24\}$ months. Shaded areas display 68 and 90 percent confidence intervals based on robust standard errors. The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

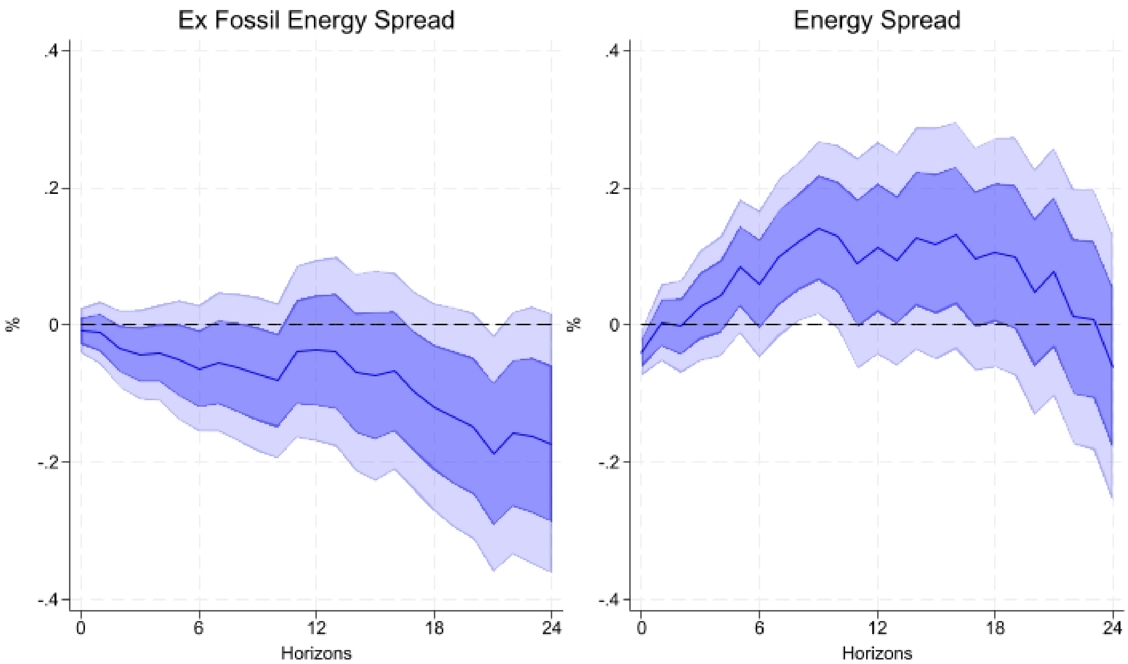

Figure 9: Impulse response of value weighted spread portfolio returns (β_h) from equation 4.1 for horizon $h \in \{0, 1, 2...24\}$ months. Shaded areas display 68 and 90 percent confidence intervals based on robust standard errors. The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

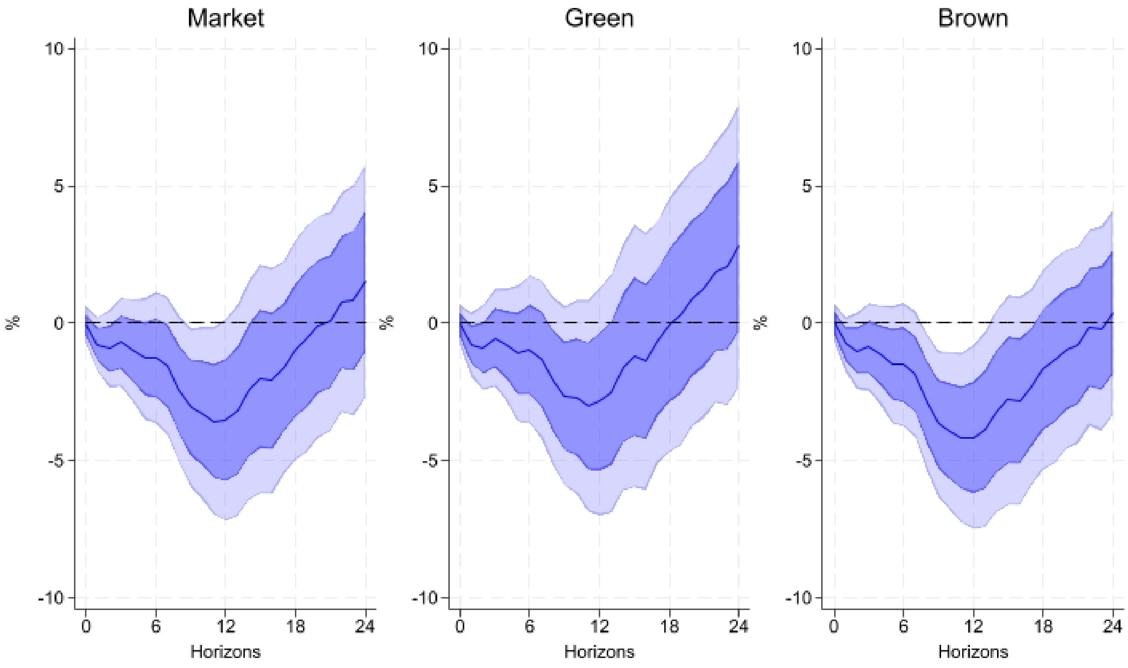

Figure 10: Impulse response of equally weighted portfolio returns (β_h) from equation 4.1 for horizon $h \in \{0, 1, 2...24\}$ months. Shaded areas display 68 and 90 percent confidence intervals based on robust standard errors. The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

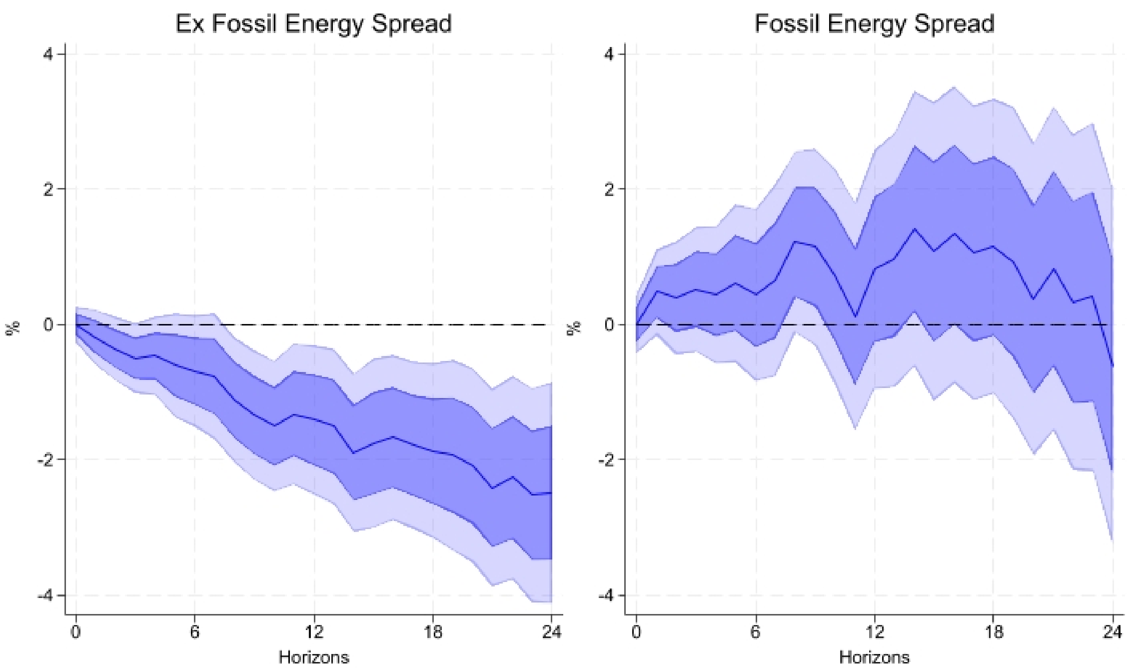

Figure 11: Impulse response of equally weighted spread portfolio returns (β_h) from equation 4.1 for horizon $h \in \{0, 1, 2...24\}$ months. Shaded areas display 68 and 90 percent confidence intervals based on robust standard errors. The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

The value weighted brown portfolio experiences a significant decline in returns, approximately 0.25 percent after one year following a carbon policy shock (Figure 8). In contrast, the green portfolio exhibits an insignificant response, similar to the overall market. Figure 9 illustrates the heterogeneous response of the two components of the BMG value weighted spread return: the ex fossil energy spread and the fossil energy spread. As expected, the ex fossil energy spread (brown excluding fossil fuels minus green) declines significantly and persistently after the shock, with the negative response lasting up to 24 months. Conversely, the fossil energy spread (fossil fuels minus other brown non fossil fuels) increases following the shock, but this rise is less persistent, dissipating within two years. This distinction is particularly insightful. It suggests that fossil energy firms do not respond to carbon policy shocks in the same way as non fossil brown firms. The latter experience return declines (as shown in Figure 8), while the response of fossil energy portfolio is statistically insignificant, resulting in a positive response of the fossil energy spread.

In the equally weighted portfolio, the effects are even more pronounced (Figure 10). The brown portfolio exhibits a 5 percent decline in returns after one year. Figure 11 shows the responses of the spread portfolios. Specifically, the ex fossil energy spread drops more sharply, by 2 percent after one year, compared to only 0.2 percent in the value weighted counterpart. This difference likely reflects the greater sensitivity of smaller firms to carbon policy shocks. On the other hand, the increase in the fossil energy spread is less significant in the equally weighted portfolio, indicating that smaller fossil energy firms react similarly to other brown firms.

4.3 State-dependent effects of carbon policy shocks (oil bull and bear regimes)

The rationale for analyzing the state dependence of carbon policy shocks across oil market regimes stems from the connected nature of oil prices and oil-related companies. Therefore, one may expect that the BMG spread return and its components are affected by oil

regimes (bull or bear). In oil bull (bear) markets, high (low) oil prices tend to increase (reduce) the financial performance of fossil energy firms. Therefore, it can potentially offset or even reverse the negative impact of carbon regulation on expected returns of fossil energy stocks with respect to other brown companies. Moreover, non fossil energy brown firms may benefit from bear scenarios because of the lower oil prices, as these reduce input costs and improve profit margins. Studying this heterogeneity helps uncover whether financial markets internalize the transition risks and whether the same policy signal has different pricing implications depending on broader macroeconomic and commodity market conditions.
Specifically, I expand the linear model from equation 4.1 to a state-dependent setup, given by

$$z_{t+h} = I_{t-1}(\alpha_h^A + \beta_h^A CPS_t + \gamma_h^A oil_t + \phi_h^A(L)y_t) + (1 - I_{t-1})(\alpha_h^B + \beta_h^B CPS_t + \gamma_h^B oil_t + \phi_h^B(L)y_t) + \epsilon_{t+h}, \tag{4.2}$$

where I_{t-1} is the probability to be in bull regime as in Figure 4. I use a lagged state to deal with possible endogeneity concerns, so I address whether a shock propagates differently conditional on the state of the oil regimes in the month before it hits. Here, β_h^k represents the response of variable z_t at horizon h in state $k \in [A, B]$ where A corresponds to oil bull regimes and B to oil bear regimes. This coefficient measures the average effect of the shock based on the initial state. I allow all coefficients to change based on the state of the economy, nesting the case of all coefficients being linear.

Figure 12 presents the impulse responses for the market returns after carbon policy shocks. The results are strongly heterogeneous based on the oil regimes. The oil bull markets resemble the linear dynamic discussed in section 4.2, with a negative effect of carbon policy shocks on stock returns. This effect is much more pronounced in the bull state of the oil market, with the value weighted (VW) equity portfolio that drops by around 0.5 percent after one year. The equally weighted (EW) equity portfolio shows a negative response to the shock of 5 percent after one year. The difference in the magnitude of the responses between the VW and the EW portfolio is nearly identical as the linear case.
The main message here is that carbon policy is much more effective during oil bull periods

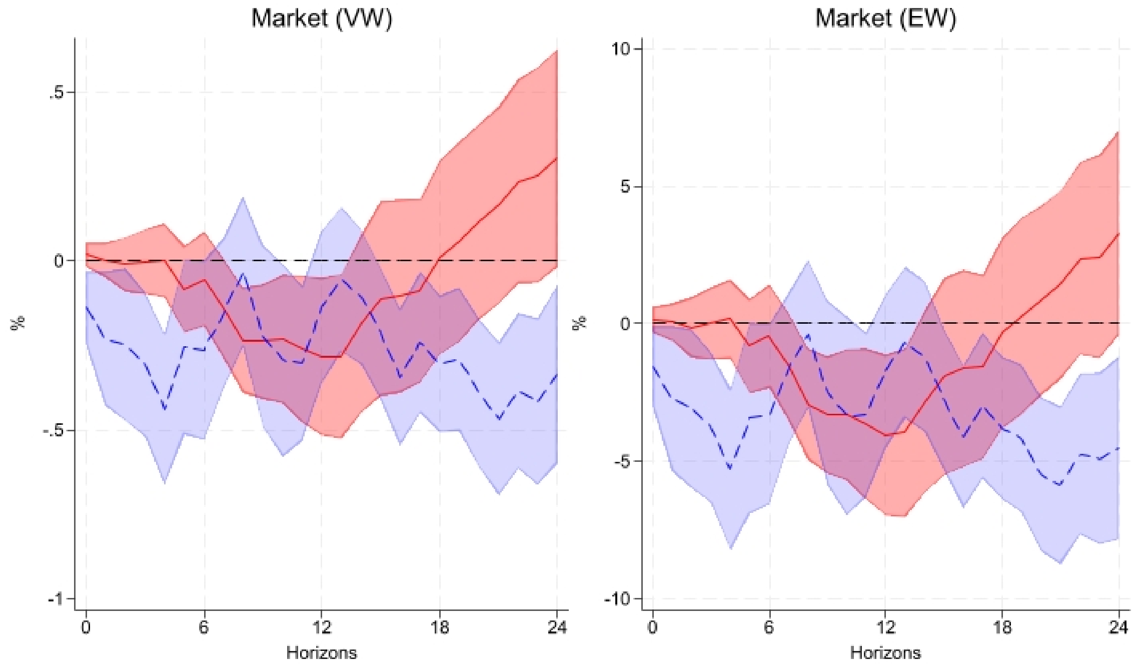

Figure 12: Impulse response of market returns (β_h) from equation 4.2 for horizon $h \in \{0, 1, 2...24\}$ months in oil bull (red solid) and oil bear (blue dashed) regimes. Left: value weighted (VW) portfolio. Right: equally weighted (EW) portfolio. Shaded areas display 68 confidence intervals based on robust standard errors. The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

compared to bear scenarios. Why is it so? The idea is that both carbon policy tightening and oil bull regimes have a similar effect on the economy: they raise production costs for the average firm. Indeed, firms face higher compliance costs (due to the carbon policy) and many firms rely on oil as input in production. Therefore, the combined effect reduces corporate earnings more with oil bull markets compared to the bear case.

During oil bear regimes instead, the carbon policy shocks have a weak effects on portfolio returns, with a response that is statistically insignificant in particular one year after the shock. This muted response can be explained by the fact that, in periods of low oil prices, the cost pressure from energy inputs is generally reduced. As a result, the potential impact of carbon pricing on firms' operating costs is partially offset, especially for the average firm across sectors. In other words, oil bear regimes act as a cost relief mechanism that dampens the effect of carbon policy shocks on equity returns.

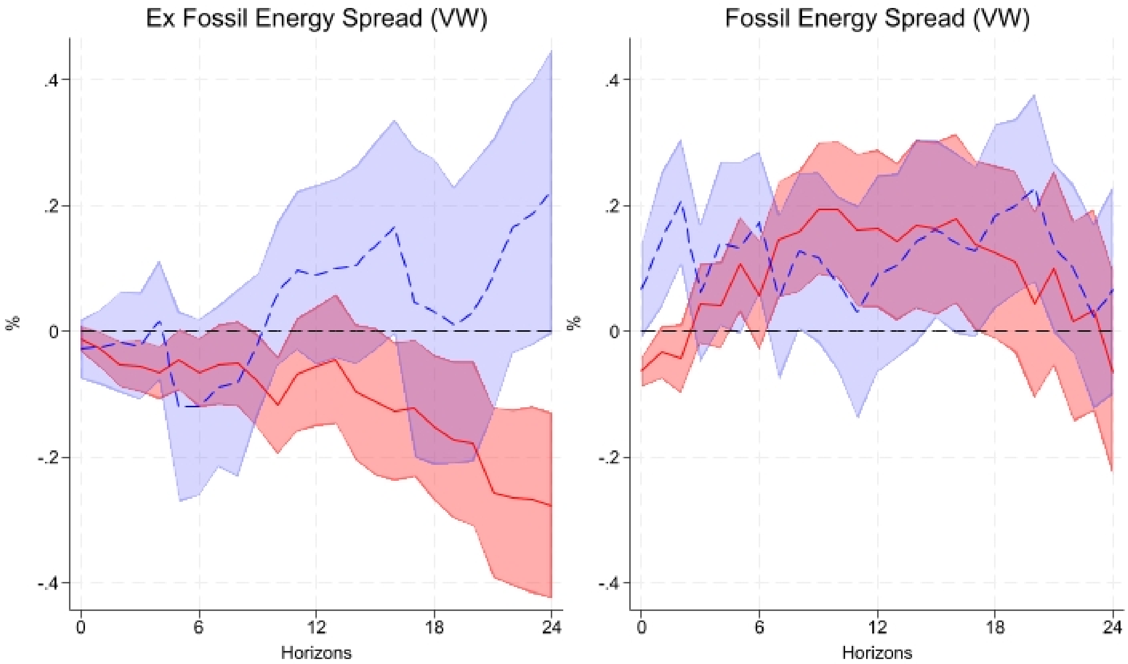

Figure 13: Impulse response of value weighted spread returns (β_h) from equation 4.2 for horizon $h \in \{0, 1, 2...24\}$ months in oil bull (red solid) and oil bear (blue dashed) regimes. Shaded areas display 68 percent confidence intervals based on robust standard errors. The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

I now discuss the non linear effects of carbon policy shocks on my spread returns. Figure 13 shows the responses of the value weighted (VW) spread portfolios during oil bull vs bear regimes. In oil bull, the ex fossil energy spread decreases and the fossil energy spread increases after the shock. The observed dynamics following carbon policy tightening highlight a key distinction within the brown portfolio between fossil energy and non fossil energy firms. Specifically, the decline in the ex fossil energy spread suggests that those brown firms bear a disproportionate burden in the face of carbon regulations. Such firms, often more reliant on carbon-intensive production processes (based on oil) and with fewer opportunities to pass through higher input costs, face increased operational and compliance costs. In contrast, the higher fossil energy spread indicates that larger fossil energy firms are comparatively less penalized, and may even benefit temporarily because of the bull regimes. This divergence can be largely attributed to the fact that fossil energy firms are much more responsive to oil price fluctuations rather then to carbon policy shocks. When oil prices rise, oil firms see their margins and valuations improve, which may partially or fully offset any negative policy effects. Hence, the increase in the fossil energy spread reflects a relative insulation or even advantage for oil-producing firms during these periods. Overall, these results point to a heterogeneous exposure to carbon policy shocks, where oil firms, though still brown, respond more like hedgers than victims, while other brown sectors bear the brunt of the regulatory cost.

In oil bear regimes instead, neither fossil energy firms nor other brown non fossil energy react significantly to carbon policy shocks. This muted response of the fossil energy spread can be interpreted through the lens of conflicting forces: on one hand, carbon regulations impose additional costs, especially on carbon-intensive firms; on the other hand, the simultaneous decline in oil prices during bear markets offers a cost relief, particularly for non fossil energy brown firms. These two effects may largely offset each other, resulting in a neutral net impact on returns. For oil firms, already under pressure due to weak oil prices and reduced profit margins, the additional burden from climate regulation may be insufficient to significantly move valuations, given that their performance is already suppressed. Moreover, the ex fossil energy spread exhibits a muted response during oil bear periods. This can be attributed to the fact that brown non fossil energy firms benefit from lower oil prices, which reduce their overall input costs. As a result, the cost relief associated with oil bear regimes offsets, at least partially, the burden imposed by carbon regulation. This dynamic weakens the relative advantage of green firms, thereby dampening the green outperformance, or greenium, observed during oil bull periods.

Figure 14 shows the responses of the equally weighted (EW) spread portfolios. In oil bull periods the ex fossil energy spread decreases immediately after the shock hit and such decline is persistent as in the value weighted case. In bear scenario the response of such spread is not significant as expected.

The behavior of the fossil energy spread, however, diverges from the value weighted case. In bull periods, the outperformance of fossil energy firms relative to other brown firms is more muted: the estimated coefficients remain positive but are less statistically significant. In contrast, during oil bear periods, the fossil energy spread increases significantly. The difference with respect to the value weighted fossil energy spread must be due to the relative importance of smaller firms in the portfolio. Indeed, the equally weighted portfolio gives the

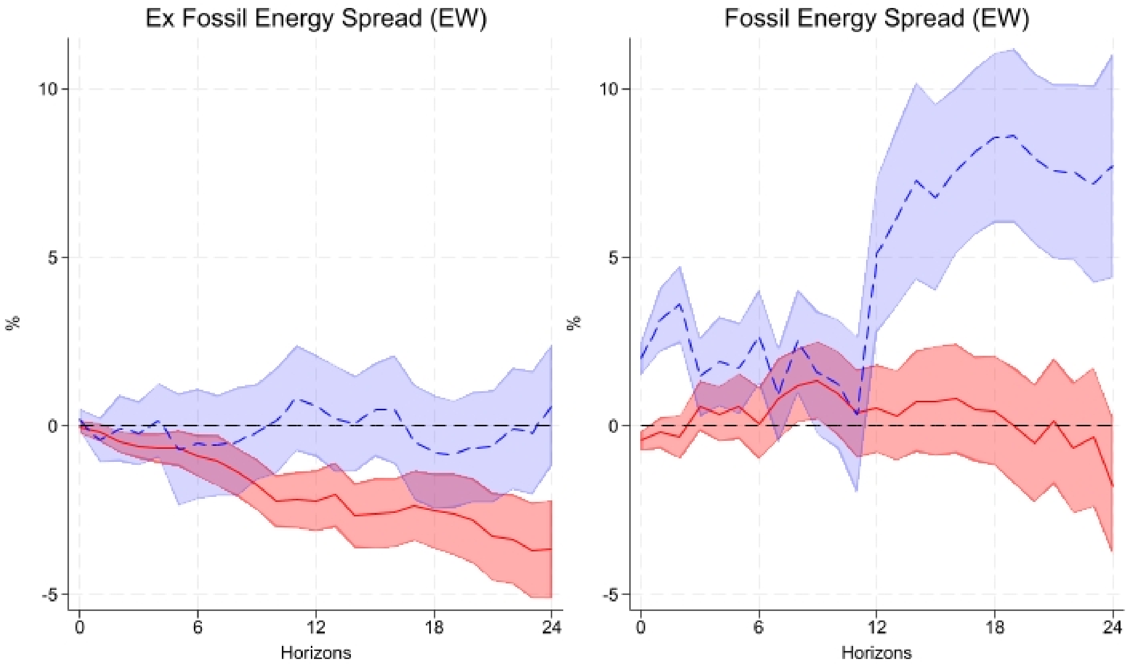

Figure 14: Impulse response of equally weighted spread return from equation 4.2 for horizon $h \in \{0, 1, 2...24\}$ months in oil bull (red solid) and oil bear (blue dashed) regimes. Shaded areas display 68 percent confidence intervals based on robust standard errors. The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

same weight to each firm in the sample. It is likely that smaller oil firms are more exposed to the carbon policy compared to bigger oil companies. This could explain why during oil bull regimes smaller oil firms do not benefit from the higher oil price compared to other small brown firms, and during bear regimes the latter can be more exposed to the carbon shocks, pushing the spread up.

5 From portfolios to panel data

My baseline analysis is based on portfolio evidence. It shows the relative performance of strategies that investors could have achieved in real time, which is an important reason for their popularity. However, as underlined by Bauer et al. (2022), simple portfolio methods may also reflect the effects of differences in industry or technological characteristics that are correlated with but do not directly contribute to carbon intensity. Therefore, as a robustness check, I also implement panel local projections of stock returns under carbon policy shocks.

This exercise is useful to see whether my results are sensitive to fixed effects or firm-level controls that enter into the panel regressions.

I start my comparison in an environment as close as possible to the baseline specification. To do so, I consider the equally weighted portfolio analysis. Since panel regressions by default also weigh each observation equally, this is the natural starting point. I define an indicator variable, D_{it}, that takes value +1 if stock i in month t belongs to the top tercile of the emission intensity distribution, -1 if stock i in month t belongs to the bottom tercile, and 0 otherwise. I further define a brown type dummy, B_{it}, that is 1 if firm i in month t belongs to the brownest tercile and to the fossil energy sector, and 0 if firm i in month t belongs to the brownest tercile but it is not fossil energy.

In cross sectional local projections of stock returns in month t, the interaction coefficients between the carbon policy shocks series and the dummy (D_{it} or B_{it}), would give the dynamic effects of the carbon policy shocks for each cross section. Then, the time series average of each cross sectional coefficient at each horizon would reproduce the coefficients I obtained from the local projections with equally weighted portfolios.

Instead of estimating separate local projections in each month, panel local projections pool all firm-month observations. To replicate the ex fossil energy spread I drop firms that belong in the fossil energy sector after having built the dummy variable D_{it}. For the fossil energy spread instead, I estimate the panel local projections with the brown type dummy, B_{it}.

I start the panel analysis with the linear case. In particular, I estimate the following panel local projections for stocks that have indicator variable D_{it} equal to 1 (brown), -1 (green) and for the entire sample:

$$z_{i,t+h} = \beta_h CPS_t + \gamma_h \, oil_t + \phi_h(L) \, y_{it} + \Gamma_h \, F_{i,t-1} + \alpha_{sh} + \epsilon_{i,t+h}, \tag{5.1}$$

where α_s is a sector fixed effect that captures permanent differences across sectors at horizon h. $F_{i,t-1}$ is a vector of firm-level controls such as leverage (total debt divided by total assets), size (log of market value), and a measure of profitability (1-year sales growth). Since these controls are annual variables, I lag each of them by one year.

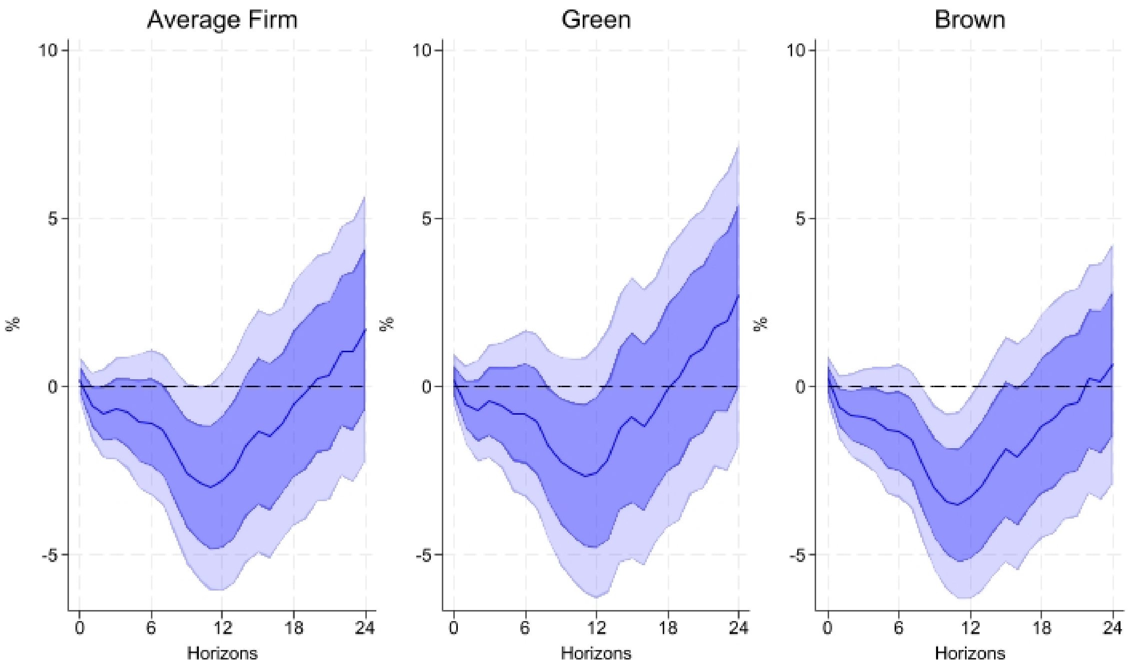

Figure 15: Impulse response of stock returns (β_h) from equation 5.1 for horizon $h \in \{0, 1, 2...24\}$ months. Shaded areas display 68 and 90 percent confidence intervals based on robust standard errors (two-way clustered, at the month and firm level). The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

Figure 15 plots the coefficient of interest β_h, which captures the dynamic effects of carbon policy shocks on equity returns for each group of stocks in my sample. Reassuringly, the impulse responses to the carbon policy shocks I obtain from firm-level data are very similar to those I obtain from the equally weighted portfolio-based local projections. Equity returns slowly fall over time, with the brownest firms that see their returns decline around 1 percent more compared to green.

I now move to investigate directly whether I reach a similar results also in terms of return spread between brown excluding fossil fuels and green firms (ex fossil energy spread). I estimate the following panel local projections:

$$z_{i,t+h} = \beta_h \left(CPS_t \times D_{it}\right) + \phi_h(L)\, y_{it} + \Gamma_h\, F_{i,t-1} + \alpha_{sh} + \alpha_{tch} + \epsilon_{i,t+h}, \tag{5.2}$$

where α_{tc} are country by time fixed effects. My coefficient of interest is the interaction between the CPS_t and the dummy D_{it}, and I drop fossil energy firms from the sample after having built the green-brown dummy.

To reproduce the fossil energy spread instead, I run a similar specification as in 5.2 but now the coefficient of interest is the interaction between the CPS_t and the brown type dummy, B_{it}:

$$z_{i,t+h} = \beta_h \left(CPS_t \times B_{it}\right) + \phi_h(L)\, y_{it} + \Gamma_h\, F_{i,t-1} + \alpha_{sh} + \alpha_{tch} + \epsilon_{i,t+h}. \tag{5.3}$$

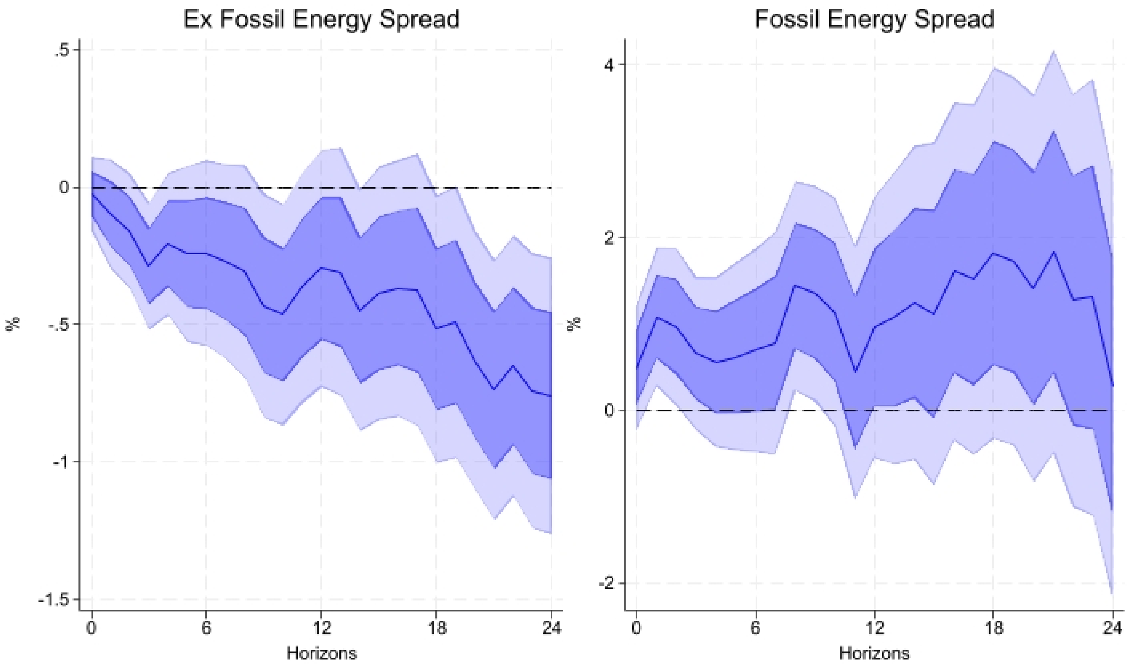

Figure 16: Impulse response of stock returns (β_h) from equation 5.2 and 5.3 respectively, for horizon $h \in \{0, 1, 2...24\}$ months. Shaded areas display 68 and 90 percent confidence intervals based on robust standard errors (two-way clustered, at the month and firm level). The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

Figure 16 shows the impulse responses of the spread returns using the dummy variables. The results are very similar to those in Figure 11, with the ex fossil energy spread that decreases over time reaching 1 percent after two years. The fossil energy spread increases on impact but the effect vanishes after two years (as it happens in Figure 11).

Motivated by the cross-sectional evidence for the entire sample, I now estimate the state-dependent panel local projections to check the different equity responses under oil bull and bear periods. The specification is as follows:

$$z_{i,t+h} = I_{t-1}(\beta_h^A CPS_t + \gamma_h^A oil_t + \phi_h^A(L)y_{it}) + (1-I_{t-1})(\beta_h^B CPS_t + \gamma_h^B oil_t + \phi_h^B(L)y_{it}) + \Gamma_h F_{i,t-1} + \alpha_{sh} + \epsilon_{i,t+h}, \tag{5.4}$$

and show that the impulse responses in Figure 17 are nearly identical to those I obtained from the equally weighted portfolio-based local projections (Figure 12).

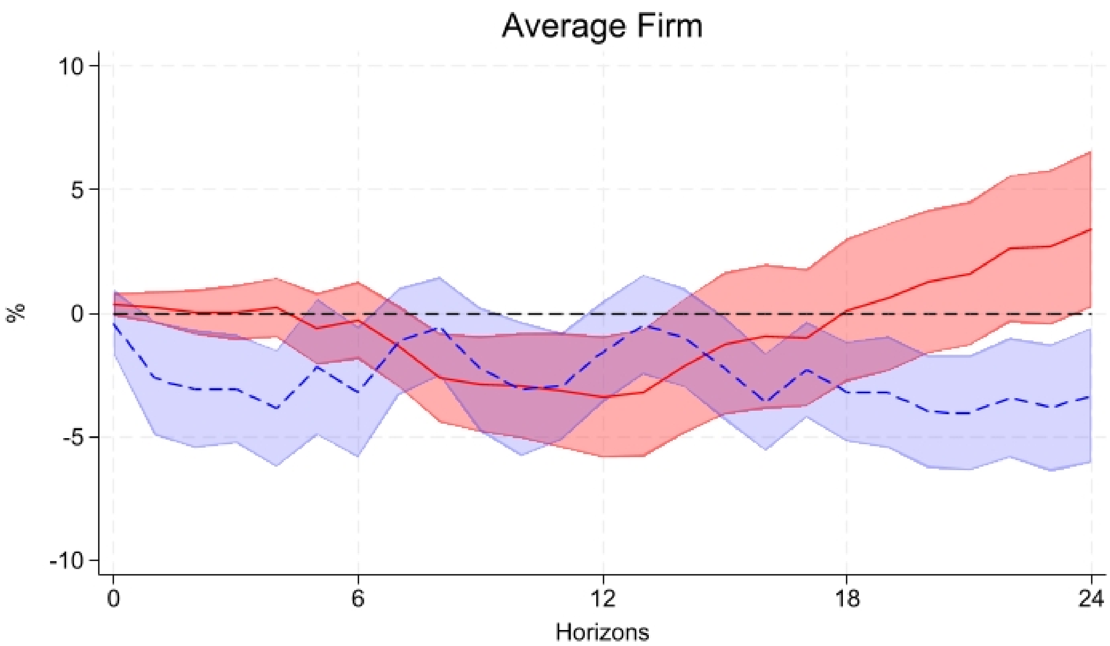

Figure 17: Impulse response for the average firm (β_h) from equation 5.4 for horizon $h \in \{0, 1, 2...24\}$ months in oil bull (red solid) and oil bear (blue dashed) regimes. Shaded areas display 68 percent confidence intervals based on robust standard errors (two-way clustered at the month and firm level). The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

Finally, I estimate the state-dependent panel local projections with the interaction term between the carbon policy shocks series, CPS_t, and the dummy variable D_{it}, where in equation 5.5 I drop fossil energy firms after having defined the dummy variable:

$$\begin{aligned}
z_{i,t+h} = {} & I_{t-1}\left(\beta_h^A(CPS_t \times D_{it}) + \phi_h^A(L)y_{it}\right) \\
& + (1 - I_{t-1})\left(\beta_h^B(CPS_t \times D_{it}) + \phi_h^B(L)y_{it}\right) \\
& + \Gamma_h F_{i,t-1} + \alpha_{sh} + \alpha_{tch} + \epsilon_{i,t+h}.
\end{aligned} \tag{5.5}$$

Equation 5.6 is instead the specification of the state-dependent panel local projections with the brown type dummy B_{it}:

$$\begin{aligned}
z_{i,t+h} = {} & I_{t-1}\left(\beta_h^A(CPS_t \times B_{it}) + \phi_h^A(L)y_{it}\right) \\
& + (1 - I_{t-1})\left(\beta_h^B(CPS_t \times B_{it}) + \phi_h^B(L)y_{it}\right) \\
& + \Gamma_h F_{i,t-1} + \alpha_{sh} + \alpha_{tch} + \epsilon_{i,t+h}.
\end{aligned} \tag{5.6}$$

Results are in Figure 18 under oil bull and bear regimes.
During oil bull markets the ex fossil fuels spread declines as in the whole sample. On the other hand, the increase of the fossil energy spread after the carbon policy shocks resembles the time series framework with equally weighted portfolios.

Under oil bear regimes, the response of the ex fossil energy spread is statistically insignificant as expected, consistent with offsetting effects from regulatory pressures and falling oil prices. In contrast, the fossil energy spread increases by 2 percent on impact and such increase is persistent. This is likely driven by smaller firms in the panel construction as in the equally weighted portfolio.

The estimated coefficients are in line with the portfolio-based local projections. However, they are half as big as the portfolio-based estimates. The differences must be due to the different number of observations in each month, which results in changes in the effective weights for each monthly return. On the other hand, the portfolio methods weigh each

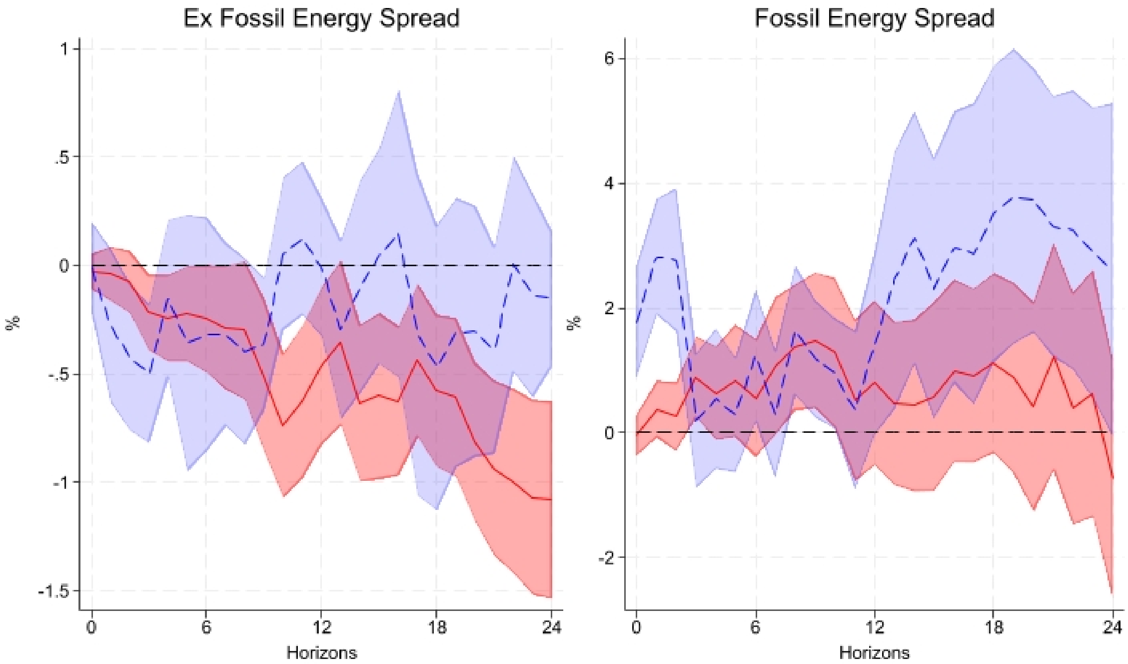

Figure 18: Impulse response of stock returns (β_h) in oil bull vs bear regimes from equation 5.5, 5.6 respectively, for horizon $h \in \{0, 1, 2...24\}$ months in oil bull (red solid) and oil bear (blue dashed) regimes. Shaded areas display 68 percent confidence intervals based on robust standard errors (two-way clustered at the month and firm level). The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

month equally. Instead, in panel regressions, the weight of each month crucially depends on the number of observations in that month, and since my panel is unbalanced, these weights are generally not equal.

5.1 Additional robustness

I run a number of robustness exercises. In the first, I consider a different definition of the CPS series. Specifically, instead of using the change in carbon prices relative to the prevailing wholesale electricity price, I use the percentage changes of carbon prices. The results do not change and they are in the Appendix A.7 and A.8. In the second, I drop the financial sector from the analysis (Appendix A.9 and A.10). In the third, I check that my results are robust to a different choice of countries (Appendix A.11 and A.12). Specifically, instead of using all 8 countries I only select the 4 biggest euro area countries (Germany, France, Italy, and Spain).

6 Conclusions

This paper contributes to the growing literature on macro-finance and climate change by uncovering important areas in the asset pricing effects of carbon policy shocks. By moving beyond the traditional green vs brown dichotomy, I show that heterogeneity within brown assets is critical for understanding equity market responses. In particular, fossil energy firms react differently from other brown firms, as their returns are more sensitive to fluctuations in the price of oil rather than to regulatory developments.

Importantly, the analysis I made reveals that the effects of carbon policy shocks are state-dependent, varying with the oil market regimes. During oil bull periods, both brown and green firms experience more pronounced reactions, with the ex fossil energy spread showing a stronger and persistent decline. This suggests that higher oil prices amplify the cost of carbon regulation for brown firms, particularly those outside the oil sector. Conversely, during oil bear markets, both the responses of stock returns and the green outperformance are more muted. Indeed, bear regimes mean lower input costs for the average firm and even advantages for non fossil energy brown firm.

Taken together, the results underscore the dual role of oil as both a fundamental driver of returns for fossil energy firms and a broader amplifier of climate policy effects across financial markets. These findings call for a more granular approach in climate finance research and have important implications for investors, policymakers, and portfolio managers in the transition to a low-carbon economy.

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Appendix

A.1 Markov-switching regression

Table 2: Markov-switching Dynamic Regression Results. *** p < 0.01, ** p < 0.05, * p < 0.1. Sample period: January 2005 to December 2019.

	Coefficient
State 1: Oil Bear	
Constant (α_1)	-0.540
	(0.361)
State 2: Oil Bull	
Constant (α_2)	0.129**
	(0.063)
Standard Deviations	
σ_1 (Oil Bear)	1.668
	(0.236)
σ_2 (Oil Bull)	0.695
	(0.051)
Transition Probabilities	
p_{11} (Stay in Oil Bear)	0.862
	(0.091)
p_{21} (Switch to Oil Bear)	0.031
	(0.020)

A.2 Firm coverage by country and sector

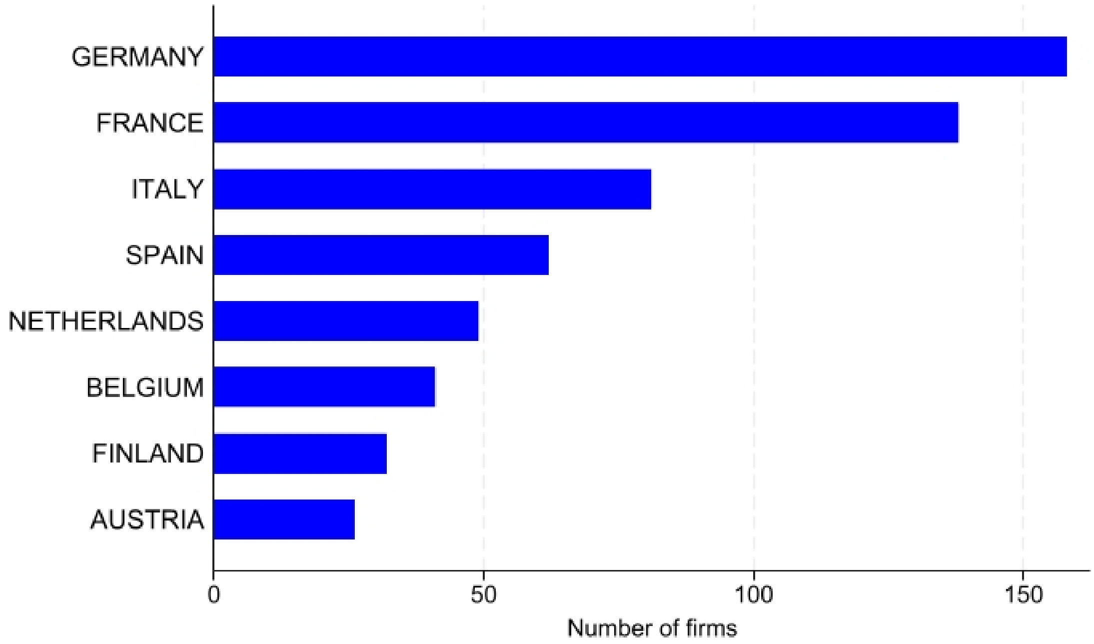

Figure 19: Number of firms in the sample by country.

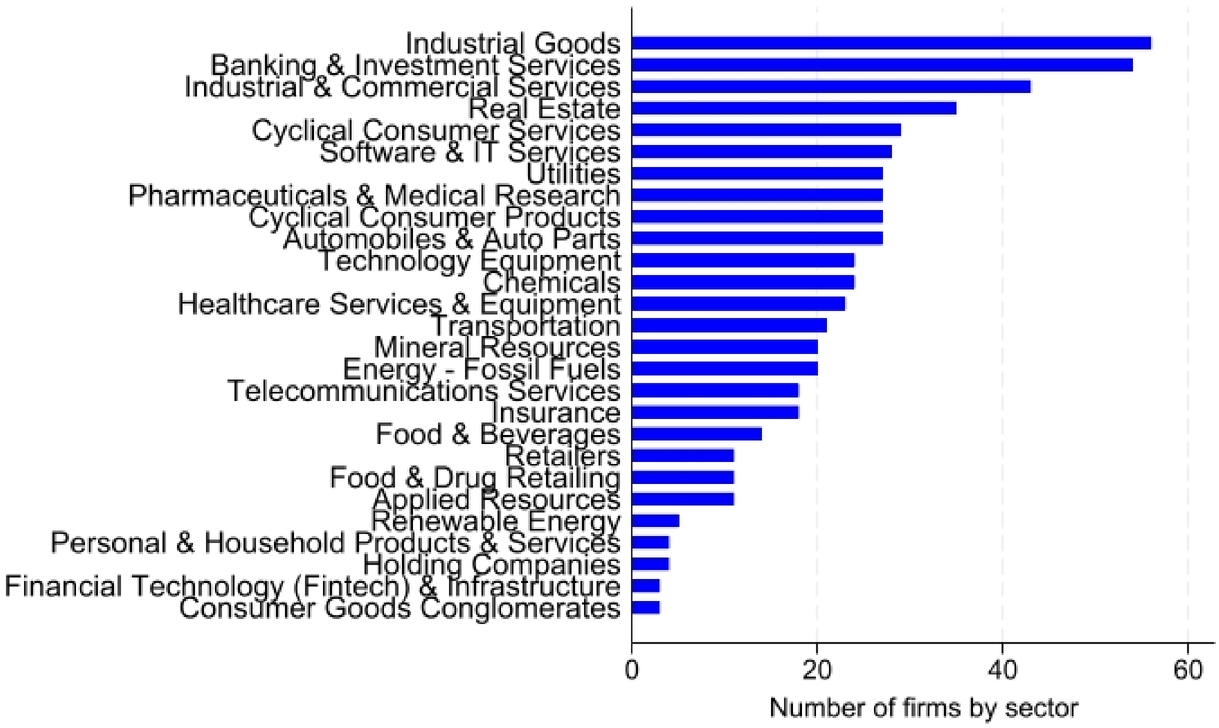

Figure 20: Number of firms in the sample by sectors.

A.3 Sectoral distribution in the green portfolios

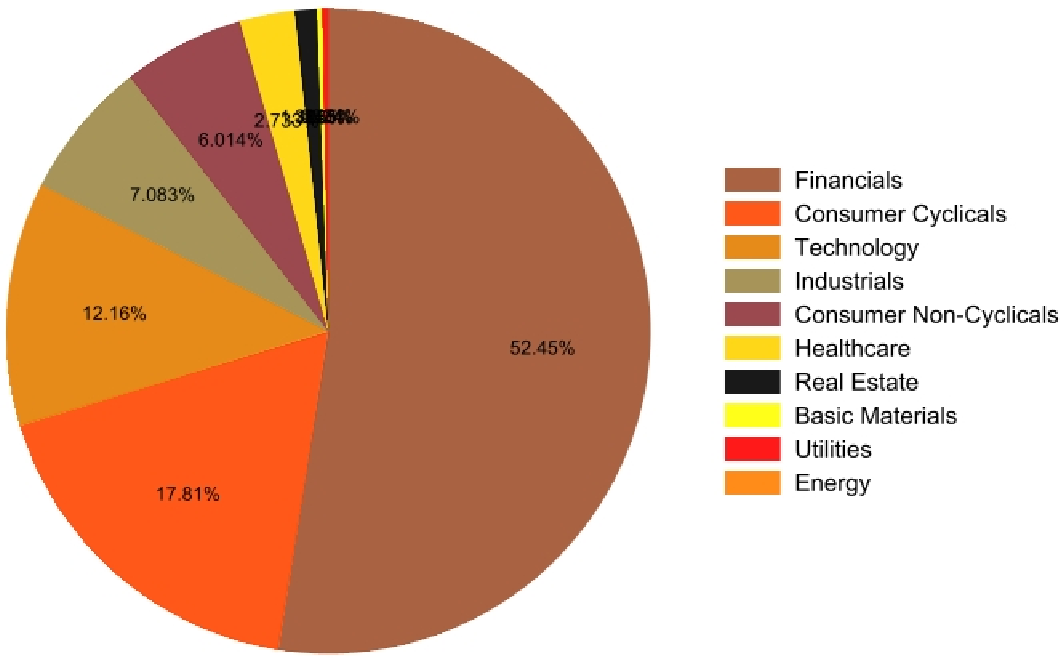

Figure 21: Average green portfolio weight by sector. The weights reflect the proportional representation of each sector within the value weighted green portfolio.

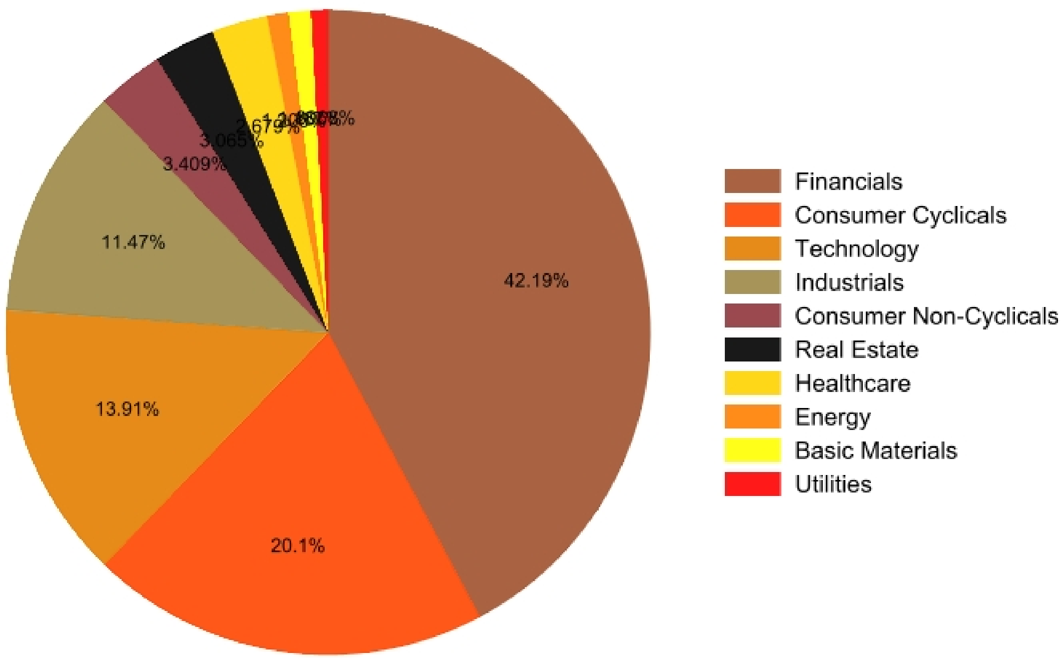

Figure 22: Average green portfolio weight by sector. The weights reflect the proportional representation of each sector within the equally weighted green portfolio.

A.4 Cumulative spread returns

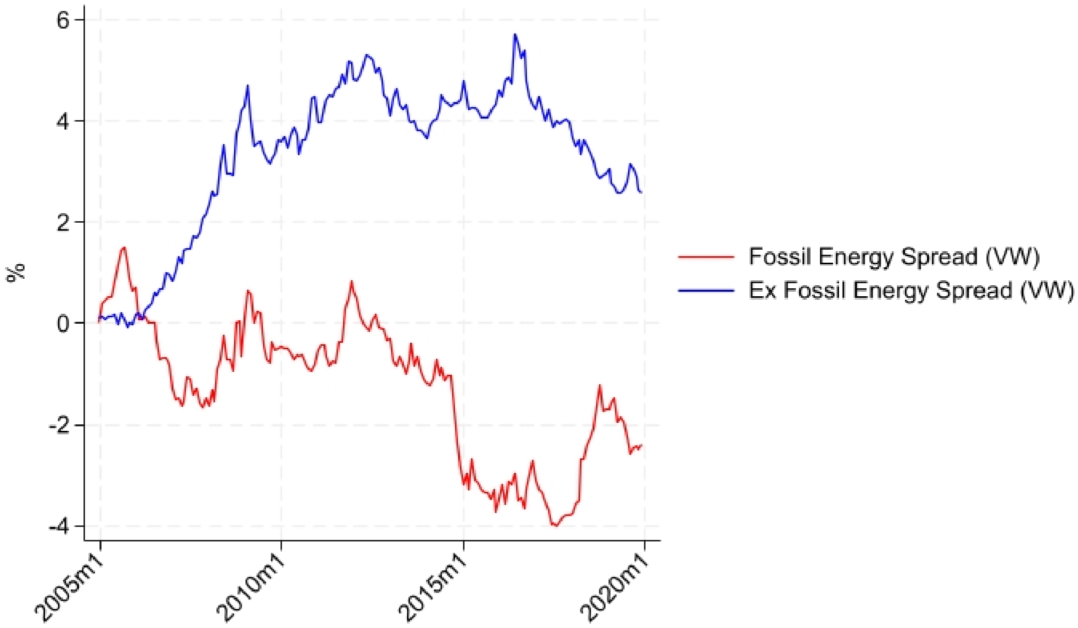

Figure 23: This figure plots the cumulative returns of the two components of the greenium: the excluding fossil energy spread (blue), and the fossil energy spread (red) for the value weighted (VW) portfolios. Sample period: January 2005 to December 2019.

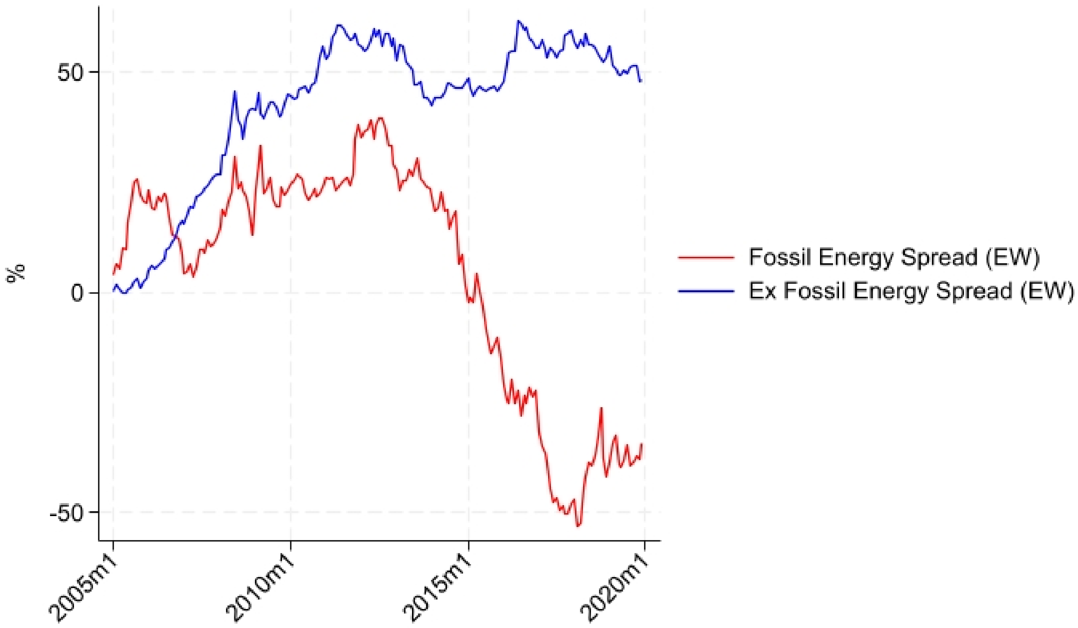

Figure 24: This figure plots the cumulative returns of the two components of the greenium: the excluding fossil energy spread (blue), and the fossil energy spread (red) for the equally weighted (EW) portfolios. Sample period: January 2005 to December 2019.

A.5 Cumulative Euro Stoxx Oil & Gas and cumulative oil return

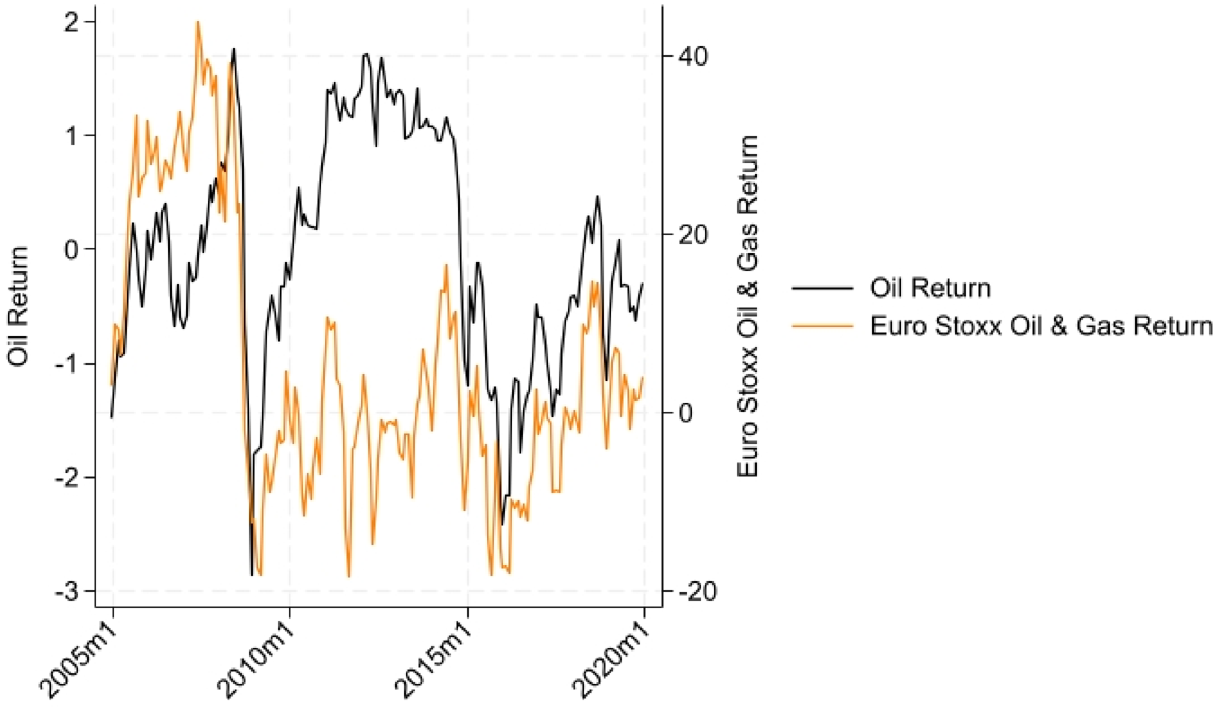

Figure 25: This figure plots the cumulative Euro Stoxx Oil & Gas Index return vs the cumulative standardized oil return. Sample period: January 2005 to December 2019.

A.6 Alternative specification of the carbon policy surprises

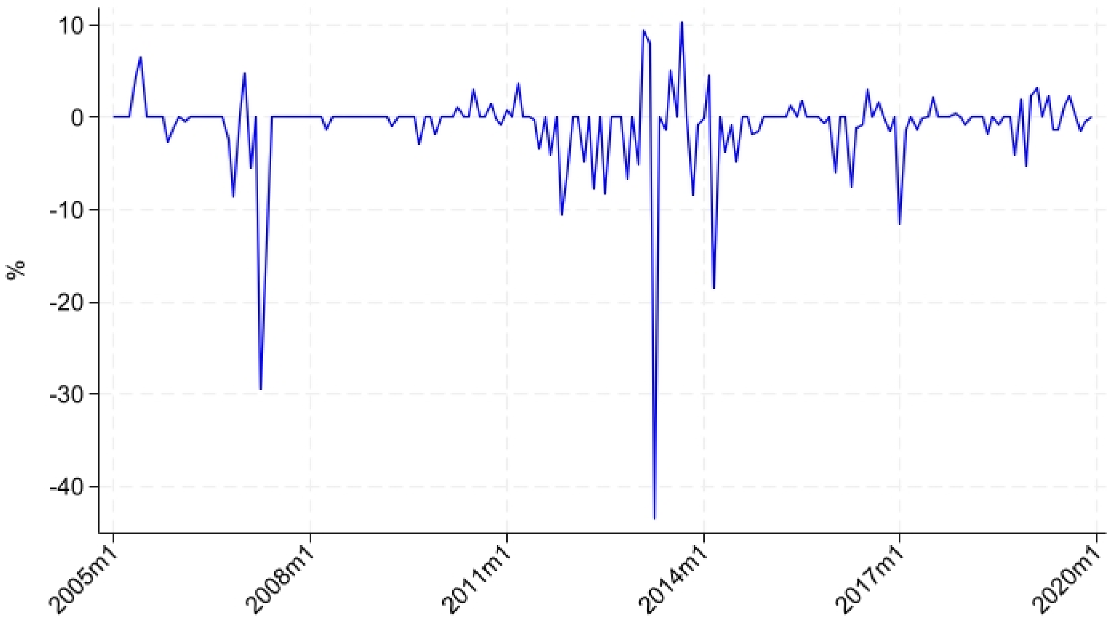

Figure 26: The carbon policy surprise series. The price change around regulatory events is defined as percentage changes at daily frequency.

A.7 Robustness of panel local projections with alternative specification of the carbon policy shocks

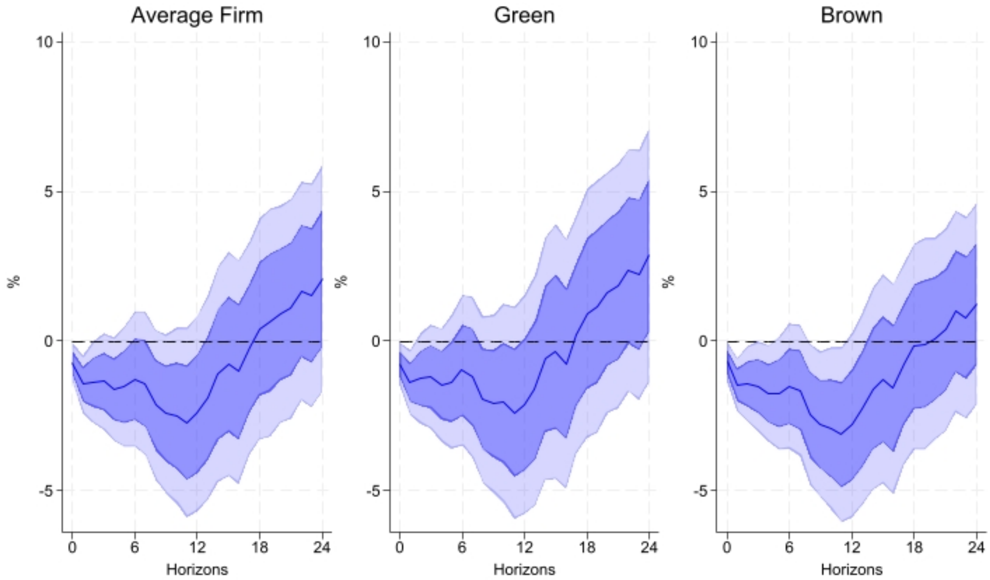

Figure 27: Impulse response of stock returns (β_h) from equation 5.1 for horizon $h \in \{0, 1, 2...24\}$ months. Shaded areas display 68 and 90 percent confidence intervals based on robust standard errors (two-way clustered, at the month and firm level). The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

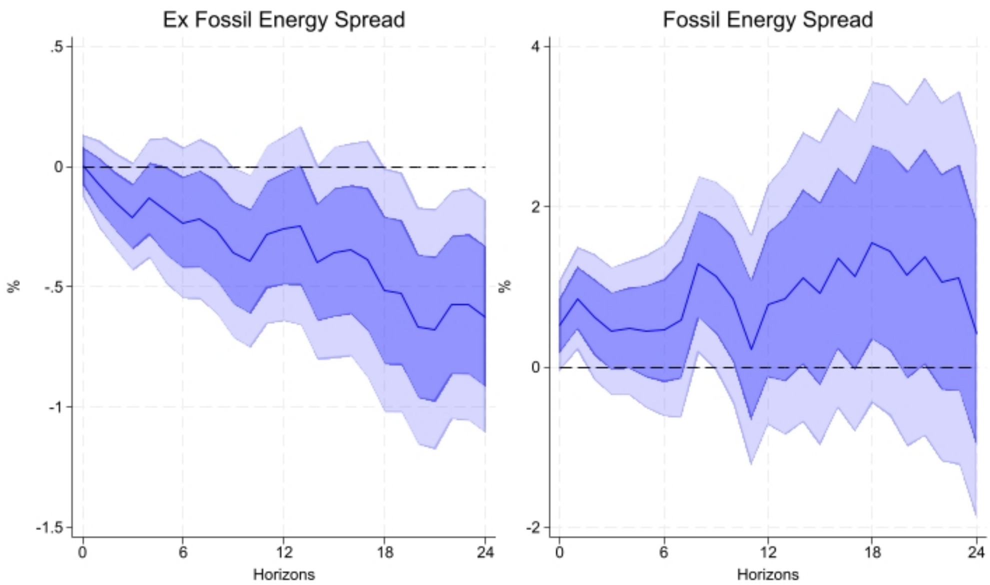

Figure 28: Impulse response of stock returns (β_h) from equation 5.2 and 5.3 respectively, for horizon $h \in \{0, 1, 2...24\}$ months. Shaded areas display 68 and 90 percent confidence intervals based on robust standard errors (two-way clustered, at the month and firm level). The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

A.8 Robustness of state-dependent panel local projections with alternative specification of the carbon policy shocks

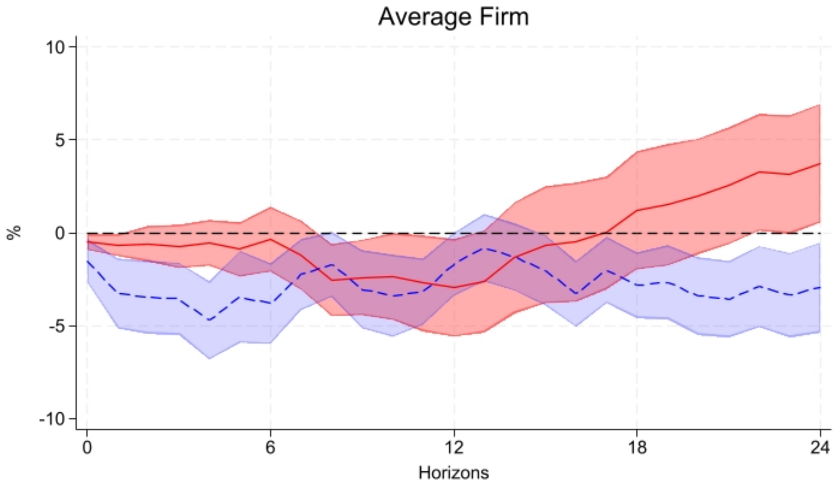

Figure 29: Impulse response for the average firm (β_h) from equation 5.4 for horizon $h \in \{0, 1, 2...24\}$ months in oil bull (red solid) and oil bear (blue dashed) regimes. Shaded areas display 68 percent confidence intervals based on robust standard errors (two-way clustered at the month and firm level). The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

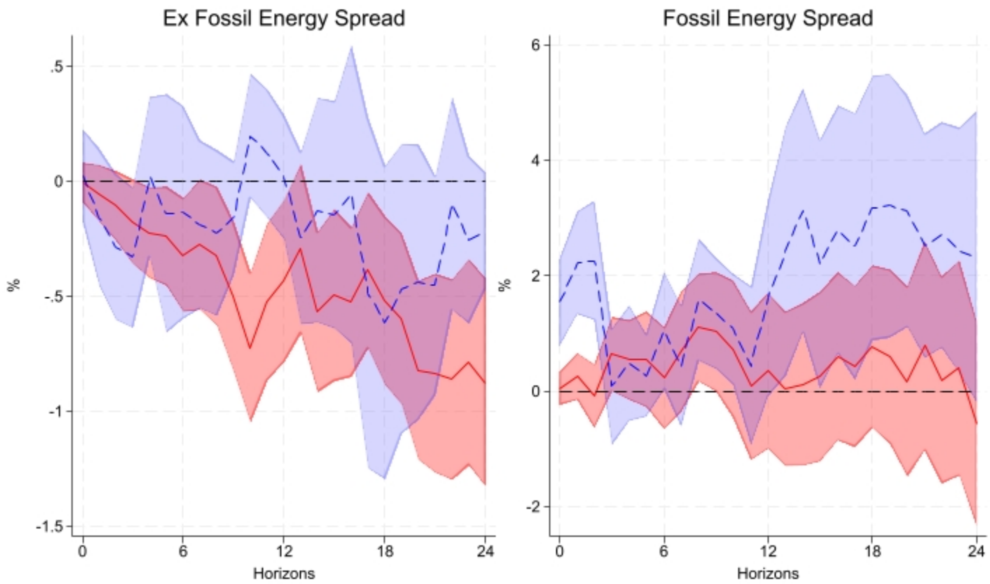

Figure 30: Impulse response of stock returns (β_h) in oil bull vs bear regimes from equation 5.5, 5.6 respectively, for horizon $h \in \{0, 1, 2...24\}$ months in oil bull (red solid) and oil bear (blue dashed) regimes. Shaded areas display 68 percent confidence intervals based on robust standard errors (two-way clustered at the month and firm level). The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

A.9 Robustness of panel local projections without Financial sector

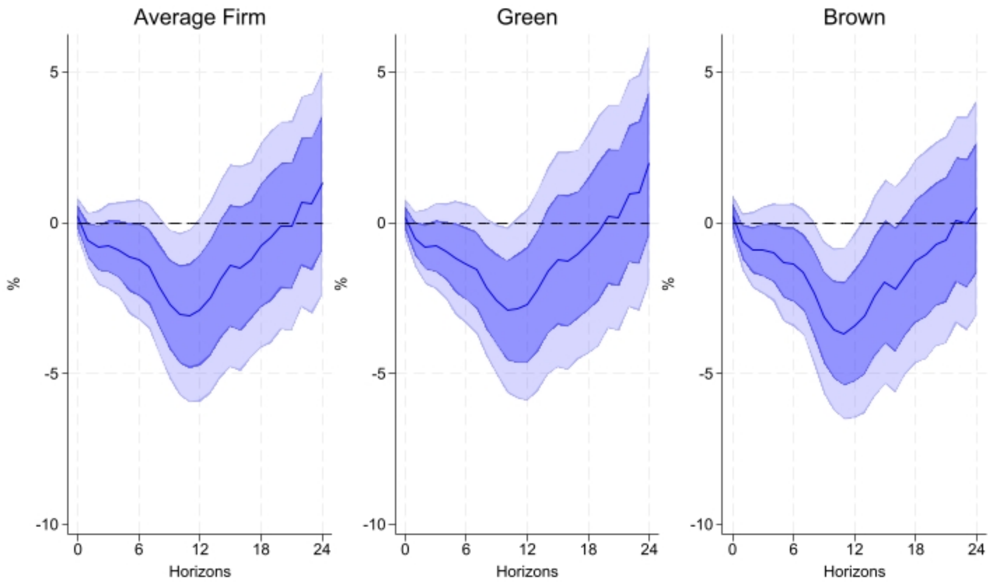

Figure 31: Impulse response of stock returns (β_h) from equation 5.1 for horizon $h \in \{0, 1, 2...24\}$ months. Shaded areas display 68 and 90 percent confidence intervals based on robust standard errors (two-way clustered, at the month and firm level). The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

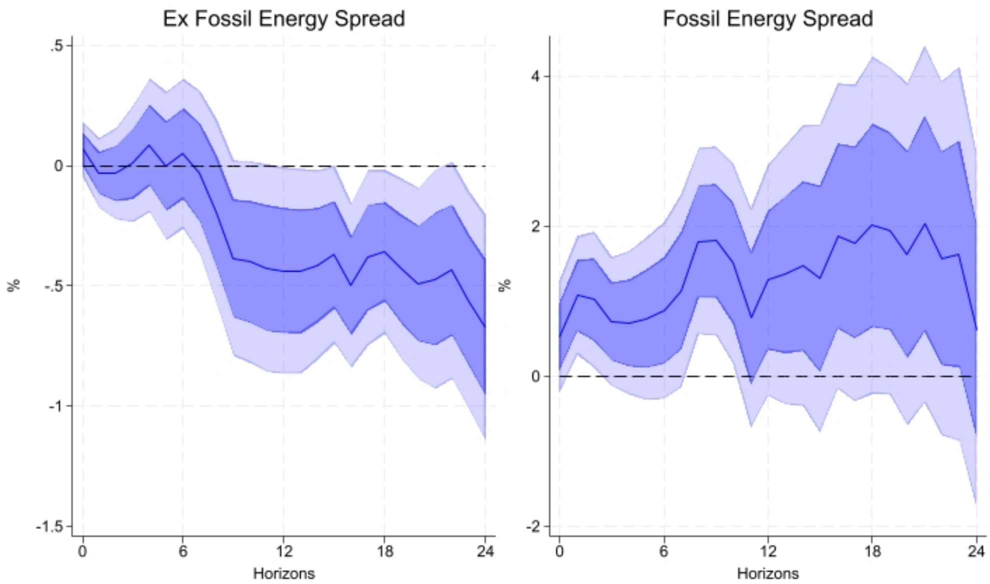

Figure 32: Impulse response of stock returns (β_h) from equation 5.2 and 5.3 respectively, for horizon $h \in \{0, 1, 2...24\}$ months. Shaded areas display 68 and 90 percent confidence intervals based on robust standard errors (two-way clustered, at the month and firm level). The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

A.10 Robustness of state-dependent panel local projections without Financial sector

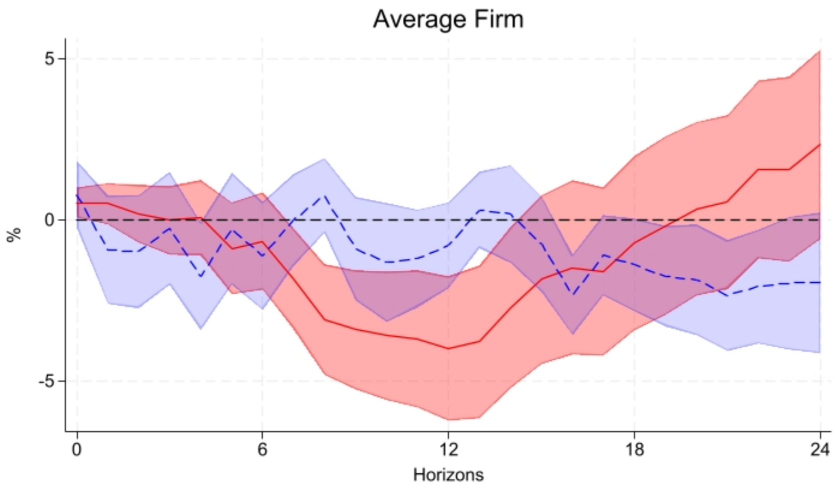

Figure 33: Impulse response for the average firm (β_h) from equation 5.4 for horizon $h \in \{0, 1, 2...24\}$ months in oil bull (red solid) and oil bear (blue dashed) regimes. Shaded areas display 68 percent confidence intervals based on robust standard errors (two-way clustered at the month and firm level). The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

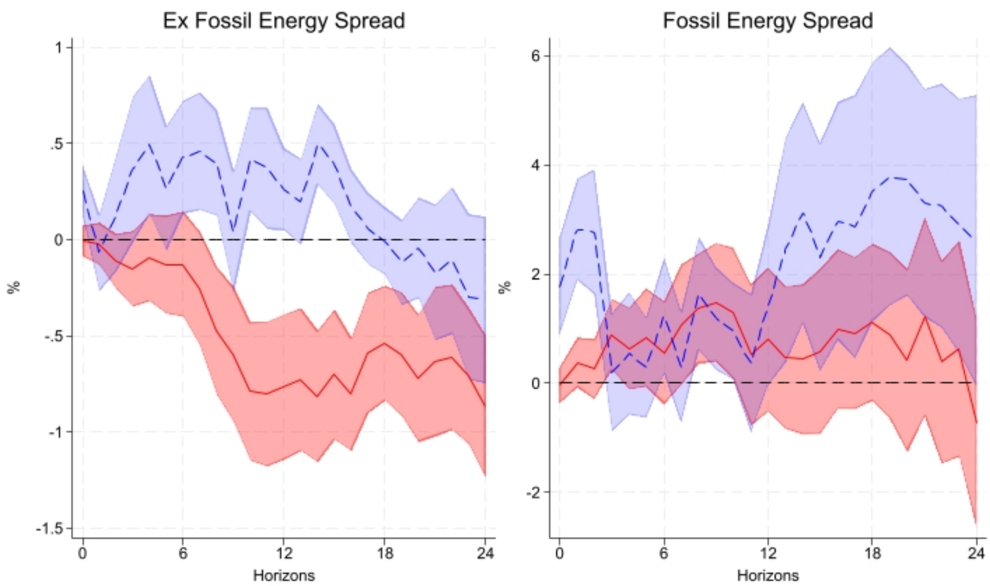

Figure 34: Impulse response of stock returns (β_h) in oil bull vs bear regimes from equation 5.5, 5.6 respectively, for horizon $h \in \{0, 1, 2...24\}$ months in oil bull (red solid) and oil bear (blue dashed) regimes. Shaded areas display 68 percent confidence intervals based on robust standard errors (two-way clustered at the month and firm level). The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

A.11 Robustness of panel local projections with different set of countries (France, Germany, Italy, and Spain)

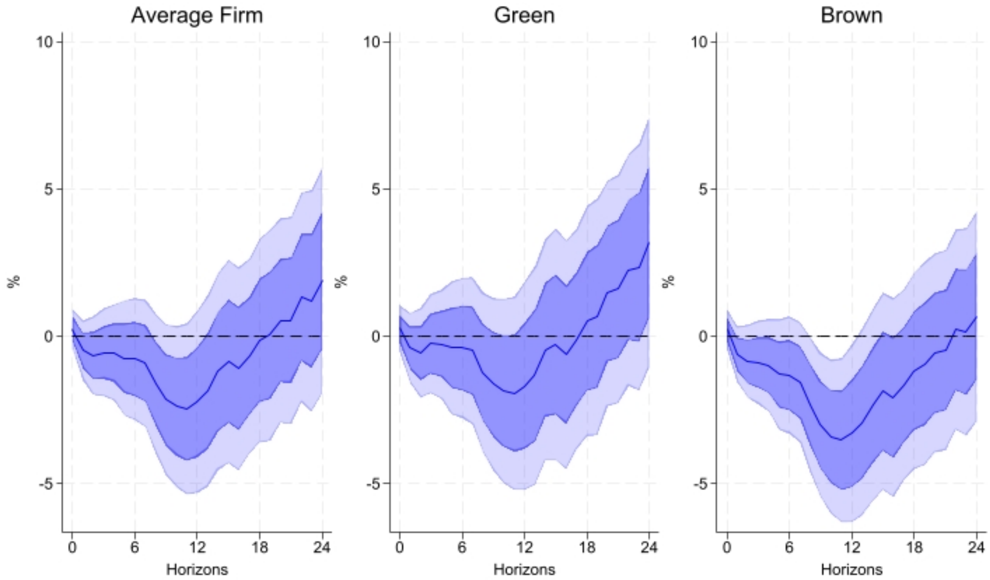

Figure 35: Impulse response of stock returns (β_h) from equation 5.1 for horizon $h \in \{0, 1, 2...24\}$ months. Shaded areas display 68 and 90 percent confidence intervals based on robust standard errors (two-way clustered, at the month and firm level). The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

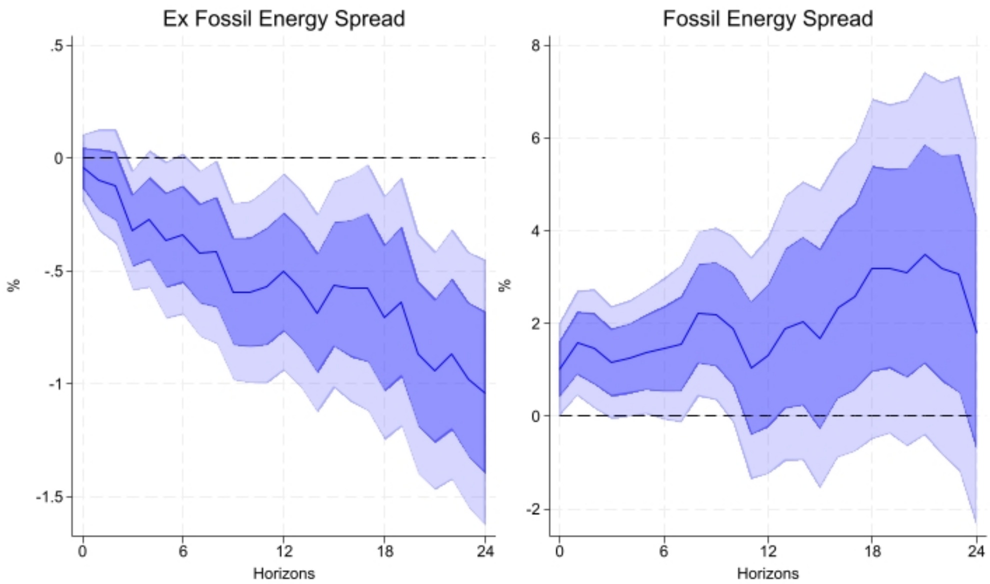

Figure 36: Impulse response of stock returns (β_h) from equation 5.2 and 5.3 respectively, for horizon $h \in \{0, 1, 2...24\}$ months. Shaded areas display 68 and 90 percent confidence intervals based on robust standard errors (two-way clustered, at the month and firm level). The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

A.12 Robustness of state-dependent panel local projections with different set of countries (France, Germany, Italy, and Spain)

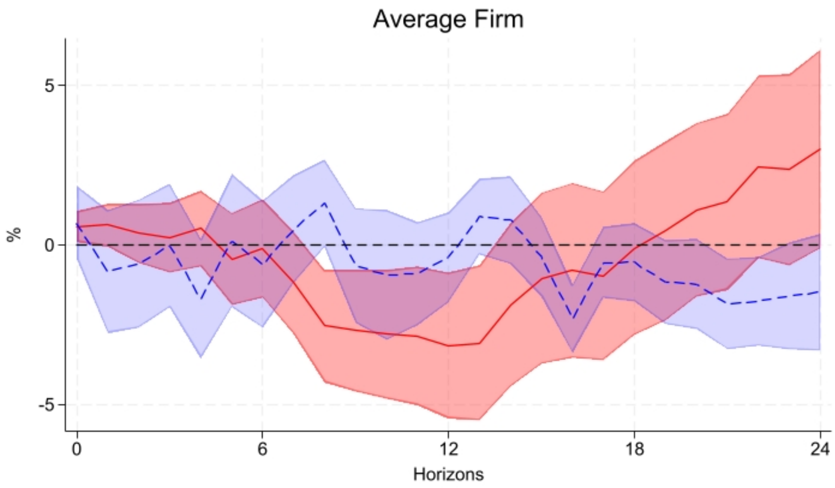

Figure 37: Impulse response for the average firm (β_h) from equation 5.4 for horizon $h \in \{0, 1, 2...24\}$ months in oil bull (red solid) and oil bear (blue dashed) regimes. Shaded areas display 68 percent confidence intervals based on robust standard errors (two-way clustered at the month and firm level). The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.

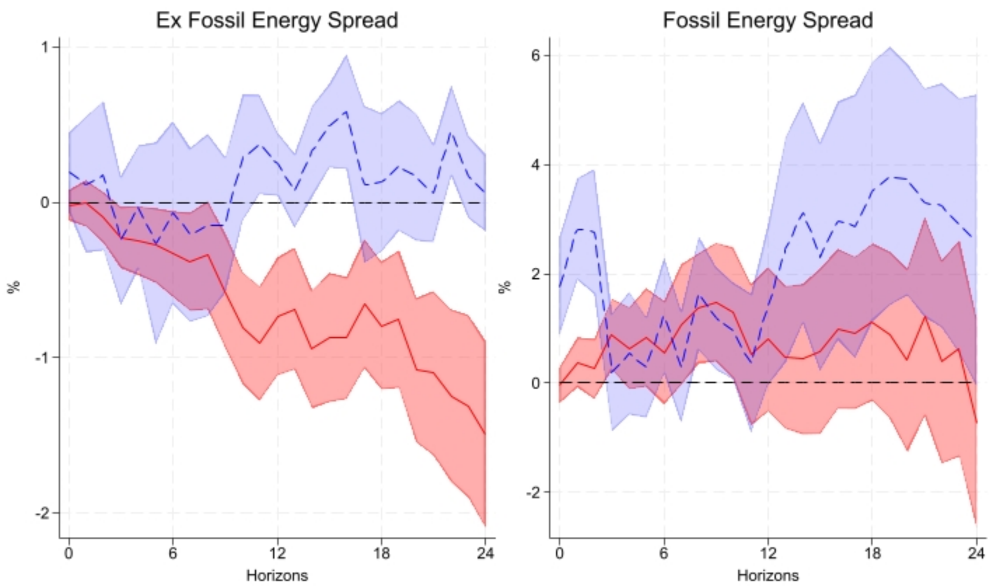

Figure 38: Impulse response of stock returns (β_h) in oil bull vs bear regimes from equation 5.5, 5.6 respectively, for horizon $h \in \{0, 1, 2...24\}$ months in oil bull (red solid) and oil bear (blue dashed) regimes. Shaded areas display 68 percent confidence intervals based on robust standard errors (two-way clustered at the month and firm level). The CPS series and the oil returns are normalized to have unit standard deviation. Sample period goes from January 2005 to December 2019.