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Is Monetary Policy Transmission Green?

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We find robust evidence that firms with high carbon intensity are significantly more affected by policy rate surprises. The sensitivity premium of brown firms remains significant when controlling for classic sources of MP heterogeneity, is persistent, and increases with climate awareness. Our results suggest that the market neutrality principle guiding the implementation of monetary policy could induce a bias toward brown firms.

Keywords: Climate change; Transition risk; Carbon emissions; Monetary policy shocks; Risk premia.

JEL: E44; E48; E48; O13; Q49; Q54; G12; G15.

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Is Monetary Policy Transmission Green?

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June 2023

Abstract

This article examines the impact of monetary policy (MP) on firms' stock prices across CO_2 emissions. We provide a theoretical model in which green firms are less sensitive to MP shocks than brown firms, because they are less exposed to transition risk and provide non-pecuniary utility to investors. We test this prediction by using a panel event-study regression approach on 857 US firms between 2010 and 2019. We find robust evidence that firms with high carbon intensity are significantly more affected by policy rate surprises. The sensitivity premium of brown firms remains significant when controlling for classic sources of MP heterogeneity, is persistent, and increases with climate awareness. Our results suggest that the market neutrality principle guiding the implementation of monetary policy could induce a bias toward brown firms.

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[..] any institution has to actually have climate-change risks and protection of the environment at the core of the understanding of its mission.

C. Lagarde.

1 Introduction

Global warming confronts central banks (CBs) with a dilemma. On the one hand, carbon emissions are, at first glance, outside the scope of CBs' mandate. On the other hand, monetary policy (MP) can be a powerful tool for incentivizing agents to invest in projects enabling a reduction in carbon emissions. This ambivalence has recently translated into a disagreement between CBs over the need to take active measures to combat climate change. In January 2023 J. Powell declared that "We are not, and will not be, a climate policymaker" (RiskBank conference, 1/10/2023). By contrast, ECB President Christine Lagarde expressed her willingness to see the ECB take a more active role (see quote). Other CBs have gone as far as to implement climate-oriented policies. In 2016, the bank of England notably launched a corporate bond purchase program tilted toward companies that satisfy certain climate-related criteria.

In the discussion over the need to "green" MP, a useful first step is to characterize how "brown" classical - non-climate-targeted - MP is. There are reasons to expect high CO_2 emissions to be positively associated with MP exposure. For instance, brown firms face more transition risk, all else being equal, and risk premia are known to depend on MP tightness as investors search for yield when risk-free rates are low (Bernanke and Kuttner, 2005). Green assets may also be less sensitive to fundamental news because financial performance is less important for the investors who hold them. On the other hand, some theoretical channels run in the opposite direction. Standard stock pricing theory for instance suggests that a change in the discount rate should have a relatively larger impact on firms whose future dividends are expected to rise over time, implying that green firms should be more sensitive to MP announcements.

This paper examines these issues by testing whether MP has a neutral impact on firms across CO_2 emission levels, and by investigating the reasons for this nonneutrality if applicable. The paper starts with a theoretical model in which a representative investor allocates her wealth between a green stock, a brown stock and a risk-free asset. The investor rebalances her portfolio following a surprise rate change to maintain a target return for her portfolio. In the model, transition risk leads the brown stock to be more risky than its green counterpart, and the investor draws nonpecuniary utility from holding stocks that conform to her principles. Two testable hypotheses emerge: (i) brown stocks are more responsive to MP rate surprises and (ii) this higher responsiveness comes from a mixture of supply factors linked to fundamentals and demand factors linked to investor preferences.

We test both hypotheses by estimating the heterogeneity of the stock price reaction of U.S. firms with varying levels of CO_2 emission intensities to Fed surprise rate changes between 2010 and 2019. Our baseline empirical model regresses the price return of a firm on a MP surprise indicator, and on the interaction of this indicator with a firm's CO_2 intensity. Our hypothesis is that the coefficients on the policy surprise indicator and on the interaction term are both negative. Negativity of the first coefficient implies that an unexpected increase (decrease) in rates leads to a decrease (increase) in stock prices. Negativity of the second coefficient implies that the relationship between rate surprises and stock prices becomes increasingly negative as CO_2 intensity rises, meaning that brown stocks are more sensitive to MP shocks.

Our empirical design requires reliable measures of exogenous policy changes and firms' brownness. Exogenous MP shocks are obtained by using high-frequency changes in interest rates around the Federal Reserve's Federal Open Market Committee (FOMC) announcements. This approach is viewed in the literature as an efficient tool to rule out reverse causality and other endogeneity problems (Kuttner, 2001; Rigobon and Sack, 2004; Gürkaynak et al., 2005; Bernanke and Kuttner, 2005).[1] The brownness of each firm by its

[1] Recent developments in this field question whether the identified surprises (from change in Federal funds or Eurodollars futures prices around FOMC announcements) are really exogenous monetary policy shocks. On the one hand, surprises could convey information about the central bank's assessment of the economic outlook as documented by the "Fed information effect" studies (Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020; Andrade and Ferroni, 2021). On the other hand, a few recent papers call into question the unpredictability assumption, i.e., the exogeneity of standard monetary policy surprises

reported total CO_2 emissions (Scope 1 + Scope 2) per unit of sales. Measuring brownness with reported emissions intensity avoids issues with third-party estimated emissions or scores as well as any mechanical correlation with firm size induced by unscaled carbon emissions (Bauer et al., 2022; Aswani et al., 2023).

Our empirical findings are in line with expectations. The variable "Emissions × MP surprise" is negative and highly significant, with a coefficient estimate of -0.052. A firm that is one standard deviation more carbon intensive than the sample average should expect a stock return of +0.504% following a one-standard-deviation decrease in monetary surprise, against +0.452% for the average stock in our sample. Importantly, the sensitivity premium of brown firms remains significant when controlling for classic sources of MP heterogeneity such as size or market beta. Brown firms react more because they are brown, not because their brownness correlates with other factors. MP heterogeneity across brownness is also not driven by a pure industry effect. The differential in carbon intensity within a given industry matters. The results are robust in terms of (i) outliers, (ii) the consideration of abnormal returns from the Fama-French 5-factor model, and (iii) alternative ways to measure the carbon footprint and MP surprises.

We provide further analysis on two points. First, we investigate the dynamics behind CO_2 nonneutrality. Based on our theoretical model, we test two hypotheses: i) the impact of CO_2 intensity on the relationship between MP and stock returns increases in absolute value with the overall level of climate awareness; (ii) the impact of CO_2 intensity on the relationship between MP and stock returns increases in absolute value with CO_2 intensity itself. To test (i), we use the climate awareness indicator of Engle et al. (2020), who rely the Crimson Hexagon proprietary sentiment measure to capture negative reports relating to climate change in a large set of news items. As expected, brown firms become even more relatively exposed to monetary policy when climate is salient in the news. To test (ii), we run estimations that allow CO_2 intensity to enter nonlinearly. As expected, MP nonneutrality is a growing and convex function of CO_2 intensity.

The second issue on which we provide further analysis is the level of persistence of the

(Cieslak, 2018; Miranda-Agrippino and Ricco, 2021; Bauer and Swanson, 2023). We account for these points in our paper.

difference between green and brown stock returns following an MP surprise. We estimate impulse response functions from local projections (Jordà, 2005) to check that the price movements during FOMC meeting days are not counterbalanced by an opposite effect over the following days. We find that the heterogeneous impact of MP surprises across carbon footprint sizes is permanent. This suggests that the initial return responses reflect an efficient incorporation of relevant information, rather than short-term frictions.

Our paper is at the intersection of two literatures. The first investigates MP nonneutrality. A long line of research that has shown that firms with varying characteristics experience varying exposure to MP shocks (Gorodnichenko and Weber, 2016; English et al., 2018; Ozdagli and Velikov, 2020). Ehrmann and Fratzscher (2004) find that financially constrained and cyclical firms are more sensitive to interest rate surprises. Ammer et al. (2010) highlight that the response of foreign firms to U.S. monetary shocks is comparable to that of U.S. firms on average, but cyclical foreign firms' responses are more marked in contrast to equally cyclical U.S. firms. Price reactions to MP innovations are also stronger among firms that are subject to greater information frictions (Ozdagli, 2018), do not hedge their loans against rate changes Ippolito et al. (2018), or have had low stock returns in past months (Kontonikas and Kostakis, 2013; Haitsma et al., 2016). Other studies concentrate on how monetary policy affects firms' investment decisions. They find that financial frictions amplify the real effects of monetary policy (Ottonello and Winberry, 2020; Durante et al., 2022; Cloyne et al., 2023). Our results complement this literature by showing that carbon intensity constitutes a new vector of nonneutrality.

The second literature connected to this paper relates to the pricing of transition risk. Textbook financial theory states that investors should demand compensation for holding the riskier brown stocks, implying that the return on green assets is lower in equilibrium. Several studies have attempted to test this idea using realized returns. Bolton and Kacperczyk (2021b) and Hsu et al. (2022) find higher realized returns for brown firms using, as we do, panel regressions of realized equity returns on CO_2 emissions. In contrast, Bauer et al. (2022) find that the realized returns on green assets exceed those of brown assets after controlling for fundamentals. These results may not as opposed as it appears. Indeed, as noted by Pástor et al. (2021), lower realized returns and higher expected returns for brown firms may coexist if the price of green assets has increased in recent years because of a change in investors' tastes. Ardia et al. (2021) and Pástor et al. (2022) provide empirical support for this possibility. Our results complement this literature by showing that some of the risk differential between green and brown stocks comes from differences in MP exposure and that climate awareness plays a role in driving realized returns around MP announcements.

The main contribution of this paper is that it provides an empirical estimation of the ecological footprint of monetary policy, an issue that bears significant policy implications that are being actively considered. To the best of our knowledge, the scarce literature relating monetary policy to carbon emissions consists exclusively of theoretical contributions. Schoenmaker (2021) estimates the change in asset holdings that a movement toward a carbon-neutral QE would imply for the ECB in 2020. Papoutsi et al. (2021) estimate the carbon footprint of QE by feeding data on ECB asset purchases between 2016 and 2018 into a multisector general equilibrium model. They conclude that the ECB private bond portfolio is biased toward high-emission firms. Our study differs from these papers in many respects, but the results share a common idea: the market neutrality principle benchmark used by central banks induces a carbon bias, which in turn may prevent an efficient allocation of resources in the transition toward a low-carbon economy.

The paper is organized as follows. Section 2 presents the theoretical model. Section 3 describes the data. Section 4 presents our empirical approach to test for heterogeneity in MP responsiveness across carbon emission levels. Section 5 presents our baseline empirical results. Section 6 presents the robustness tests. Section 7 provides further analysis on CO_2 nonneutrality. Finally, section 8 concludes the paper.

2 Theoretical model

This section formally presents some channels through which CO_2 emissions can lead to heterogeneity in the transmission of MP. We emphasize that the model is built to convey intuition as concisely as possible, and thus features some simplifying assumptions.

2.1 Framework

2.1.1 Basics

Consider an investor who allocates a share w_g of her wealth in a green stock, a share w_b in a brown stock, and a share $w_c = (1 - w_g - w_b)$ in a riskless bond. The investor follows a simple buy-and-hold strategy. The wealth she is willing to invest at every period is constant and denoted by W.

Let $d_{g,t}$ and $d_{b,t}$ be the dividend rate on the green and brown asset respectively between t and $t+1$, a timespam referred to as period t. In contrast, the riskless bond pays a certain coupon rate of c_t. The investor can secure c_t at t, but the rate c_{t+1} that can be secured at the following period may change. The total monetary amount received during period t is $W\left(w_{g,t}d_{g,t} + w_{b,t}d_{b,t} + w_{c,t}c_t\right)$, which can be reexpressed as :

$$\Pi_t = Wc_t + W\left(w_{g,t}(d_{g,t} - c_t) + w_{b,t}(d_{b,t} - c_t)\right)$$

$d_{g,t}$ and $d_{b,t}$ are two normally distributed random variables, with expected values of $\mu_{g,t}$ and $\mu_{b,t}$ respectively, and variances of $\sigma^2_{g,t}$ and $\sigma^2_{b,t}$ respectively. For conciseness and without loss of generality, both assets are assumed to be independent.

The investor has classic mean-variance preferences regarding the financial performance of her portfolio :

$$MV = E(\frac{\Pi_t}{W}) - \frac{1}{2\tau}V(\frac{\Pi_t}{W}) = c_t + w_{g,t}(\mu_{g,t} - c_t) + w_{b,t}(\mu_{b,t} - c_t) - \frac{1}{2\tau}\left((w_{g,t})^2\sigma^2_{g,t} + (w_{b,t})^2\sigma^2_{b,t}\right) \tag{1}$$

with $E(\frac{\Pi_t}{W})$ and $V(\frac{\Pi_t}{W})$ the expected value and variance of the total portfolio return, and $\frac{1}{2\tau}$ the coefficient of risk aversion.

2.1.2 Green utility and search for yield

Two key elements are added to the investor's problem. First, the investor draws non financial utility from holding stocks that match her principles. Formally, holding one monetary unit of the green asset provides the investor with a utility of $u_g \times (\mu_{g,t} - c_t)$, where u_g is the utilitarian gain of holding a green asset relative to its financial gain. We break down this utility gain as $u_g = \phi \triangle CO2$ where $\phi > 0$ is the non pecuniary utility provided by a drop of one unit in the total emissions in the portfolio, and $\triangle CO2 = CO2_b - CO2_g > 0$ is the number of units of C02 saved by investing in the green asset instead of the brown one.

The second addition to the investor's problem is that she is set to have a target return of $E(\frac{\Pi_t}{W}) = G > c_t$. This constraint is a crude way of capturing search-for-yield dynamics. To maintain her expected return at G following a drop in c_t the investor must rebalance her portfolio towards the risky assets.

Accounting for non-financial utility and search-for-yield, the maximisation problem of the investor is :

$$\begin{cases} Max \quad U = c_t + w_{g,t}(\mu_{g,t} - c_t)(1 + \phi \triangle CO2) + w_{b,t}(\mu_{b,t} - c_t) - \frac{1}{2\tau}\left((w_{g,t})^2\sigma_{g,t}^2 + (w_{b,t})^2\sigma_{b,t}^2\right) \\ s/c \quad w_{g,t}(\mu_{g,t} - c_t) + w_{b,t}(\mu_{b,t} - c_t) = G - c_t \end{cases} \tag{2}$$

2.1.3 Asset moments

We turn to the modeling of the relationship between the brown asset and the green asset in terms of expected return and variance. First, we set that the variance of the brown stock is higher than the variance of the green stock. Theoretically this comes from the fact that, holding all other risk factors constant, brown firms' assets are more exposed to transition risk. Formally :

$$\sigma_{b,t}^2 = (1 + \psi \triangle CO2)\sigma_{g,t}^2 \tag{3}$$

where $\psi > 0$ is the relative increase in asset risk spurred by an additional unit of CO2, and $\triangle CO2$ is the number of units of C02 saved by investing in the green asset instead of the brown one.

Though the idea that brown stocks are more exposed to transition risk is not controversial, a complex question relates to the way this risk translates into expected returns. As discussed the introduction, standard theory predicts that investors should demand compensation for holding the more risky brown stocks, and several empirical studies have confirmed this assertion. However it is unclear “how much” returns should rise to compensate for transition risk. Because we have no prior on this issue, and because it eases presentation, we set that the relative difference in expected returns matches exactly the relative difference in variances. Formally:

$$\mu_{b,t} - c = (1 + \psi \triangle CO2)(\mu_{g,t} - c)$$

. This implies that both assets have the same Sharpe ratio S :

$$S = \frac{(\mu_{g,t} - c_t)}{\sigma^2_{g,t}} = \frac{(\mu_{d,t} - c_t)}{\sigma^2_{d,t}} \tag{4}$$

2.2 Equilibrium

2.2.1 Quantities and prices

Maximizing yields:

$$w_{b,t} = \tau(1 - \lambda_t)S \tag{5}$$

$$w_{g,t} = \tau(1 + \phi \triangle CO2 - \lambda_t)S \tag{6}$$

where λ_t is the Lagrange multiplier and is equal to:

$$\lambda_t = 1 + \frac{1}{2 + \psi \triangle CO2}\left(\phi \triangle CO2 - \frac{(G - c_t)}{\tau S^2 \sigma^2_{g,t}}\right) \tag{7}$$

The market for equities clears when the monetary demand for an asset is equal to its market value. Assuming the number q of shares is fixed in the short run, the market equilibrium condition for any asset $k = (b, g)$ is :

$$w_{k,t} W = p_{k,t} q \tag{8}$$

Plugging equations (5) and (7) into (8) yields:

$$p_{b,t} = \frac{W}{q} \tau S \left(\frac{1}{2 + \psi \triangle CO2} \right) \left(\frac{(G - c_t)}{\tau S^2 \sigma^2_{g,t}} - \phi \triangle CO2 \right) \tag{9}$$

$$p_{g,t} = \frac{W}{q} \tau S \left(\frac{1}{2 + \psi \triangle CO2} \right) \left(\frac{(G - c_t)}{\tau S^2 \sigma^2_{g,t}} + \phi \triangle CO2(1 + \psi \triangle CO2) \right) \tag{10}$$

Note that $p_{b,t} < 0$ if $\frac{(G-c_t)}{\tau S^2 \sigma^2_{g,t}} < \phi \triangle CO2$. This means that it is theoretically possible that investors are so climate sensitive –and/or the brown asset is so brown– that investors require payment to hold the brown stock. Of course this is an extreme case, and in what follows we focus on parameter sets for which $p_{b,t} > 0$.

Equations (9) and (10) directly yield the first result on MP responsiveness.

Lemma 1: both green and brown stock prices returns respond negatively to a shock in interest rate.

Proof: $\frac{d p_{g,t}}{d c_t} < 0$ and $\frac{d p_{b,t}}{d c_t} < 0$ as immediate from (9) and (10), thus $\frac{d p_{g,t} / d c_t}{p_{g,t}} < 0$ and $\frac{d p_{b,t} / d c_t}{p_{b,t}} < 0$ for any $p_{g,t} > 0$ and $p_{b,t} > 0$

2.2.2 Price reaction to changes in the riskless rate

We can now compare the brown price return reaction $\frac{d p_{b,t} / d c_t}{p_{b,t}}$ to a change in the interest rate to the green price return reaction $\frac{d p_{g,t} / d c_t}{p_{g,t}}$ to the same change in the interest rate.

Using equations (9) and (10), the price ratio $\frac{p_{g,t}}{p_{b,t}}$ can be expressed as:

$$\frac{p_{g,t}}{p_{b,t}} = 1 + \frac{\phi \triangle CO2(2+\psi\triangle CO2)}{\left(\frac{(G-c_t)}{\tau S^2 \sigma_{g,t}^2} - \phi\triangle CO2\right)} \tag{11}$$

Let NN, which stands for non neutrality, be defined by the difference in MP responsiveness between the green and the brown asset, i.e. $NN = \frac{d\,p_{g,t}/d\,c_t}{p_{g,t}} - \frac{d\,p_{b,t}/d\,c_t}{p_{b,t}}$. Appendix A-1 shows that deriving both sides of equation (11) with respect to c_t yields:

$$NN = \frac{p_{b,t}}{p_{g,t}} \left(\frac{\phi\triangle CO2(2+\psi\triangle CO2)}{(\frac{(G-c_t)}{\tau S^2\sigma_{g,t}^2} - \phi\triangle CO2)^2} \right) \left(\frac{1}{\tau S^2 \sigma_{g,t}^2} \right) \tag{12}$$

This expression spurs the main proposition of the model.

Proposition 1: brown asset returns respond more negatively than green asset returns to an innovation in the risk free rate

Proof: $NN = \frac{d\,p_{g,t}/d\,c_t}{p_{g,t}} - \frac{d\,p_{b,t}/d\,c_t}{p_{b,t}} > 0$

As a final step, we investigate how the impact $\frac{d\,NN}{d\,\triangle CO2}$ of CO_2 on non neutrality changes with CO2 itself, with the green preference ϕ, and with the brown risk channel ψ. This leads to lemmas 2 and 3

Lemma 2: CO_2 has a growing and convex impact on non neutrality, i.e. $\frac{d\,NN}{d\,\triangle CO2} > 0$ and $\frac{d^2\,NN}{d^2\,\triangle CO2} > 0$

Proof: see appendix A-2

Lemma 3: the impact of CO_2 on non neutrality rises with the investors' preference for green asset ϕ, and the relative increase in risk ψ involved in holding the brown asset, i.e. $\frac{d^2\,NN}{d\,\triangle CO2\;\,d\,\psi > 0}$ and $\frac{d^2\,NN}{d\,\triangle CO2\;\,d\,\phi} > 0$

Proof: see appendix A-2

2.3 Comments

In the model above brown assets respond relatively more to monetary policy shocks for two reasons. First, they provide higher returns in compensation for their higher risk. This makes them the best adjustment variable for portfolio managers with an increased (decreased) need for finding yield following a fall (rise) in interest rate. This is the search-for-yield channel. Second, green assets provide non-financial returns, which makes investor demand less elastic to a change in excess returns. This is the non-financial utility channel.

The model generates testable implications. Consider estimating the following linear regression, for any firm i :

$$r_{i,t} = \alpha_i + \beta_1 c_t + \beta_2 \left(c_t \times CO2_{i,t}\right) + \varepsilon_{i,t}$$

$$\Rightarrow \frac{d\, r_{i,t}}{d\, c_t} = \frac{d\, p_{g,t}/d\, c_t}{p_{g,t}} = \beta_1 + \beta_2 \times CO2_{i,t}$$

If all stock returns are negatively linked to rate innovations for any positive level of CO_2 emissions as posited by lemma 1, we should have $\beta_1 < 0$. If the reaction of high emissions stocks is more negative than that of low emissions stocks as posited by proposition 1, we should have $\beta_2 < 0$. Lemma 1 and proposition 1 are jointly tested in section 5 and and checked for robustness in section 6.

Furthermore, if the MP response of stock returns in absolute value is a growing convex function of CO_2, as posited by lemma 2, we should have $\frac{d\beta_2}{d\,CO_2} < 0$. Similarly if the impact of CO_2 on the MP response of stock returns in absolute value increases with ϕ and ψ, as posited by lemma 3, we should have $\frac{d\beta_2}{d\phi} < 0$ and $\frac{d\beta_2}{d\psi} < 0$. These possibilities is investigated in section 7, which is dedicated to further analyzing the dynamics of CO_2 non neutrality.

3 Empirical framework

3.1 Econometric specification

Our estimation strategy relies on an event-study approach: we consider the stock price response to monetary policy innovations on the day of FOMC announcement only. This approach has become the standard in the literature on the transmission of MP to asset prices since the pioneering work of by Cook and Hahn (1989) and Kuttner (2001) (see for example, Bernanke and Kuttner (2005); Gürkaynak et al. (2005); Hanson and Stein (2015); Nakamura and Steinsson (2018)). It can be easily amended to panel data and to assess the heterogeneity of the transmission. Our baseline regression takes the following form:

$$r_{i,t} = \beta_1 MP_t + \beta_2 MP_t \times CO2_{i,t} + \beta_3 CO2_{i,t} + \sum_{k=4}^{K} \beta_k \mathbf{X}_{k,i,t} + \alpha_i + \varepsilon_{i,t} \tag{13}$$

where t indexes the days in which an FOMC announcement occurs, $r_{i,t}$ is the daily returns of firm i on day t, MP_t refers to the change in MP on day t, $CO2_{i,t}$ represents firm's carbon intensity at time t, $\mathbf{X}_{k,i,t}$ is a set of control variables, α_i refers to firms fixed effects, and $\varepsilon_{i,t}$ is the error term.[2] The interaction term, $MP_t \times CO2_{i,t}$, is our main variable of interest. As stated in the theoretical model we expect $\beta_1 < 0$ and $\beta_2 < 0$, meaning that a monetary tightening (loosening) leads to a drop (rise) in stock prices, and that this negative relationship is stronger for polluting firms. We estimate our regressions using Ordinary Least Squares (OLS) and report two-way cluster-robust standard errors to account for correlation within firms and within FOMC meetings.

The dependent variable is constructed using stock prices data is obtained from Thomson Reuters. We take all common shares listed on US major stock exchanges, excluding financial companies, from January 1st 2010 through December 31th 2019. Daily returns are computed as the logarithm of the first difference in prices:

[2]The vector $\mathbf{X}_{k,i,t}$ comprises firm-level and macro-level variables. Further details are provided below.

$$r_{i,t} = ln(P_{i,t}) - ln(P_{i,t-1}) \quad (14)$$

where $P_{i,t}$ is the price of a stock i on trading day t. To mitigate the impact of outliers, returns are windsorized at the 1% level in the baseline estimation. Other levels are considered in robustness.

3.2 Monetary policy data

Our baseline indicator of MP surprises is taken from Bauer and Swanson (2022).[3] These authors measure policy announcement surprises using changes in the first four quarterly Eurodollar futures contracts (ED1, ED2, ED3 and ED4) in a 30 minute window around the time of the FOMC's press release. The price movements on the four contracts are turned into a single indicator through a first principal component analysis. The Bauer and Swanson (2022) indicator thus provides a broad measure of the overall MP stance that incorporates both the change in the federal funds rate target as well as the change in forward guidance.

Generally, the identification of causal effects from monetary policy to stock prices must satisfy three conditions. First, there is no reverse causation, i.e., MP actions do not react to asset price changes. Second, there are no omitted variables that impact jointly and contemporaneously $r_{i,t}$ and MP_t. Third, the impact of MP on prices is observable on the day of the meeting, meaning that movement in prices and/or in the monetary policy indicator cannot be predicted –and thus priced in– ex ante. The use of daily returns on FOMC days at the firm level ensures that the causality runs from MP to stocks. Condition 1 is likely filled. Using daily returns also ensures that there are no macroeconomic shocks systematically biasing the results. Nevertheless two problems may arise regarding conditions 2 and 3.

The first problem is that high-frequency interest rate surprises could reveal information not just about policy but also about the central bank's assessment of the economic outlook

[3]The data are obtained from Michael Bauer's personal site: https://www.michaeldbauer.com/research/.

that does not identify a purely exogenous MP shock (?Jarociński and Karadi, 2020; Andrade and Ferroni, 2021). Reassuringly, in their paper Bauer and Swanson (2022) find that the effects of MP on financial markets are largely unchanged when bias-adjusted indicators are considered. They argue that FED communication influences only the relationship between MP and the economic outlook, not the relationship between MP and daily stock prices. Nevertheless to evacuate any concerns, we provide estimations using the indicator of MP surprises of Jarociński and Karadi (2020) in robustness. These authors decompose the standard measure of MP surprise into "pure monetary" shocks and "central bank information" shocks based on the observation of the co-movement of interest rates and stock prices around policy announcements. A negative co-movement identifies "pure monetary" shocks, while a positive co-movement identifies "central bank information" shocks. The indicator is downloaded from Martin Jarocinski's personal site.[4] We also estimate the model using the "central bank information" surprise indicator instead of the "pure monetary" surprise indicator, as a placebo test.

The second problem is that policy rate surprise may in fact be predictable using information available prior to the FOMC announcements, which violates the third condition (Cieslak, 2018; Miranda-Agrippino and Ricco, 2021; Bauer and Swanson, 2023, 2022). To make sure we identify pure surprises, we include in the baseline regression the set of macroeconomic and financial variables that have been identified as potential predictors of MP surprises by Bauer and Swanson (2022): non-farm payrolls release, employment growth over the last year, the log change in the S&P500 from 3 months before to the day before the FOMC announcement, the change in the yield curve slope over the same period, the log change in a commodity price index over the same period, and the option-implied skewness of the 10-year Treasury yield. The data is obtained from Michael Bauer's personal site.[5] The Bauer-Swanson controls are included in the baseline regressions as control variables. Following Bauer and Swanson (2023, 2022), we also provide a robustness test in which the monetary policy surprise indicator is orthogonalized with respect to the Bauer-Swanson controls.

[4]https://marekjarocinski.github.io/
[5]https://www.michaeldbauer.com/research/

3.3 Emission data

Data on CO_2 emissions at the firm level -measured in tonnes of CO_2 per year- is obtained from Thomson Reuters. According to the Greenhouse Gas Protocol nomenclature[6] established in 2001, a company's greenhouse gas emissions are categorized into three scopes (or levels) that represent its emissions perimeter. Scope 1 encompasses direct carbon emissions originating from sources owned or controlled by the company. Scope 2 comprises indirect carbon emissions resulting from the consumption of purchased energy due to the company's activities. The combination of Scope 1 and Scope 2 emissions constitutes Total emissions. Scope 3 encompasses carbon emissions produced by the production units within the company's value chain. We concentrate on Total emissions calculated as the sum of Scope 1 and Scope 2, primarily because Scope 3 data is scarcer and harder to measure.[7] Specifications using scope 1 or scope 2 emissions separately are provided for robustness.

Another choice involved in defining CO_2 emissions is whether to use reported emissions or estimated emissions. While the number of companies disclosing their carbon emissions (either mandatorily or voluntarily) has grown over the years, a significant portion of companies still do not report their carbon footprint. Using reported emissions then reduces the size of the sample. However, as argued by Aswani et al. (2023); Bauer et al. (2022), there are significant discrepancies between estimated and reported emissions, which casts doubts on the reliability of estimated emissions. With this in mind, reported emissions are used in the baseline estimations. Nonetheless, carbon emissions as estimated by Thomson Reuters are considered in robustness tests.

The last step in defining our CO_2 indicator is to divide the emissions of a firm by its sales, obtained from Thomson Reuters. This carbon intensity approach is standard in the literature. It prevents CO_2 from measuring the size of a firm rather than its ecological footprint. We consider in robustness alternative measures such as carbon emissions per unit of equity value, to account for the fact that the exposure to climate risk may be

[6] see https://ghgprotocol.org/.

[7] Busch et al. (2022) show that the consistency of the CO_2 emission intensities (disclosed by firms or estimated by third-party) between third-party providers is very high even though decreasing in Scope 2 to Scope 3.

relatively higher for firms with low market value (Ilhan et al., 2021). The carbon intensity measure is standardized to ease the interpretation of the results.

3.4 Control variables

To account for variation in returns that stems from non-CO_2 related factors, we add six firm-level variables to the set of controls (vector $\mathbf{X}$ of eq.13), in addition to the macro-level predictors from Bauer and Swanson (2022) discussed previously. These variables include size, debt, cash flows, market beta, price-to-earning ratio, and return on equity. Size is proxied by the natural logarithm of market capitalization. Debt is expressed as the proportion of both short-term and long-term debt to total assets. Cash flow is expressed as a percentage of total sales. Market beta is estimated by running a CAPM model on each stock over a one-year window. The price-to-earning ratio is computed by dividing operating income by market value. Return on equity is obtained by dividing net profit by book value. All relevant firm-level data is obtained from Thomson Reuters.

In the baseline regression (section 5.1) the firm-level controls are included on their own, but in section 5.2 they enter both directly and in interaction with MP. Interacting the controls means allowing other variables than CO_2 intensity to influence the relationship between stock returns and MP surprises, which allows us to pin down the pure effect of CO_2 on non-neutrality. The intuition is as follows: section 5.1 seeks to measure whether there exists a difference in MP exposure between brown stocks and green stocks, regardless of its source. Section 5.2 investigates whether brownness is relevant in itself, as suggested by the theoretical model, or simply correlates with other factors that cause MP heterogeneity.

We sort our variables into 4 vectors of MP heterogeneity identified by Ozdagli and Velikov (2020) : financial constraints, cash flow duration, cash flow cyclicality and operating profitability. Financially constrained firms are expected to be more affected by MP shocks through the credit channel (Gertler and Gilchrist, 1994; Perez-Quiros and Timmermann, 2000). We use firm's size, debt, and cash flows as (inverse) proxies of financial constraints. Duration leads to heterogeneity in MP responses because cash-flows that are far in the future are relatively more discounted (Ozdagli, 2018). We measure this channel through the price-to-earning ratio. Cyclical stocks typically rely on external financing more often, which increases their sensitivity to the cost of external financing. We measure a firm's cyclicality through its market beta. Finally, firms that generate profits should be less sensitive to variation in the cost of external financing. Profitability is estimated through the return on equity (ROE).

4 Preliminary evidence

4.1 Summary statistics

Merging the financial data base with the reported CO_2 emissions data leads to an unbalanced sample of 857 companies in our baseline estimation[8]. In the time dimension, our sample contains a total of 81 FOMC meeting days. Overall the total number of observations is 315,157.

Table 1 summarizes all firm-level variables in the sample. The average firm in our sample is large but not necessarily profitable. Its scope 1 emissions represents the bulk of its total emissions.

Table 2 shows the correlation between our preferred CO_2 intensity measure and reported emissions in absolute value. As expected, the relationship is positive and significant, but far from 1, which shows that total emissions partly reflect size.

Figure 1 plots the MP indicator over our sample period. Table 3 displays its correlation with the orthogonalized indicator of Bauer and Swanson (2022), and the "pure monetary" and "central bank information" surprises indicators of Jarociński and Karadi (2020). As expected correlations are high among all indicators except the "central bank information" surprise one.

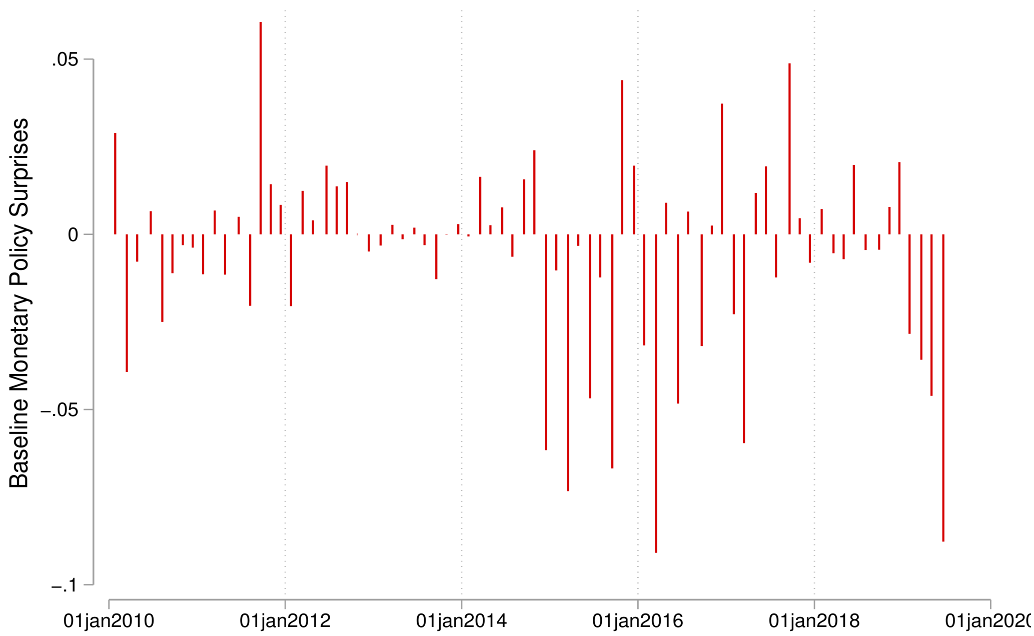
[8]The sample with estimated emissions covers 2325 companies

Table 1: Summary statistics

	Mean	Std.Dev.	p25	p50	p75	Min.	Max.
Emissions measures							
Total emissions	13.15	2.33	-2.21	18.89	11.55	13.02	14.71
Total emissions intensity	0.50	1.54	0.00	51.82	0.02	0.05	0.28
Scope 1	12.02	2.94	-3.22	18.79	10.01	11.87	14.13
Scope 1 intensity	0.40	1.37	0.00	40.20	0.00	0.02	0.16
Dependent variable							
Returns	0.03	1.83	-8.34	8.60	-0.81	0.06	0.93
Firms' controls							
ROE	16.72	32.00	-407.98	138.50	6.90	13.53	23.03
Historic volatility	0.31	0.14	0.00	1.45	0.20	0.27	0.37
Size	16.28	1.40	10.42	21.26	15.34	16.25	17.13
Tobin Q	1.09	0.81	-0.84	3.95	0.55	0.98	1.50
Debt	0.27	0.26	0.00	1.39	0.05	0.22	0.41
Margins	0.19	1.25	-11.87	53.74	0.00	0.01	0.07
Cash flows	-0.00	0.01	-0.17	0.00	0.00	0.00	0.00

Note: The table represents the summary statistics of variables used in our estimation during the sample period 2010-2019.

Figure 1: Monetary policy surprises



Note: monetary policy surprises over the period 2010-2019, baseline indicator.

Table 2: Cross-correlation between environmental variables

	Total emissions	Total emissions intensity	Scope 1 emissions	Scope 1 emissions intensity
Total emissions	1			
Total emissions intensity	0.744***	1		
Scope 1 emissions	0.902***	0.757***	1	
Scope 1 emissions intensity	0.683***	0.890***	0.872***	1

Note: This table provides correlation between all environmental variables that we used as our firm's brownness indicators. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3: Correlation of the monetary policy surprises

	Baseline	Orth.	PM	CBI
Baseline	1			
Orth.	0.927	1		
PM	0.857	0.791	1	
CBI	0.305	0.233	-0.036	1

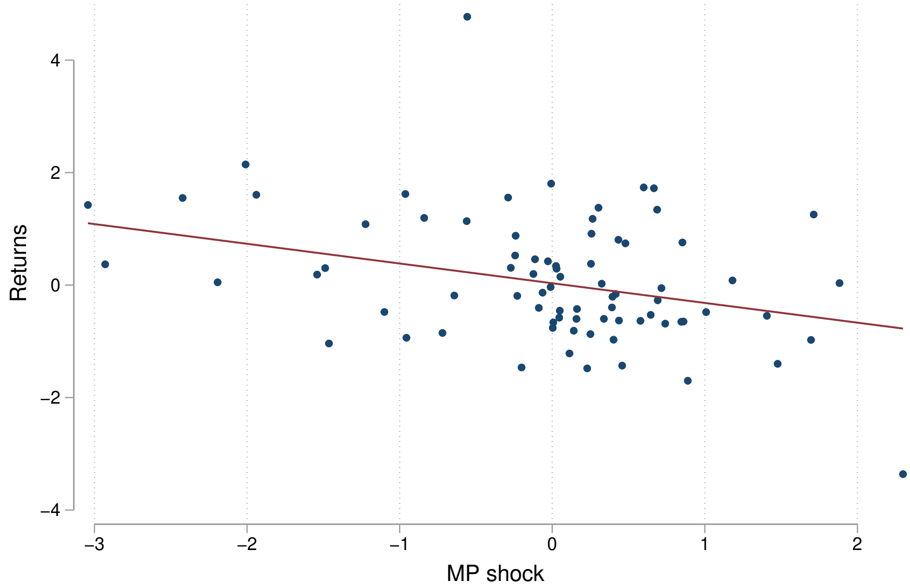
Note: This table presents the correlation between baseline, orthogonalized (Orth.), Pure Monetary (PM) and Central Bank Information (CBI) surprises.

4.2 Prima-facie evidence

This section examines the correlation between stock returns and MP surprises. Figure 2 plots the average returns of stocks on FOMC meetings days against the average policy surprises. As expected, the relationship is negative: a loosening (tightening) MP surprise has positive (negative) impact on stock returns in average.

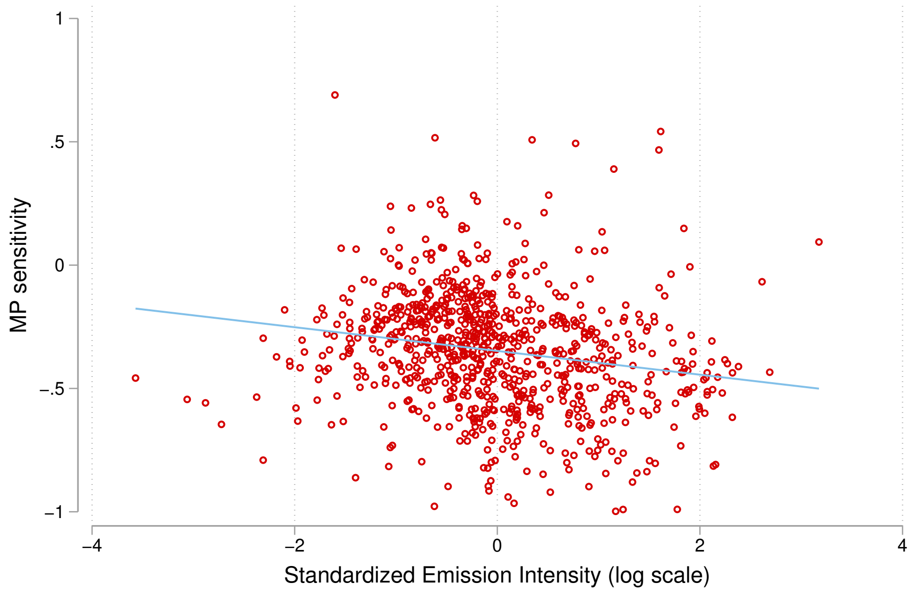
We next look for preliminary evidence on the impact of CO_2 emissions on the relationship between returns and MP. Each stock returns of a firm i is regressed on the MP indicator throughout the sample period, to obtain a estimate of the firm's sensitivity to MP shocks. We then connect the estimated coefficient to the average carbon intensity of the firm. Figure 3 shows the results across all firms. Consistent with our prior, the effect of an MP shock on stock returns becomes increasingly negative as carbon emission intensity increases.

Figure 2: Relationship between Stock Price Returns and Monetary Policy Shock



Note: The figure shows the relationship between the average firm return in our sample and the average monetary policy surprise over the observation period 2010-2019. The full line plots the estimated returns from a naive regression of returns on MP shock

Figure 3: MP sensitivity & CO_2 emissions intensity



Note: Figure 3 plots the relationship between the sensitivity of firm returns to a MP surprise (estimated coefficient per firm) and the carbon footprint quantified by scope 1 emissions intensity (calculated as the natural logarithm of the ratio of scope 1 emissions to company sales).

5 Baseline results

5.1 The carbon effect on MP transmission

Table 4 reports the results from estimating different specifications of equation 13.

Table 4: Heterogeneous Responses of Stock Returns to Monetary Policy

Returns	(1)	(2)	(3)	(4)	(5)	(6)
MP surprise	-0.451***		-0.429***	-0.450***	-0.395***	-0.375***
	(0.109)		(0.103)	(0.110)	(0.109)	(0.135)
Emission × MP surprise	-0.052***	-0.051***	-0.057***	-0.052***	-0.054***	-0.047***
	(0.018)	(0.019)	(0.018)	(0.018)	(0.019)	(0.014)
Emission	0.013	0.010	-0.006	-0.018	0.037	0.003
	(0.067)	(0.071)	(0.070)	(0.015)	(0.037)	(0.066)
Control variables	Yes	Yes	No	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	Yes	Yes
Date FE	No	Yes	No	No	No	No
Year & Month FE	Yes	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	No	No
Industry × Year FE	No	No	No	No	Yes	No
Industry × MP FE	No	No	No	No	No	Yes
R-squared	0.124	0.288	0.103	0.105	0.104	0.127
Observations	28062	28062	35157	28065	28062	28062
Nb. of Firms	771	771	857	771	771	771

Note: This table represents the estimation results of our baseline equation 13 considering only the days of the FOMC meeting during the sample period 2010-2019. The independent variable represents the daily stock return. The columns correspond to the 8 different specifications we estimate. They are differentiated by the inclusion or not of certain variables, controls or fixed effects necessary for our analysis. Standard errors are clustered at the firm and time level, and reported below the coefficient estimates. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Column 1 shows our baseline estimation which features Bauer-Swanson controls, financial controls, and firm/year fixed effects. As expected, the variables " MP surprise" and "Emissions × MP surprise" are both negative and highly significant. More specifically, a one standard deviation of "MP surprise" induces an immediate average contraction of 0.452% of U.S. individuals stocks returns. This is closely in line with the macro-estimates provided by Jarociński and Karadi (2020). "Emissions × MP surprise" has a coefficient estimate of -0.052, which means that a firm that is one standard deviation more carbon intensive than the sample average should expect a stock return of +0.504% following a one standard deviation decrease in monetary surprise, against +0.452% for the average stock in our sample.

Column 2 removes the MP surprise variable and controls for FOMC time fixed effects. This implies that the parameter estimates are based on the within-firm-meeting variation, to verify that the results are not driven by an omitted variable bias or a fixed meeting component. The estimates displayed are very similar to the baseline. Column 3 removes the Bauer-Swanson controls to maximise the sample size, which has little impact on our estimates. Columns 4, 5 and 6 correspond to different ways of capturing the industry effect of MP. Column 4 replaces the firm fixed effects by industry fixed effects. Column 5 adds an industry × year fixed effect to our baseline specification, to account for time-varying industry shocks. Both specifications have limited impact on the estimates. Column 6 exploits the variation in the data that is orthogonal to the industry average effect of MP surprises. The point estimate of the "Emissions × MP surprise" is slightly lower than in our baseline estimate, but still significant. This implies that our findings are not driven by a systematic different sectoral responses to MP surprises: intra-industry variation in CO_2 intensity also matters.

The general message of Table 4 is that the variables " MP surprise" and "Emissions × MP surprise" are both negative and highly significant in all specifications. Brown stocks are relatively more impacted by MP surprises. From a policy standpoint, this result implies that a central bank that takes an accommodative stance indirectly subsidizes firms with a high carbon footprint. Another interesting implication of our results is that, since brown stocks are more likely to experience large fluctuations on FOMC meeting days, investors should demand compensation for this risk. However we do not observe this: firms with higher carbon emission do not earn higher return across FOMC meetings days.[9]

[9]This result is in contrast with basic economic logic and with the general message of Bolton and Kacperczyk (2021a). However, these authors also find insignificant climate premia when using carbon intensity, as we do, rather than the total emissions.

5.2 A new channel of MP transmission?

This section turns to the issue of whether the CO_2 is relevant in itself, or simply correlates with other sources of MP heterogeneity. We interact our MP indicator with the set of firm-level control variables described in subsection 3.4. Table 5 plots the results.

Table 5: Heterogeneous Responses of Stock Returns to Monetary Policy: Controlling for alternative heterogeneity sources

Returns	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MP surprise	-0.452***	-0.518***	-0.469***	-0.449***	-0.192***	-0.552***	-0.481***	-0.383**
	(0.109)	(0.130)	(0.113)	(0.109)	(0.043)	(0.126)	(0.112)	(0.146)
Emission MP surprise	-0.052***	-0.052***	-0.053***	-0.052***	-0.052***	-0.072***	-0.047***	-0.067***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.011)	(0.017)	(0.019)
Size MP surprise		0.004						0.004
		(0.004)						(0.004)
Debt MP surprise			0.046					0.040
			(0.043)					(0.050)
Cash flows MP surprise				1.357				1.270
				(1.317)				(1.333)
PER MP surprise					-0.000			-0.000
					(0.000)			(0.000)
Beta MP surprise						-0.260***		-0.249*
						(0.037)		(0.126)
ROE MP surprise							0.002***	0.001***
							(0.001)	(0.000)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	Yes	No	No
Industry × Year FE	No	No	No	Yes	No	No	Yes	No
Industry × MP FE	No	No	No	No	No	No	No	Yes
R-squared	0.124	0.124	0.124	0.124	0.124	0.128	0.125	0.129
Observations	28062	28062	28062	28062	28062	27627	28062	27627
Nb.of Firms	771	771	771	771	771	771	771	771

Note: This table represents the estimation results corresponding to our baseline equation 13. The independent variable represents the daily stock return. We consider financial variables (Size, Debt ratio, Cash flows ratio, Beta, PER, ROE) identified in the literature that can impact returns in interaction with monetary policy surprise to control for other sources of heterogeneity. The columns correspond to the 6 different specifications we estimate. Standard errors are clustered at the firm and time level, and reported below the coefficient estimates. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Specification (1) is a reminder of the baseline results of Table 4. In specifications (2) to (7), interacted controls are introduced individually. The coefficients on all interacted control are of the expected sign, but are only significant for the indicators of cyclicality (Beta), and profitability (ROE). Our indicators of financial constraint (size, debt, and cash flows) and duration (PER) are non-significant. For conciseness we do not seek to explain these results, or discuss how they contribute to the literature on non-neutrality. We focus on the way the interacted controls impact the non-neutrality of $\boldsymbol{CO_2}$ intensity.

Unsurprisingly, the effect of CO_2 intensity is unimpacted by the introduction of the insignificant financial constraint and duration indicators. In contrast, the coefficient on "Emissions × MP surprise" becomes more negative when "Beta × MP surprise" is included. This result implies that the coefficient of "Emissions × MP surprise" in the baseline regression was driven up by the fact that emissions are negatively correlated with cyclicality, which itself negatively impacts the relationship between returns and MP. The coefficient of correlation of -0.1686 between CO_2 intensity and market beta in our sample supports this view. Conversely, the coefficient on "Emissions × MP surprise" becomes less negative when "Beta × ROE" is included. This result implies that the coefficient of "Emissions × MP surprise" in the baseline regression was driven down by the fact that emissions are negatively correlated with profitability, which itself positively impacts the relationship between returns and MP. The coefficient of correlation between CO_2 intensity and ROE in our sample is of -0.1083.

The general message of Table 5 is that CO_2 emissions remain a significant driver of MP heterogeneity even after including known drivers of MP heterogeneity in the estimations. In column 8 confirms this by showing that the channel does not disappear and remains statistically and financially significant when we include all channels together.

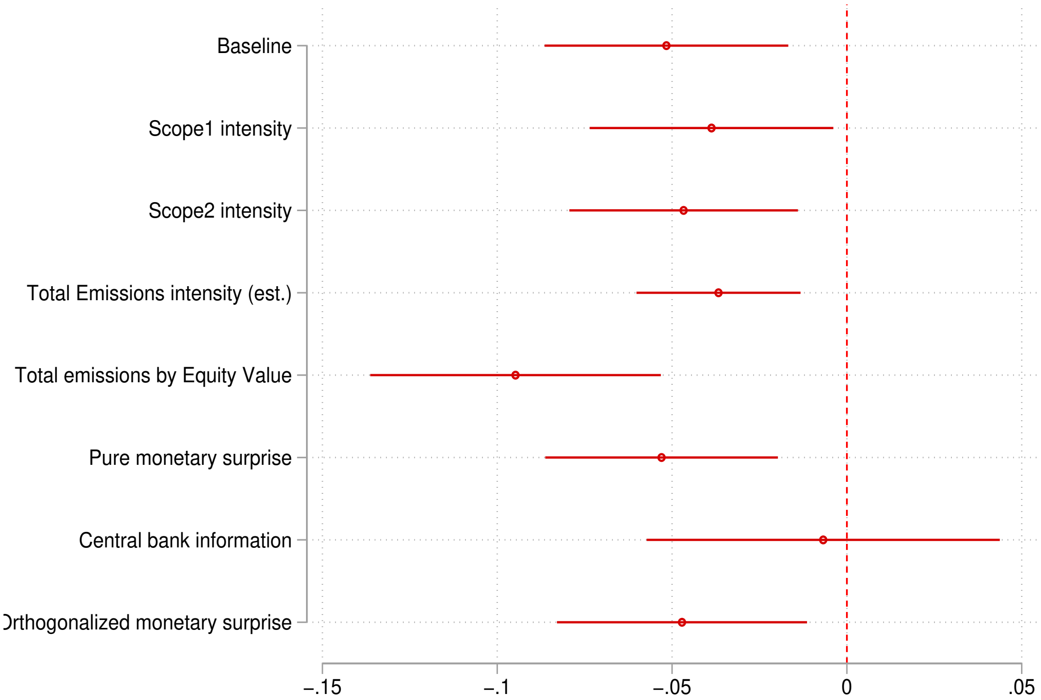
6 Robustness checks

6.1 Alternative explanatory variables

We explore the sensitivity of our results to changes in the definition of our variables. We first consider alternative measures of emissions intensity: using scope 1 and Scope 2 emissions instead of their sum, using estimated emissions instead of reported ones, and using total emissions per unit of equity value instead of sales. We then consider the alternative measures of MP surprises defined in subsection 3.2: the "pure monetary" surprise indicator of Jarociński and Karadi (2020), the orthogonalized Bauer and Swanson

(2022) indicator, and the "central bank information" indicator of Jarociński and Karadi (2020). Figure 4 compares the coefficient on our main variable "Emissions × MP surprise" in these alternative specifications to the baseline estimates.

Figure 4: Responses of Stock Returns to Alternative Indicators



Note: This figure plots the "Emissions × MP surprise" coefficient estimates from equation 13 considering alternative indicators for both emissions and MP surprises measures. For the emissions variable, we consider the decomposition of Total emission intensity into Scope 1 intensity and Scope 2 intensity (emissions scaled by firms' revenues), the total estimated emissions intensity and total emissions scaled by equity value. In terms of MP surprises, we use Orthogonalized MP, Pure MP and Central bank information surprise. Bars represent 95 percent confidence interval and standard errors are clustered at firm and time level.

The results are robust to alternative definitions of CO_2 emissions. The "pure monetary" surprise indicator of Jarociński and Karadi (2020) produces estimates that are very similar to our baseline results, suggesting that movement in rates stemming from communication do not drive our result. As expected, the placebo test using the "central bank communication" indicator makes the non neutral impact of CO_2 intensity disappear. The orthogonalized indicator of Bauer and Swanson (2022) yields point estimates that are almost identical to our baseline.

6.2 Abnormal returns

This section considers an alternative version of the model in which abnormal returns are used instead of returns. The goal is to verify that the stock returns variation picked up by the baseline estimation does not stem from differences in exposures to global factors. We rely on the classic Fama-French factor model for our choice of variables.[10] The data is obtained from Kenneth French's website for the US market. In column (1) the factors are included as controls, and the dependent variable is the return of firm i on day t. In all subsequent specifications the dependent variable is abnormal returns of firm i on day t, as estimated by the residual of the regressions of returns of i on the five factors. Table 6 presents the results.

Table 6: Fama and French controls

	Returns	Abnormal returns					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MP surprise	-0.102***	-0.097***		-0.100***	-0.097***	-0.106***	-0.157*
	(0.023)	(0.021)		(0.022)	(0.021)	(0.024)	(0.088)
Emission × MP surprise	-0.051***	-0.075***	-0.073***	-0.075***	-0.075***	-0.076***	-0.043***
	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.016)
Emission	0.016	0.047	0.045	0.026	-0.007	0.037	-0.006
	(0.073)	(0.070)	(0.070)	(0.068)	(0.014)	(0.058)	(0.013)
Control variables	Yes	Yes	Yes	No	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	No	Yes	Yes
Date FE	No	No	Yes	No	No	No	No
Year & month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes	No	No
Industry × Year FE	No	No	No	No	No	Yes	No
Industry × MP FE	No	No	No	No	No	No	Yes
R-squared	0.287	0.042	0.050	0.037	0.014	0.046	0.018
Observations	27691	27691	27691	35157	27692	27691	27692
Nb. of Firms	771	771	857	771	771	771	771

Note: This table represents the estimation results corresponding to our baseline equation 13. As a measure of robustness, we consider abnormal returns instead of returns as the independent variable in the specification. The columns correspond to the 7 different specifications we estimate. They are differentiated by the inclusion or not of certain variables, controls or fixed effects necessary for our analysis. Standard errors are clustered at the firm and time level, and reported below the coefficient estimates. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

In all specifications the average effect of MP surprise decreases significantly. This is not surprising : the effects of MP surprise on firm-return are largely channeled by the

[10]The five factors are: the Small Minus Big (SMB) factor, the High Minus Low (HML) factor, the Conservative Minus Aggressive (CMA) factor, the Robust Minus Weak (RMW) factor and the excess return on the market.

impact of MP on the global factors. By rendering MP surprises orthogonal to the factors, we close several transmission channels of MP (which is in fact the reason why the factors were not included in the baseline estimation). Most importantly from our perspective, the coefficient on "Emissions × MP surprise" remains negative and significant specifications. Stocks with a higher carbon footprint react more to a MP shock. From a quantitative viewpoint, the point estimates for the interaction term is slightly higher in absolute value than the baseline estimate of -0.052. Carbon intensity induces more heterogeneity in the response of MP when we consider abnormal stock price returns. This further supports the idea that CO_2 intensity is a channel of non neutrality of its own.

6.3 Outliers sensitivity

This section explores the sensitivity of our results to outliers. First, we winsorize returns at the 2.5% level, instead of 1%. Second, we conduct a new regression restricted to observations in which the standardized residuals are less than 1.96 in absolute value in the baseline regression. Third, we restrict the sample to observations for which Cook's distance is is less than $4/n$, with n the number of observations used in computing the estimates. Fourth, we perform a robust regression à la Huber. Finally column (5) implements a placebo test that lags the policy surprises by one week. Table 7 plots the results.

Table 7: Heterogeneous Responses of Stock Returns to Monetary Policy: Outliers sensitivity

Returns	(1)	(2)	(3)	(4)	(5)
MP surprise	-0.438***	-0.399***	-0.395***	-0.378***	0.074
	(0.106)	(0.086)	(0.086)	(0.011)	(0.093)
Emissions × MP surprise	-0.050***	-0.043***	-0.047***	-0.043***	0.002
	(0.017)	(0.016)	(0.016)	(0.008)	(0.020)
Emissions	0.011	-0.048	-0.079	-0.039	0.022
	(0.063)	(0.044)	(0.049)	(0.038)	(0.050)
Control variables	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Date FE	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.134	0.174	0.167	0.154	0.098
Observations	27691	26125	26182	27692	27691
Nb. of Firms	771	771	771	771	771

Note: This table represents the estimation results of our baseline equation 13 considering all sample period 2010-2019. The independent variable represents the daily stock return. The columns correspond to the 8 different specifications we estimate. They are differentiated by the inclusion or not of certain variables, controls or fixed effects necessary for our analysis. Standard errors are clustered at the firm and time level, and reported below the coefficient estimates. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

In all cases, the estimates remain similar to our baseline, except for the placebo MP surprise test in which the interaction term has no significant impact on stock returns, as expected.

More robustness can be found in appendix B. Table B1 reports estimates based on a sample including all business days, not only FOMC meeting days. Table B2 reproduces Table 4 with estimated emissions instead of reported emissions.

7 Further investigation

7.1 Is the impact of CO_2 on MP responsiveness non-linear?

In the theoretical model of section 2, the impact of CO_2 on non neutrality was positive and convex. If this assertion is correct, the coefficient on "Emissions × MP surprise" should become increasingly negative as CO_2 rises.

To explore this possible non-linearity, we decompose our interest variable "Emissions × MP surprise" into different variables according the level of CO_2 intensity of companies. In the baseline form we create three dummies which indicate whether an observation is below the 25th percentile of firm emissions, between the 25th percentile and the 75th percentile of firm emissions, or above the 75 th percentile of firm emissions. We then interact the dummies with "Emissions × MP surprise" to capture the impact of CO_2 intensity on MP responsiveness for low, medium, and high CO_2 intensity firms. For robustness we also create dummies based on quintiles (column 2 and 3). The difference between columns 2 and 3 is that we exclude in column 3 the top 5% observations of the fifth quintile. Table 8 presents the results.

As expected from the model, we find that the marginal impact of CO_2 intensity on MP responsiveness typically increases with CO_2 intensity. The increase is remarkably monotonic in column (1). The stock price of a company with high emissions decreases by 0.595% on average after a standard monetary surprise, against 0.414% when the emissions is moderate and 0.387% only when the emissions are relatively low. In column (2) and (3) the relationship is not perfectly monotonic since the stock return effect is lower -in absolute term- for the second quintile than it is for the first quintile. However, the estimates for the other quintiles confirm that the more a firm is carbon intensive, the more its equity prices react to a MP shock.

7.2 Do climate change concerns matter?

In the theoretical model of section 2 the relationship between CO_2 and MP responsiveness was strengthened by two factors: the non pecuniary utility ϕ involved in holding green assets, and the relative increase in risk ψ involved in holding brown assets which carry transition risk. This section tests these predictions by introducing in the model a variable that should be positively correlated with both green utility and transition risk: climate awareness.[11] We expect CO_2 intensity to have an increasingly negative impact on

[11] We have attempted to separate the investor green utility channel from the transition risk channel, but have not found a way to do this.

Table 8: Non-linear effects

Returns	(1)	(2)	(3)
Low emissions × MP	-0.387***		
	(0.114)		
Medium emissions × MP	-0.414***		
	(0.111)		
High emissions × MP	-0.595***		
	(0.123)		
Q1 emissions × MP		-0.404***	-0.381***
		(0.114)	(0.110)
Q2 emissions × MP		-0.368***	-0.346***
		(0.114)	(0.109)
Q3 emissions × MP		-0.407***	-0.385***
		(0.110)	(0.105)
Q4 emissions × MP		-0.520***	-0.498***
		(0.123)	(0.120)
Q5 emissions × MP		-0.560***	
		(0.118)	
Q5 (without top 5%) × MP			-0.541***
			(0.125)
Control variables	Yes	Yes	Yes
Firm FE	Yes	Yes	
Year & month FE	Yes	Yes	Yes
R-squared	0.140	0.142	
Observations	27691	27691	
Nb. of Firms	771	771	

Note: This table represents the estimation results corresponding to our baseline equation 13 when we interact policy surprise with dummies based on both percentile (Low, Medium, High) and quintile (Q1–Q5) emissions (panel A) as well as when we introduce our two indicators of change in media Climate Change Concerns (CCC) in our regressions (Panel B). Standard errors are clustered at the firm and time level, and reported below the coefficient estimates. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

MP responsiveness as climate concerns increase.

Our measure of climate awareness is based on newspapers coverage of climate change related events. The underlying idea is that newspapers may both lead investors to update their subjective probabilities of climate risk, and their feeling of doing good by owning shares in green firms. In order to proxy newspapers coverage of climate change, we use two different time-series indicators drawn from textual analysis of news sources. The first indicator is from Engle et al. (2020) and relies on the Crimson Hexagon proprietary sentiment measure to capture negative reports relating to climate change from a large corpus of over one trillion news articles. We also use the Media Climate Change Concerns (MCCC) indicator from Ardia et al. (2021), which use a different algorithm and corpus to extract a climate change news series.[12]

Our estimation strategy is based on decomposing our interest variable "Emissions × MP surprise" into three variables according the level of climate concerns, as done for CO_2 intensity in the previous section. We consider "Emissions × MP surprise" when climate concerns are low (all observations inferior to the 33th percentile), moderate (all observations between the 33th percentile and the 66th percentile) and high (all observations superior to the 66th percentile). Table 9 presents the results.

Table 9: Climate awareness

Returns	(1)	(2)
Low climate concerns - Emissions × MP	-0.060***	-0.048*
	(0.021)	(0.027)
Moderate climate concerns - Emissions × MP	-0.024	-0.063**
	(0.063)	(0.032)
High climate concerns - Emissions × MP	-0.135***	-0.097***
	(0.034)	(0.036)
Control variables	Yes	Yes
Firm FE	Yes	Yes
Year & month FE	Yes	Yes
R-squared	0.140	0.142
Observations	27691	27691
Nb. of Firms	771	771

Note: This table represents the estimation results corresponding to our baseline equation 13 when we interact policy surprise with dummies based on both percentile (Low, Medium, High) and quintile (Q1–Q5) emissions (panel A) as well as when we introduce our two indicators of change in media Climate Change Concerns (CCC) in our regressions (Panel B). Standard errors are clustered at the firm and time level, and reported below the coefficient estimates. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

As expected, MP responsiveness is higher during periods of high estimated climate concerns, using either the Crimson Hexagon's negative sentiment climate change news index (column 1) or the MCCC indicator (column 2). The coefficient estimate in column

[12]The Crimson Hexagon's negative sentiment climate change news index is obtained from Stefano Giglio's website (https://sites.google.com/view/stefanogiglio/data-code), while the CCC indicator is available at https://sentometrics-research.com.

(1) is 2.6 times higher during periods of high climate concerns than across periods (-0.135 vs. -0.052). The MCCC indicator generates a coefficient on "Emissions × MP surprise" that is more negative when climate concerns are moderate when climate concerns are low, but this does not hold for the Crimson index. Overall these empirical results align with our theoretical expectations: the higher (lower) the increase in climate change concerns, the more (less) brown stocks react to a MP surprise.

7.3 Is the non-neutral impact of CO_2 persistent?

This section assesses the persistence of the differential in MP responsiveness between green stocks and brown stocks. We estimate Impulse Response Functions (IRF) using the local projections (LP) procedure of Jordà (2005), which is a standard approach to capture the dynamic effect of MP shock on stock returns. LPs are based on using simple regression methods to predict cumulative returns at different time horizons. They are well suited to our event-study framework with possible non-linear effects. Formally, the dynamic response of cumulative stock returns to a MP shock for different horizons (h = 0,...,10) takes the following form:

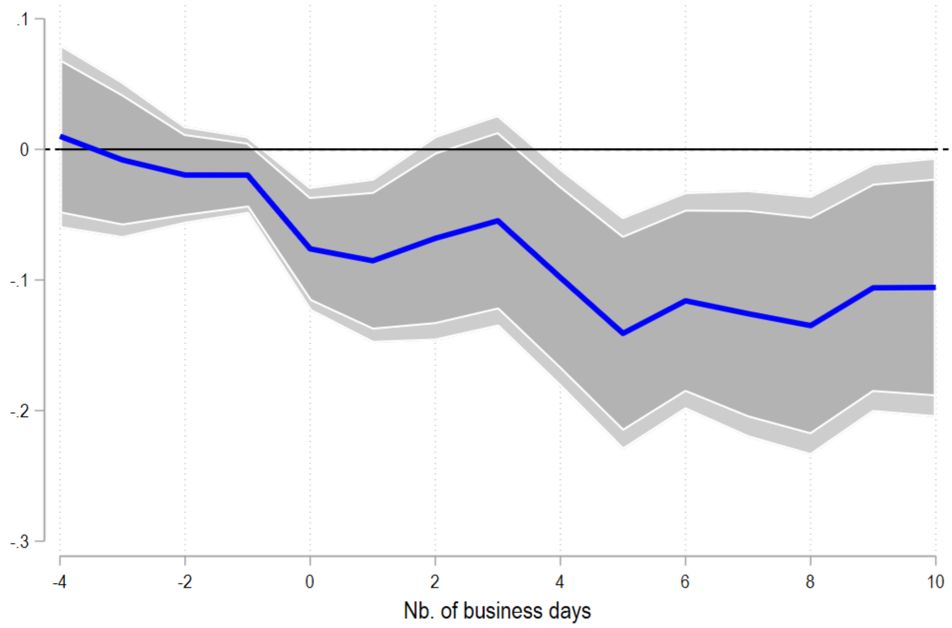
$$r_{i,t+h} = \alpha_i^h + \beta^h MP_t + \phi^h CO2_{i,t} + \psi^h MP_t \times CO2_{i,t} + \theta^h \mathbf{Z}_{i,t} + \varepsilon_{i,t}^h \tag{15}$$

where h is the time horizon and $r_{i,t+h}$ is the cumulative stock return between $t-1$ and $t+h$. ψ^h represents the difference in MP response between the average firm and a firm that is one standard deviation more carbon-intensive than the average firm, at the horizon h. Our estimation uses the same explanatory variables as those used in the baseline equation 13, and considers returns within a window of 4 days before each FOMC meeting up until 10 days after. Figure 5 displays the estimated ψ^h.

The figure shows that the differential impact of a monetary policy surprise on cumulative returns is not significant before the event, but begins to be statistically significant on the day of the FOMC meeting (h=0).[13] A positive monetary policy surprise leads to a

[13]This pattern suggests that our panel estimates do not violate the parallel trend assumption.

Figure 5: Response of US stock returns to MP shock (baseline)



Note: This figure shows the difference in response of stock returns to a MP shock (solid line) between a firm that is one standard deviation more carbon intensive than the sample average and the average firm. It depicts the sequence of estimates of ψ from the equation 15 over horizons from -4 to 10 business days. The shaded areas correspond to the 90% (darkest) and 95% (lightest) confidence intervals computed with standard errors clustered at the firm and time level.

more immediate and pronounced contraction in stock returns for brown firms, as expected. This supports the notion that the monetary policy shock is exogenous with respect to other macroeconomic factors as well as the communication component of MP on FOMC meeting days.

The heterogeneous impact of a monetary policy shock on returns across different carbon footprints appears to be permanent: there is no reversion to the mean in the business days following the shock. The effect remains statistically significant up to the 10 business days considered (except for the third day). This finding has interesting implications. From a market efficiency perspective, it suggests that the market successfully prices in long-term information on FOMC days, as opposed to being driven by short-term frictions. From a the ecological policy standpoint, the long-lived heterogeneity between browns and greens implies that the ecological footprint of MP is not negligible.

More information on impulse response functions can be found in appendix. Figure C1 estimates LPs for each of the specifications considered in Table 4. It shows that the differential in MP responsiveness across carbon emissions is significant for all horizons

(h=0,..,10) in 5 specification out of 6.[14] Figure C3 and Figure C2 break down the local projection into 3 groups according to their carbon intensity. The results show that the impact of a positive policy surprise leads to a larger negative response in the cumulative returns for the highest carbon-emitting firms' category, confirming our previous results.

8 Conclusion

This paper tests the theoretically plausible hypothesis than brown firms are more affected by monetary policy than green firms. We find strong evidence that this is the case. A one standard deviation MP surprise results in an immediate 0.452% drop in returns on average, but this decline is 0.052 higher for a firm that is one standard deviation more carbon-intensive than average. The non neutral impact of CO_2 intensity remains robust to several alternative specifications. In particular it is not solely driven by sectoral factors, as is often the case in the literature.

Investigating the mechanisms behind CO_2 non neutrality, we uncover that CO_2 intensity constitutes a new channel on its own. It remains significant when we allow classic sources of MP heterogeneity to influence the relationship between rate surprises and stock prices. We also provide theoretical and empirical elements suggesting that the impact of CO_2 on MP responsiveness grows with climate awareness, and with CO_2 intensity itself. Finally, the difference in stock prices reaction to MP shocks across CO_2 intensity does not revert the days that follow a given FOMC meeting, indicating that the initial price reaction reflects relevant information, not short-term frictions.

Our results imply that a central bank that decides to lower interest rates indirectly subsidizes polluting firms. This stylized fact can be of interest to central bankers who are currently reflecting on their role in promoting a greener financial system. A possible policy path for central banks is to attempt to neutralize the differentiated effects of their announcement across CO_2 intensity, through either communication and/or asset purchases. Nevertheless the benefit of such a policy should be weighted against the cost in terms of

[14]The specification for which the impact of a MP surprise on cumulative returns is only transitory corresponds to the one where we control for time-varying industry shocks using Sector × Year fixed effects.

credibility associated with taking such active measures on issues that are only distantly related to inflation.

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Appendix A

A-1

Using equations (9) and (10):

$$\frac{p_{g,t}}{p_{b,t}} = \frac{\frac{W}{q}\tau S\left(\frac{1}{2+\psi\triangle CO2}\right)\left(\frac{(G-c_t)}{\tau S^2\sigma_{g,t}^2}+\phi(1+\psi\triangle CO2)(\triangle CO2)\right)}{\frac{W}{q}\tau S\left(\frac{1}{2+\psi\triangle CO2}\right)\left(\frac{(G-c_t)}{\tau S^2\sigma_{g,t}^2}-\phi\triangle CO2\right)}$$

$$\frac{p_{g,t}}{p_{b,t}} = \frac{\frac{(G-c_t)}{\tau S^2\sigma_{g,t}^2}-\phi\triangle CO2+\phi\triangle CO2+\phi\triangle CO2(1+\psi\triangle CO2)}{\frac{(G-c_t)}{\tau S^2\sigma_{g,t}^2}-\phi\triangle CO2}$$

$$\Rightarrow \frac{p_{g,t}}{p_{b,t}} = 1+\frac{\phi\triangle CO2(2+\psi\triangle CO2)}{\left(\frac{(G-c_t)}{\tau S^2\sigma_{g,t}^2}-\phi\triangle CO2\right)}$$

Let us define $f = \frac{(G-c_t)}{\tau S^2\sigma_{g,t}^2}-\phi\triangle CO2$ to ease notation. Deriving both sides of the equation above with respect to c_t leads to :

$$\frac{d\left(p_{g,t}P_{b,t}\right)}{d c_t} = (\phi\triangle CO2(2+\psi\triangle CO2))\frac{d\frac{1}{f}}{d f}\frac{d f}{d c_t}$$

$$\Rightarrow \frac{\frac{d p_{g,t}}{d c_t}p_{b,t}-\frac{d p_{b,t}}{d c_t}p_{g,t}}{\left(p_{b,t}\right)^2} = -(\phi\triangle CO2(2+\psi\triangle CO2))\frac{1}{f^2}\left(-\frac{1}{\tau S^2\sigma_{g,t}^2}\right)$$

$$\Rightarrow \frac{d p_{g,t}/d c_t}{p_{g,t}}-\frac{d p_{b,t}/d c_t}{p_{b,t}} = \frac{\left(p_{b,t}\right)^2}{p_{g,t}p_{b,t}}(\phi\triangle CO2(2+\psi\triangle CO2))\frac{1}{f^2}\left(\frac{1}{\tau S^2\sigma_{g,t}^2}\right)$$

$$NN = \frac{d p_{g,t}/d c_t}{p_{g,t}}-\frac{d p_{b,t}/d c_t}{p_{b,t}} = \frac{p_{b,t}}{p_{g,t}}\left(\frac{1}{\tau S^2\sigma_{g,t}^2}\right)\left(\frac{\phi\triangle CO2(2+\psi\triangle CO2)}{(\frac{(G-c_t)}{\tau S^2\sigma_{g,t}^2}-\phi\triangle CO2)^2}\right) > 0$$

A-2

Let $C = \frac{p_{b,t}}{p_{g,t}}\left(\frac{1}{\tau S^2\sigma_{g,t}^2}\right) > 0$, $u = \phi\triangle CO2(2+\psi\triangle CO2) > 0$, and $v = \frac{1}{(\frac{(G-c_t)}{\tau S^2\sigma_{g,t}^2}-\phi\triangle CO2)^2} = \frac{1}{f^2} > 0$

$$\frac{d u}{d\triangle CO2} = \phi(2+2\psi\triangle CO2) > 0$$

$$\frac{d v}{d\triangle CO2} = \frac{d v}{d f}\frac{d f}{d\triangle CO2} = \left(-\frac{2}{f^3}\right)(-\phi) = \frac{2\phi}{f^3} > 0$$

Using the expressions of C, u and v, NN in equation (12) can be reexpreed as $NN = C\times u\times v$. It follows that

$$\frac{d NN}{d\triangle CO2} = C\left(\frac{d u}{d\triangle CO2}v+\frac{d v}{d\triangle CO2}u\right)$$

which is positive since all terms involved are positive, which proves lemma 2.

Let us now take the derivative of $\frac{d\,NN}{d\,\triangle CO2}$ with respect to $\triangle CO2$

$\frac{d^2\,u}{d^2\,\triangle CO2} = \frac{d\,(d\,u/d\,\triangle CO2)}{d\,\triangle CO2} = \frac{d\,\phi(2+2\psi\triangle CO2)}{d\,\triangle CO2} = 2\psi\phi > 0$

$\frac{d^2\,v}{d^2\,\triangle CO2} = \frac{d\,(d\,v/d\,\triangle CO2)}{d\,\triangle CO2} = \frac{d\,\left(2\phi/f^3\right)}{d\,\triangle CO2} = 2\phi\frac{d\,\left(1/f^3\right)}{d\,f}\frac{d\,f}{d\,\triangle CO2} = 2\phi\left(\frac{-3}{f^4}\right)(-\phi) = \frac{6\phi^2}{f^4} > 0$

The second derivative of NN with respect to $\triangle CO2$ is thus:

$$\frac{d^2\,NN}{d^2\,\triangle CO2} = \frac{d\,\left(C\left(\frac{d\,u}{d\,\triangle CO2}v + \frac{d\,v}{d\,\triangle CO2}u\right)\right)}{d\,\triangle CO2}$$

$$\frac{d^2\,NN}{d^2\,\triangle CO2} = C\left((\frac{d^2\,u}{d^2\,\triangle CO2}v + \frac{d\,u}{d\,\triangle CO2}\frac{d\,v}{d\,\triangle CO2}) + (\frac{d^2\,v}{d^2\,\triangle CO2}u + \frac{d\,u}{d\,\triangle CO2}\frac{d\,v}{d\,\triangle CO2})\right)$$

$\frac{d^2\,NN}{d^2\,\triangle CO2} > 0$ since all the terms are positive, which proves lemma 2.

Let us now take the derivative of $\frac{d\,NN}{d\,\triangle CO2}$ with respect to ϕ. First note that:

$\frac{d\,u}{d\,\phi} = \frac{d\,\phi\triangle CO2(2+\psi\triangle CO2)}{d\,\phi} = \triangle CO2(2+\psi\triangle CO2) > 0$

$\frac{d\,v}{d\,\phi} = \frac{d\,v}{d\,f}\frac{d\,f}{d\,\phi} = \left(-\frac{2}{f^3}\right)(-\triangle CO2) = \frac{2\triangle CO2}{f^3} > 0$

$\frac{d^2\,u}{d\,\triangle CO2\ \ d\,\phi} = \frac{d\,(d\,u/d\,\triangle CO2)}{d\,\triangle\phi} = \frac{d\,\phi(2+2\psi\triangle CO2)}{d\,\phi} = (2+2\psi\triangle CO2) > 0$

$\frac{d^2\,v}{d\,\triangle CO2\ \ d\,\phi} = \frac{d\,(d\,v/d\,\triangle CO2)}{d\,\triangle CO2} = \frac{d\,\left(2\phi/f^3\right)}{d\,\triangle CO2} = \frac{2}{f^3} > 0$

The cross derivative of NN with respect to $\triangle CO2$ and ϕ is:

$$\frac{d^2\,NN}{d\,\triangle CO2\ \ d\,\phi} = \frac{d\ (d\,NN/d\,\triangle CO2)}{d\,\phi} = \frac{d\,\left(C\left(\frac{d\,u}{d\,\triangle CO2}v + \frac{d\,v}{d\,\triangle CO2}u\right)\right)}{d\,\phi}$$

$$\frac{d^2\,NN}{d\,\triangle CO2\ \ d\,\phi} = C\left((\frac{d^2\,u}{d\,\triangle CO2\ \ d\,\phi}v + \frac{d\,u}{d\,\triangle CO2}\frac{d\,v}{d\,\phi}) + (\frac{d^2\,v}{d\,\triangle CO2\ \ d\,\phi}u + \frac{d\,v}{d\,\triangle CO2}\frac{d\,u}{d\,\phi})\right)$$

$\frac{d^2\,NN}{d\,\triangle CO2\ \ d\,\phi} > 0$ since all the terms are positive. Taking the derivative of $\frac{d^2\,NN}{d\,\triangle CO2\ \ d\,\psi}$ with respect to ψ involves the same steps and leads to the same outcome $\frac{d^2\,NN}{d\,\triangle CO2\ \ d\,\psi} > 0$, which proves lemma 3.

Appendix B

Table B1: Heterogeneous Responses of Stock Returns to Monetary Policy: All days

Returns	(1)	(2)	(3)	(4)	(5)	(6)
MP surprise	-0.327***		-0.347***	-0.327***	-0.327***	-0.281**
	(0.103)		(0.108)	(0.103)	(0.105)	(0.110)
Emissions × MP surprise	-0.057***	-0.051***	-0.058***	-0.057***	-0.057***	-0.046***
	(0.018)	(0.019)	(0.017)	(0.018)	(0.018)	(0.017)
Emissions	0.001	0.001	-0.003	0.001	-0.003	0.001
	(0.012)	(0.012)	(0.010)	(0.003)	(0.009)	(0.012)
Controls	Yes	Yes	No		Yes	Yes
Yes						
Firm FE	Yes	Yes	Yes	No	Yes	Yes
Date FE	No	Yes	No	No	No	No
Year & Month FE	Yes	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	No	No
Industry × Year FE	No	No	No	No	Yes	No
Industry × MP FE	No	No	No	No	No	Yes
R-squared	0.05	0.284	0.04	0.04	0.04	0.06
Observations	848373	848373	1079943	848373	848373	848373
Nb. of Firms	771	771	857	771	771	771

Note: This table represents the estimation results of our baseline equation 13 considering all the business days (and not only the days of FOMC meetings) over the period 2010-2019. The independent variable represents the daily stock return. The columns correspond to the 6 different specifications we estimate. They are differentiated by the inclusion or not of certain variables, controls or fixed effects necessary for our analysis. Standard errors are clustered at the firm and time level, and reported below the coefficient estimates. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

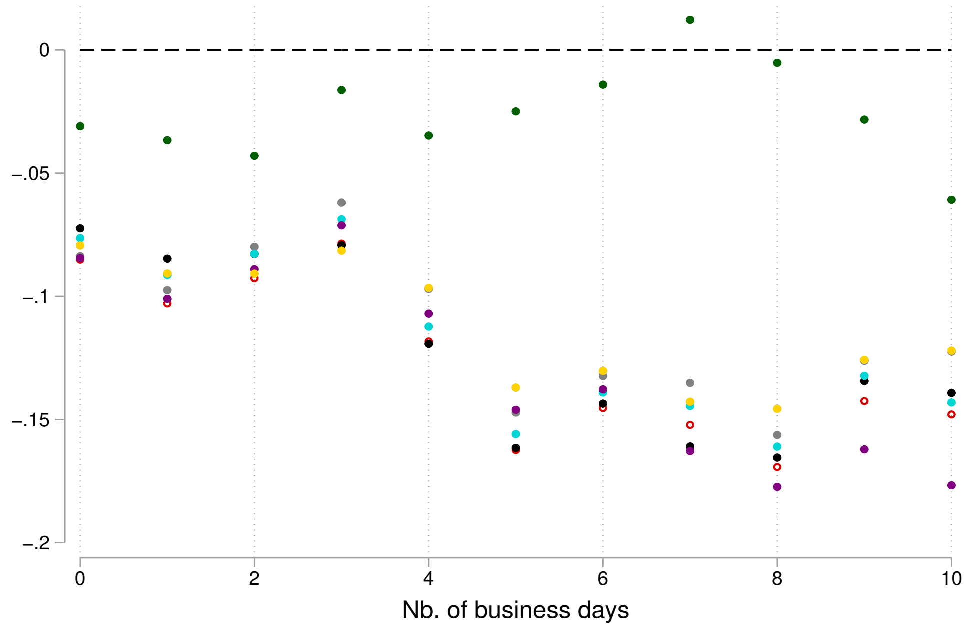
Table B2: Estimated total emissions

Returns	(1)	(2)	(3)	(4)	(5)	(6)
MP surprise	-0.392***		-0.402***	-0.390***	-0.392***	-0.442***
	(0.131)		(0.135)	(0.131)	(0.131)	(0.136)
Emissions × MP surprise	-0.076***	-0.072***	-0.084***	-0.073***	-0.079***	-0.031**
	(0.024)	(0.024)	(0.027)	(0.025)	(0.023)	(0.015)
Emissions	-0.044	-0.058*	-0.084**	-0.042***	-0.042	-0.030
	(0.030)	(0.033)	(0.036)	(0.015)	(0.029)	(0.027)
Controls	Yes	Yes	No	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	Yes	Yes
Date FE	No	Yes	No	No	No	No
Year & Month FE	Yes	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	No	No
Industry × Year FE	No	No	No	No	Yes	No
Industry × MP FE	No	No	No	No	No	Yes
R-squared	0.079	0.245	0.073	0.048	0.083	0.081
Observations	67500	67500	89657	67508	67500	67500
Nb. of Firms	2041	2041	2325	2041	2041	2041

Note: This table represents the estimation results of our baseline equation 13 using estimated emissions intead of reported emissions. The independent variable represents the daily stock return. The columns correspond to the 6 different specifications we estimate. They are differentiated by the inclusion or not of certain variables, controls or fixed effects necessary for our analysis. Standard errors are clustered at the firm and time level, and reported below the coefficient estimates. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Appendix C

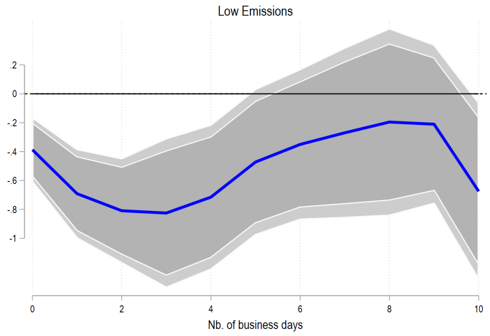
Figure C1: Response of US stock returns to MP shock from local projections, across specifications)



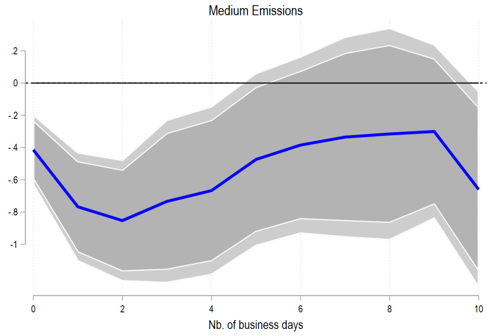
Note: This figure shows the coefficient on the variable 'Emissions × MP surprise" as estimated by local projections, for all specification considered in Table 4. The x-axis represents the horizon at which the cumulative return is estimated. The y-axis represents the value of the point estimate. Each dot correspond to a given specification (list here).

Figure C2: Impulse response function by carbon group

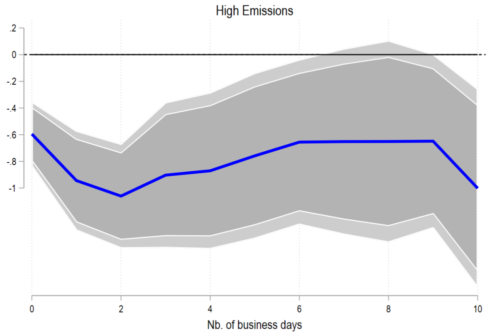
(a) Low emissions



(b) Medium emissions



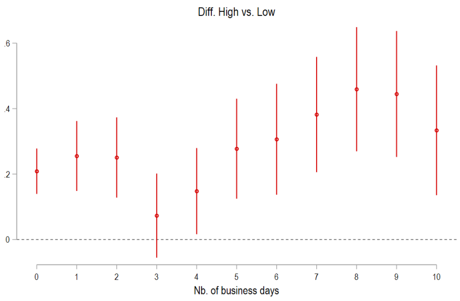
(b) High emissions



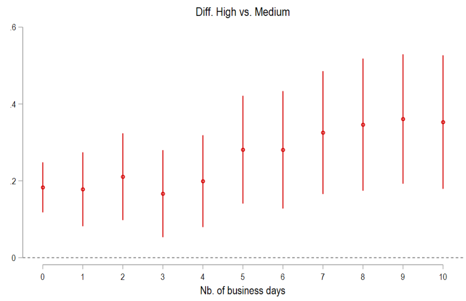
Note: Theses 3 figures show the response of cumulative stock returns over horizons from 0 to 10 (business days) to a one standard deviation monetary policy shock for 3 carbon groups sorted by Total emissions intensity. The "low" group defines observations below the 25^{th} percentile, the "medium" group includes observations between the 25^{th} and 75^{th} percentile and the "high" group represents observations above the $75^t h$ percentile. The shaded areas correspond to the 90% (darkest) and 95% (lightest) confidence intervals computed with robust standard errors.

Figure C3: Response of US stock returns to MP shock (difference in estimated coefficient between carbon group)

(a) High vs Low emissions



(b) High vs Medium emissions



Note: Theses 2 figures figures depict the difference in estimated coefficients β^h between the different CO_2 groups at each h time horizon and the associated 90% confidence intervals. The "low" group defines observations below the 25^{th} percentile, the "medium" group includes observations between the 25^{th} and 75^{th} percentile and the "high" group represents observations above the $75^t h$ percentile.

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