Monetary Policy, Carbon Transition Risk, and Firm Valuation

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February 2024

Abstract

This paper empirically examines the interaction between monetary policy and carbon transition risk. Using an event study design, we find that the stock prices of firms with higher carbon emissions are more responsive to monetary policy shocks around FOMC announcements. Cross-sectional tests reveal that this effect is driven by firms that are more capital intensive, with lower ESG ratings, or with greater perceived climate risk exposures. Using instrumental-variable local projections, we find that high-emission firms reduce emissions relative to low-emission firms, but slow down these efforts when monetary policy is restrictive. Taken together, our results indicate that monetary policy has a relatively stronger effect on the financial and environmental performance of firms more exposed to carbon transition risk.

JEL Classification: G12, G38, E52

Keywords: Carbon transition risk, monetary policy, firm valuation

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For helpful comments and suggestions, we thank Paul Smeets, Theresa Spickers, Magdalena Rola-Janicka, Mathijs van Dijk, Jean-Stéphane Mésonnier, as well as seminar participants at the Erasmus University Rotterdam, Goethe University Frankfurt, the 10th EFI Workshop, Hong Kong Baptist University, and De Nederlandsche Bank. Adrian Lam gratefully acknowledges the financial support of the A Sustainable Future initiative, financed by the faculty of Economics & Business at the University of Amsterdam. This paper was previously circulated under the title "Does Monetary Policy Shape the Path to Carbon Neutrality?"

1 Introduction

There is a striking divergence in how central banks address climate change-related risks. Jerome Powell, Chairman of the Federal Reserve System, stated that the Fed is not, and will not be, a "climate policymaker".[1] In contrast, the Bank of England and the European Central Bank take a more proactive stance on facilitating an economy-wide transition to climate neutrality.[2] Despite the ongoing debate on whether central banks should embrace a climate mandate, there is little empirical evidence on how monetary policy shapes firms' path to net-zero emissions. Such evidence is not only relevant for central banks, but it can also inform about the effects of impact investing strategies aimed at raising polluting firms' cost of capital.

In this paper, we empirically investigate how monetary policy affects brown and green firms' performance by examining how firms' stock prices respond to Federal Open Market Committee (FOMC) announcements. Our headline result is that the stock price reaction to monetary policy shocks is statistically and economically significantly higher among firms with higher carbon emissions. In analyzing real effects, we find that high-emission firms on average reduce emissions relative to low-emission firms, but this gap in emissions growth shrinks when monetary policy is restrictive. Collectively, our results indicate that monetary policy shapes firms' path to carbon neutrality, irrespective of whether central banks embrace a climate target. Our results also suggest that impact investing strategies aimed at increasing polluting firms' cost of capital may backfire, consistent with recent evidence showing that high-emission firms' environmental performance responds more to cost-of-capital changes (Hartzmark and Shue, 2023).

Conceptually, firms with higher carbon emissions are more exposed to *carbon transition risk*, which encompasses technological, regulatory, market, and reputational risks associated with a carbon-intensive business model. As outlined in the TCFD (2017), these risks are likely to have a financially material impact. Accordingly, carbon transition risk has moved up the agenda of investors (Krueger et al., 2020) and policy makers

[1] See https://www.federalreserve.gov/newsevents/speech/powell20230110a.htm.

[2] For the Bank of England, see https://www.bankofengland.co.uk/climate-change. For the European Central Bank, see https://www.ecb.europa.eu/ecb/climate/html/index.en.html.

(TCFD, 2017). As net-zero targets are gaining traction, firms with high emissions need to mitigate their exposure to carbon transition risk by replacing polluting assets and reducing emissions.[3] Consistent with this notion, we document in Figure 2 that firms with higher emissions on average reduce emissions relatively more in subsequent years.

Monetary policy can shape firms' path to carbon neutrality because a tighter monetary policy stance increases funding costs, which suppresses corporate investment and slows down the replacement of existing assets. This may affect firms with higher carbon emissions relatively more for two reasons. First, tighter funding conditions may be particularly costly for firms with higher emissions because they have greater needs to replace polluting assets to begin with. Second, high-emission firms may decide to delay transitioning and therefore retain a large exposure to carbon transition risk. In the presence of convex adjustment costs, speeding up capital replacement in the future may also be costlier.

While carbon transition is inherently a long-term process, we utilize an event study design to provide a forward-looking, market-based assessment of how monetary policy interacts with carbon transition risk of firms. Based on our conceptual framework, we argue that a restrictive monetary policy stance heightens firms' carbon transition risk and increases the cost of transition, whereas an accommodative stance eases these costs. In our main empirical analyses, we test the joint hypotheses that monetary policy affects the cash flows of firms based on their exposures to carbon transition risk, and that this is reflected in company valuations in response to monetary policy shocks. If monetary policy shocks amplify the cost of transitioning, then firms with a greater exposure to transition risk should have a higher stock price sensitivity to monetary policy shocks.

Our empirical methodology uses monetary policy shocks from Jarociński and Karadi (2020), who exploit high-frequency responses in interest rate derivatives around FOMC announcements to identify surprises in monetary policy changes, following Bernanke and Kuttner (2005) and Gürkaynak et al. (2005). These shocks are based on movements

[3] There are international pledges to achieve net-zero emissions by 2050. See, for example, the article by United Nation's Net Zero Coalition: https://www.un.org/en/climatechange/net-zero-coalition and the International Energy Agency's Road Map for the Global Energy Sector: https://www.iea.org/reports/net-zero-by-2050

in interest rate derivatives of up to one year, and have strong explanatory power for changes in longer-term rates at the 2–10 year horizons, which are relevant for firms' investment decisions. To capture a firm's exposure to carbon transition risk, we use firm-level carbon emissions data from Trucost, as a higher level of emissions implies a greater exposure to climate-related shocks and a greater need to transition. We focus on scope 1 emissions, which are emissions directly and physically emitted by a firm. In our main empirical specification, we regress a firm's intra-FOMC day realized stock return on the interaction between the log of carbon emission levels and monetary policy surprise, controlling for firm characteristics and their interaction with the monetary policy shock. We also include firm fixed effects, which absorb time-invariant unobserved heterogeneity between firms, and narrow event-date-by-NAICS-4 industry fixed effects, which control for unobserved differences between industries on a given event day.

Our main finding is that the sensitivity of stock price reactions to monetary policy shocks is higher among high-emission firms. Our headline result shows that a one-standard deviation increase in the log of a firm's total scope 1 carbon emissions is associated with a 0.487 to 0.628 percentage points stronger stock price increase (decline) to a surprise 25bps monetary policy easing (tightening). The effect is economically large: It translates into a one-sixth amplification of the average full-sample response. Similarly, a value-weighted "brown-minus-green" portfolio that goes long in the top quintile and short in the bottom quintile of carbon-emitting firms earns an intra-day return of 1.4% to 2.27% in response to a surprise 25bps easing in the Fed Funds rate. As a robustness check, we find consistent results when we use emissions intensity (i.e. emissions levels scaled by sales) to measure a firm's exposure to carbon transition risk.

Given the multi-faceted nature of carbon transition risk, we perform a series of sample splits to examine which dimensions drive our headline result. The Task Force on Climate-Related Financial Disclosures (TCFD) identifies climate-related technology, policy, market and reputation risks as components of carbon transition risk that are potentially financially material. The sample splits show that the greater stock price sensitivity of high-emission firms is driven by firms that are more capital intensive, highlighting a key role for technological risks. The effects are also stronger among subsamples of firms that have a greater perceived or self-assessed exposure to regulatory climate risks, as captured by the textual analysis-based measures based on earnings call reports from Sautner et al. (2023), and annual reports from Baz et al. (2023), respectively. In contrast, we find no clear differences between subsamples split by pressure from investors, proxied by ownership by socially responsible investors, or pressure from customers, proxied by product market power or product substitutability. These results suggest that the interactive effects between monetary policy and carbon transition risk are primarily driven by technology and policy risks, but less so by market and reputation risks.

In a last set of splits, we also find that our headline result is strongest in subsamples of firms that are (perceived to be) less equipped to transition, as measured by low environmental, social, and governance (ESG) ratings from MSCI, and by a firm's decision not to participate in the Carbon Disclosure Project (CDP).

The greater stock-price sensitivity of high-emission firms may be driven by a differential effect of monetary policy on cash flows or discount rates (or a combination thereof). While disentangling cash flow effects from discount rate effect is inherently challenging, we use the bond market as a laboratory in a best-effort attempt to distinguish these effects. In a first test, we find that there is no statistically different response in the bond prices of high- and low-emission firms to monetary policy shocks. As bond prices are relatively less sensitive to cash flow news, we argue that this null result indicates that cash flow rather than discount rate effects are the main driver explaining our headline stock market-based results. Consistent with this, we also find no difference in the response of green and regular bonds by the same issuer to monetary policy shocks. This indicates that the preference-based premium bond investors are willing to pay is not affected by monetary policy shocks, and therefore likely not a key driver explaining our headline results.

Next, we use instrumental-variable local projections to assess whether the medium-run real effects are in line with the event study results. While evaluating the causal effect of monetary policy on slow-moving variables such as emissions is challenging, we follow the recent state-of-the-art approach similar to, among others, Gertler and Karadi (2015), Bu et al. (2021), and Cloyne et al. (2023), to obtain cleaner identification. Specifically, we use the 2-year Treasury rate as our main measure of the monetary policy stance, and instrument the 2-year Treasury rate using the high-frequency monetary policy shocks around FOMC announcements, while controlling for key macroeconomic variables.

We first examine the average effect of the monetary policy stance on carbon emissions. Based on our approach, we estimate that an instrumented 25bps increase in the 2-year Treasury rate results in a decline of up to 2.5% in firm-level scope 1 emissions after two years. This decline in emissions appears to be entirely driven by lower output: While we find a concurrent decline in investment and sales in response to monetary tightening, there is no concurrent decline in emissions intensity. At the longer 3–4 year horizons, emissions intensity even slightly increases. This suggests that, while monetary policy tightening reduces emissions due to its negative effect on output, it also results in lower carbon efficiency down the road, as firms likely forgo investments in abatement and low-carbon technologies.

We then examine cross-sectional heterogeneity in the real effects by estimating the interactive effects between monetary policy and firms' scope 1 emissions. We find that, on average, future emissions growth is negatively associated with current emissions levels. However, when monetary policy tightens emissions growth among high-emission firms increases relative to low-emission firms. Taken together, these findings suggest that firms with relatively higher emissions to begin with reduce emissions faster going forward, but slow down emissions reductions disproportionately when monetary policy tightens.

In short, our high-frequency stock price sensitivity analyses and the low-frequency local projections paint a consistent picture: Investors recognize that transitioning to a low-carbon business model is cheaper when funding conditions are accommodative, but costlier when monetary policy is restrictive. Therefore, tight monetary policy hampers firms' emissions reduction efforts, leaving high-emission firms more exposed to climate transition risk. These effects are reflected in stock prices on FOMC announcement dates, resulting in an amplified response among high-emission firms. Over the medium run, despite high-emission firms bringing down emissions more relative to low-emission firms, this gap in emissions growth shrinks when monetary policy tightens. Taken together, our results indicate that monetary policy affects firms' transition to a low-carbon economy, regardless of whether a central bank embraces a climate mandate.

Our results also speak to recent debates on the optimal design of ESG investing strategies. One such strategy aims to incentivize firms to reduce emissions by excluding brown firms from portfolios and driving up their cost of capital (e.g., Berk and Van Binsbergen, 2022). Consistent with evidence in Hartzmark and Shue (2023), our results indicate that such cost-of-capital effects may backfire because they have a negative effect on brown firms' environmental performance.

Related literature. This paper relates to two strands of literature. First, we relate to the literature on the effects of carbon transition risk on asset prices. Heinkel et al. (2001), Fama and French (2007), Pastor et al. (2021), and Pedersen et al. (2021) show theoretically that stocks of greener firms have lower expected stock returns if such stocks provide a hedge against climate risks or investors have non-pecuniary preferences for holding green stocks. Consistent with this notion, Bolton and Kacperczyk (2021, 2022) document that carbon transition risk is priced in stock returns, and Pastor et al. (2022) find that stocks with high ESG ratings have lower expected returns.[4] Additionally, a number of studies find that carbon transition risk is priced in other assets such as bonds, bank loans and options (Baker et al., 2018; Delis et al., 2019; Ilhan et al., 2021; Seltzer et al., 2022; Pastor et al., 2022; Altavilla et al., 2023).[5] We contribute to this literature by providing evidence that carbon risk is priced in stock returns in a novel, event study-based setting. A key benefit of our setting is that we can cleanly identify the effect of carbon transition risk on stock returns because preferences and climate awareness are

[4]Several studies find that firms with higher total emissions have higher stock returns, but that there is no or even inverse relation between stock returns and emissions intensity (see Bolton and Kacperczyk, 2021, 2022; Aswani et al., 2022; Zhang, 2023). In our setting, we find very similar results whether we use emissions levels or intensity.

[5]Next to transition risk, several papers document the relevance of physical climate risk for asset prices (e.g., see Giglio et al., 2021b; Issler et al., 2020; Giglio et al., 2021a). In this paper, we focus on heterogeneity in firms' carbon emissions, which implies a greater exposure to climate transition risk but not necessarily physical climate risk.

plausibly constant within the intra-day window around FOMC announcements that we consider.[6]

Second, we relate to papers that examine the economic and financial consequences of monetary policy shocks. Several contributions have documented how firm financial conditions and collateral can dampen or amplify the effects of monetary policy (Kashyap et al., 1994; Gertler and Gilchrist, 1994; Ozdagli, 2018; Chava and Hsu, 2020; Ottonello and Winberry, 2020; Gurkaynak et al., 2022; Döttling and Ratnovski, 2023; Cloyne et al., 2023). Relative to these papers, we focus on a different and unexplored dimension of heterogeneity. Some recent papers analyze central bank policies with a climate-related objective, such as "Green QE" (e.g., see Papoutsi et al., 2022; Ferrari and Landi, 2023; Giovanardi et al., 2023). Our results are consistent with monetary policy shocks shaping carbon transition risk even absent an explicit climate mandate, and highlight the need for additional research on how central banks affect the transition to a low-carbon economy.

The rest of this paper is organized as follows. Section 2 describes our data. Section 3 lays out the main hypothesis and methodology. The results based on stock market reactions are presented in Section 4, and Section 5 presents results on real effects. Section 6 concludes.

2 Data

Our main sample is a pooled cross-section of stock returns on FOMC announcement days. The sample begins in 2010 and ends in 2018. We exclude the years prior to 2010 to focus on a period with relatively greater climate change concerns and better emissions data coverage, and to ensure that our results are not driven by the Global Financial Crisis. We end the sample in 2018 as we only have data on monetary policy shocks for the full year up to 2018. The sample consists of all firms in the linked Trucost and CRSP/Compustat databases (to be described below). We exclude financial firms

[6] Several papers document that the responsiveness of stock prices to monetary policy and other macro news announcements has implications for equity risk premia (e.g., Lucca and Moench, 2015; Ozdagli and Velikov, 2020; Ai et al., 2022). This suggests the greater responsiveness of high-emission firms' stock prices may by itself be reflected in expected stock returns, consistent with a carbon premium.

(2-digit NAICS code 52) and firms with less than $5M in assets. We also exclude firms missing any of our key control variables (market value, leverage, return on equity, book-to-market ratio, property, plant and equipment, investment, sales growth or momentum).

[Insert Table 1 Here]

Table 1 presents descriptive statistics of our main sample. Panel A reports the industry distribution, and Panel B reports summary statistics. As shown in Panel A, our sample consists primarily of manufacturing firms (47.74%), followed by information (11.68%), and retail trade (6.04%). The most polluting industries in terms of scope 1 emissions intensity are Utilities, which make up 3.89% of the sample, Mining, Quarrying, Oil and Gas Extraction (4.91% of the sample), and Transportation and Warehousing (3.22% of the sample).

2.1 Stock Returns and Firm Financial Data

We obtain annual firm-level financial statements from Compustat and stock returns on FOMC announcement days from CRSP. In our sample, the average return on FOMC announcement days is -0.076%, with a standard deviation of 1.94%.

Since our observations are at the event-day level, we merge the data from the latest annual report before the announcement day.[7] We use annual rather than quarterly financial data to align the frequency with the annual publication frequency of carbon emissions data.

2.2 Monetary Policy Shocks

We obtain monetary policy shocks from Jarociński and Karadi (2020). Jarociński and Karadi (2020) build on the methodology pioneered in Kuttner (2001), Bernanke and Kuttner (2005), and Gürkaynak et al. (2005), where monetary policy shocks are identified using changes in interest rate futures rates in the 30-minute window around the Federal

[7] For example, for a firm with a fiscal year ending in February, we merge the 2015 fiscal year data to all FOMC meetings between March 2015 and February 2016.

Reserve Banks' Federal Open Market Committee (FOMC) meetings. Given interest rate futures incorporate market expectations before the announcement, this approach identifies the unanticipated component of an FOMC announcement.

A problem with this approach is that FOMC announcements may partially reflect private information about the economy that the Fed releases to the market (see Nakamura and Steinsson, 2018). As articulated in Jarociński and Karadi (2020), while a surprise monetary tightening raises interest rates but lowers equity valuation, a complementary positive assessment of the economic outlook by the central bank raises both interest rates and equity valuation. Capitalizing on this insight, Jarociński and Karadi (2020) exploit the high frequency co-movements between interest rates and stock prices around FOMC meetings to disentangle monetary policy shocks from central bank information shocks using a structural vector autoregression approach. We obtain these monetary policy shocks purged from central bank information shocks for all 72 FOMC meetings between 2010 and 2018 directly from Marek Jarocinski's website. The shocks are plotted in Figure 1. In our sample, the monetary policy shocks have a mean of -0.005% and a standard deviation of 0.029%. Consistent with rational expectations, the average monetary policy surprise is not statistically different from zero.

[Insert Figure 1 Here]

The monetary policy shock measure from Jarociński and Karadi (2020) is based on the first principal component of the surprises in interest rate derivatives with maturities from one month to one year. Using derivatives with maturities of up to one year ensures that the shock measure also captures the effects of unconventional monetary policy, which was prevalent during our sample period. Accordingly, we confirm in the Internet Appendix (Table IA7) that the shocks have a significant effect on longer-term yields of Treasuries with 6 months to 10 years maturity. Therefore, the shocks can be interpreted as broadly capturing the effects of conventional and unconventional monetary policy shifting the entire yield curve.

2.3 Corporate Carbon Emissions Data

We obtain corporate carbon emissions data from Trucost. Trucost's Environment dataset provides annual global greenhouse gas (GHG) emissions data for approximately 15,000 of the world's largest listed companies, which represent 95% of global market capitalization.

Trucost uses a four-step procedure to construct the data. First, it maps company business segments into business activities in the Trucost model. Second, it estimates a data-modelled profile for each firm using an environmentally extended input/output (EEIO) model across business operations of the firm. Third, it collects publicly available information including regulatory filings (e.g. filings to United States Environmental Protection Agency), corporate sustainability reports, third-party data vendors (e.g. Carbon Disclosure Project), and corrects for potential reporting errors. Fourth, it liaises with all companies to ensure the data is accurate and up-to-date.

Trucost provides data on three types of emissions: scope 1, scope 2 and scope 3 (upstream) emissions. Scope 1 emissions measure direct emissions from sources that are owned or controlled by the company itself. Scope 1 emissions include, for example, emissions associated with fuel combustion in boilers, furnaces and vehicles. Scope 2 emissions measure indirect emissions, such as emissions from the consumption of purchased electricity, heat or steam. Scope 3 (upstream) emissions represent emissions from indirect activities attributable to suppliers.

As we are interested in understanding how monetary policy interacts with carbon transition risk, we focus on emissions that are *directly* and *physically* tied to a company's assets, scope 1 emissions. Scope 1 emissions reflect a company's capital replacement needs and technological needs to transition to a low-emissions regime, which are directly shaped by the company's investment and financing policies. Hence, we argue that scope 1 emissions better capture a company's exposure to carbon transition risks in the context of monetary policy shocks.[8] In a robustness exercise, we also show our main results are robust to using scope 2 or scope 3 instead of scope 1.

[8] In contrast, scope 2 emissions primarily gauge indirect emissions from electricity usage, whereas scope 3 emissions capture emissions along the supply chain. In other words, scope 2 and scope 3 emissions capture aspects of carbon transition risk over which a firm has less direct control.

There is an active debate in the literature on whether total emissions or emissions intensity better capture exposure to carbon transition risk.[9] We use scope 1 emission levels as the variable that captures carbon transition risk in the main analyses, while controlling for the market value of a firm's assets to ensure our results are not driven by firm size. Reassuringly, we confirm that all our results are robust when replacing total emissions with emissions intensity. Given emission levels are positively skewed and contain outliers, we take the log of scope 1 emissions, which has a mean of 11.1 and a standard deviation of 2.64.

A related debate concerns the use of reported or estimated emissions. In our sample, approximately 67.6% of scope 1 emissions are estimated.[10] Therefore, we also conduct additional tests to ensure our results are not driven by the use of estimated emissions.

2.4 Other Data Sources

We provide a brief summary of the other data sources used in additional analyses here. The Internet Appendix (Section IA.1) provides a detailed description of these data sources and summary statistics of the variables.

We obtain firm-level data on: environmental, social and governance (ESG) ratings from MSCI ESG Ratings; climate change exposures based on transcripts of earnings conference calls from Sautner et al. (2023), and climate change exposures based on 10-K filings from Baz et al. (2023); firms' climate survey responses from Carbon Disclosure Project's (CDP) Climate Change dataset; institutional ownership data from WRDS Thomson Reuters Institutional (13f) Holdings; investors who have signed up to the Principles for Responsible Investment (PRI) from the PRI; economic value of innovations

[9] On the one hand, as discussed in Bolton and Kacperczyk (2021), and Bolton and Kacperczyk (2022), total emission levels have the advantage that (1) regulations are more likely to target the largest emitters, which is reflected in absolute emission levels and (2) given fixed costs in technological investments, renewable energy is more likely to displace fossil fuels in large emitters, where the returns to scale are highest. On the other hand, carbon intensity, which scales carbon emissions by sales, measures how carbon-efficient firms generate profits and accounts for size effects (Aswani et al., 2022; Zhang, 2023).

[10] We classify a firm's scope 1 emissions as "estimated" if Trucost mentions the data point as estimated (variable: `di_319403_text`).

at the firm-patent level from Kogan et al. (2017); and product similarity scores from Hoberg and Phillips (2016).[11] We obtain bond transaction data from Trade Reporting and Compliance Engine (TRACE), and bond characteristics from WRDS Bond Returns and Bloomberg.

3 Methodology

3.1 Hypothesis

We test the joint hypothesis that monetary policy affects the cash flows of firms based on their exposures to carbon transition risk, and that this is reflected in company valuations in response to monetary policy shocks. Carbon transition risk captures a range of risks that can have a material effect on firm performance. For example, Krueger et al. (2020) find that institutional investors view the financial materiality of climate risks as between "important" and "somewhat important", with regulatory and technological risks being more prominent than physical risks. As shown in Krueger et al. (2020), investors have already taken steps to manage climate risks, including performing analyses on the carbon footprints of portfolio firms and stranded asset risks.

Policymakers are also paying increasing attention to the financial implications of climate change (TCFD, 2017). The Financial Stability Board created the Task Force on Climate-Related Financial Disclosures (TCFD) to develop a disclosure framework that facilitates voluntary climate-related disclosures that are financially material and decision-useful (Financial Stability Board, 2015). The TCFD (2017) discusses the multi-faceted nature of climate change-related risks, highlighting the role of policy and legal, technology, market, reputational, and physical risks, the disclosure of which will enable investors, creditors, insurers and other stakeholders to "*undertake robust and consistent analyses of the potential financial impacts of climate change.*"

[Insert Figure 2 Here]

[11] We thank Salim Baz, Lara Cathcart, Alexander Michaelides and Yi Zhang for sharing their data with us.

As climate change moves up the agenda of regulators, investors, and other stakeholders, firms face increasing pressure to reduce their carbon footprint. Indeed, Figure 2 shows that, both in our sample and the entire Trucost universe, firms with higher emissions on average reduce their emissions more in subsequent years relative to firms that have lower emissions to begin with. This indicates that high-emission firms enter a gradual path towards carbon neutrality as they face rising needs to replace polluting assets and reduce emissions.[12]

Monetary policy affects a firm's path to carbon neutrality for two reasons. First, tight funding conditions directly increase the cost of replacing polluting assets. Second, this may induce some firms to delay transitioning and, as a result, retain a high exposure to climate transition risk. Additionally, in the presence of convex adjustment costs, delaying capital replacement may lead to higher costs down the road. To the extent that the costs associated with carbon transition risk are financially material, these two effects should imply that monetary policy has a relatively greater effect on the performance of firms that are more exposed to carbon transition risk. As stock price responses capture investors' perception about the effect of monetary policy on firms' performances, this should be reflected in a higher stock price sensitivity to monetary policy shocks. Therefore, we hypothesize that the stock prices of firms with higher carbon emissions are more sensitive to monetary policy shocks.[13]

[12] In the Internet Appendix (Table IA6), we show that this pattern is also evident in regressions that control for industry-by-year fixed effects and other firm-level controls. Consistent with greater investment needs, in our sample firms with above-median total scope 1 emissions have average capital expenditures of 5.7% relative to book assets, compared to 3.9% for firms below the median and 4.9% in the whole sample (see Table 1).

[13] A higher stock price sensitivity of high-emission firms may further be reinforced by the effect of monetary policy on risk premia (see Gertler and Karadi, 2015; Drechsler et al., 2018a,b), and hence the price of carbon transition risk. For example, Gertler and Karadi (2015) find that the excess bond premium increases (decreases) in response to monetary tightening (easing).

3.2 Methodology

We assess a firm's stock price response to monetary policy shocks using the following regression specification:

$$\begin{aligned} Ret_{i\tau}^{FOMC} &= \beta_1 \cdot Log(Scope\ 1_{it-1}) + \beta_2 \cdot MPShock_\tau \times Log(Scope\ 1_{it-1}) \\ &+ \gamma_1^{'} \cdot X_{it-1}^{f} + \gamma_2^{'} \cdot MPShock_\tau \times X_{it-1}^{f} + \eta_{j\tau} + \mu_i + \varepsilon_{i\tau} \end{aligned} \tag{1}$$

where $Ret_{i\tau}^{FOMC}$ is the intra-day stock return of firm i on event-day τ of the FOMC meeting, and $MPShock_\tau$ is the high-frequency monetary policy shock from Jarociński and Karadi (2020), which is based on movements in interest rate derivatives in the 30 minutes around the FOMC announcement. $Log(Scope\ 1_{it-1})$ is the log of firm i's scope 1 emissions in the latest fiscal year $t-1$ before the announcement. We control for firm-level variables in the vector X_{it-1}^{f}. These include the log of a firm's market value, leverage, return on equity, book-to-market value, log property, plant & equipment, investment over assets, sales growth, and momentum. Importantly, we also control for the interaction of these control variables with the monetary policy shock, to ensure that the results are not driven by other observables that are correlated with emissions. The model includes 4-digit NAICS industry-by-event date fixed effects. These fixed effects absorb any differences between industries in a given event date, including any unobserved heterogeneity in the effects of monetary policy shocks on different industries. Therefore, any regressions with industry-by-event date fixed effects are equivalent to de-meaning emissions within industry on each event date.[14] We also include firm fixed effects to control for unobserved, time-invariant firm heterogeneity. Standard errors are clustered at the firm and event-date levels.

The parameter of interest is β_2. Based on our hypothesis, the stock price sensitivity to monetary policy shocks is higher for firms more exposed to carbon transition risk.

[14] The coefficient of $MPShock_\tau$ is absorbed by the 4-digit NAICS industry-by-event date fixed effects ($\eta_{j\tau}$). To estimate the baseline effect of monetary policy shocks captured by this coefficient, we also run separate regressions without industry-by-event date fixed effects. The industry-by-event date fixed effect would also absorb an interaction between $MPShock_\tau$ and industry fixed effect because this interaction would only vary at the industry-by-event date level.

In response to a surprise monetary tightening (easing), realized stock returns should fall (increase) by more for firms with higher carbon emissions. Hence, we expect β_2 to be significantly negative. We also perform a number of sample splits by characteristics that measure different dimensions of carbon transition risk, such as technological risks, regulatory risks, and market and reputational risks.

4 Results

4.1 Main Results

We begin the empirical analyses by examining whether the stock price sensitivity to monetary policy shocks is higher among high-emission firms. Table 2 reports the results. In Column 1, we quantify the average stock price reaction to monetary policy shocks. We only include non-interacted control variables and firm fixed effects, but not the 4-digit NAICS industry-by-date fixed effects, to be able to estimate the coefficient of *MP Shock*. The coefficient is -16.580 and is statistically significant at the 1% level. The economic magnitude is large: An unexpected 25 basis points monetary tightening translates into a 4.15% ($\approx$-16.580$\times$0.25) drop in stock prices on average. Given the shock captures only the monetary policy component, the magnitude is larger than prior findings that use Fed Funds futures changes (i.e. without decomposing monetary policy and central bank information shocks) (e.g., see Bernanke and Kuttner (2005)).[15]

[Insert Table 2 Here]

Next, in Columns (2) – (4) we examine the interactive effect of carbon risk and monetary policy shocks. In all three columns, we control for uninteracted firm-level controls, firm fixed effects and event-date fixed effects. The key coefficient of interest is the coefficient on the interaction of the monetary policy shock with a firm's log scope 1 emissions (β_2 in Eq. (1)). We also control for the interaction of monetary policy shocks

[15] Additionally, in our post-2010 sample period the stock market response to monetary policy appears to be generally larger. We confirm that we find similar-magnitude responses as in Bernanke and Kuttner (2005) when we use non-decomposed FF4 shocks during the pre-2010 sample period.

with the log of a firm's market value (measured as the market value of equity plus the book value of debt), to ensure the effect of higher carbon emissions is not driven by a firm's size. In Column (2), the coefficient estimate is -2.514 and is statistically significant at the 1% level. Since *Log Scope* 1 is standardized, this implies a one-standard deviation increase in *Log Scope* 1 is associated with a 0.628% ($\approx -2.514 \times 0.25$) stronger response in stock prices to a 25 basis points shock. This represents an amplification of roughly one-sixth of the average response.

Columns (3) and (4) include additional control variables and a more stringent set of fixed effects. In Column (3), we fully interact the control variables with the monetary policy shock, in order to control for the interactive effects between the shock and observable firm characteristics. The coefficient of *MP Shock* $\times$ *Log Scope* 1 becomes larger in size and significance. In Column (4), we replace the FOMC announcement date fixed effect with the 4-digit NAICS industry-by-date fixed effects, which captures the unobserved heterogeneity at the industry-date level. Not surprisingly, the coefficient becomes slightly smaller, at -1.948, but remains statistically significant at the 5% level (p-value of 1.3%).

In Column (5), we address the concern that there may be an estimation bias in Trucost's carbon emissions data. We include a triple-interaction between *MP Shock*, *Log Scope* 1, and a dummy for whether emissions data are estimated. If our results are driven by firms with estimated emissions, then the triple interaction term should be negative and statistically significant, while the double-interaction term *MP Shock* $\times$ *Log Scope* 1 would become statistically insignificant. However, as shown in Column (5), this is not the case. This suggests that, at a minimum, the use of estimated emissions is not a major concern in this setting.

Another concern is that our results may be driven exclusively by utilities, which is the industry with the highest average scope 1 emissions. To address this concern, we exclude firms in the utilities industry from our sample. As shown in Column (6), the coefficient of *MP Shock* $\times$ *Log Scope* 1 is quantitatively similar to that in Column (4). This shows that the higher stock price sensitivity to monetary policy shocks by high-emission firms is an economy-wide effect, not just an industry-specific effect driven by utilities firms.

Finally, in Columns (7) and (8), we replicate our analyses in Columns (2) and (3) but use the log of scope 1 emission intensity as an alternative measure of carbon transition risk instead of the level of log scope 1 emissions. Depending on the specification of fixed effects, the coefficient of $MP\ Shock \times Log\ Scope\ 1\ Intensity$ ranges from -2.075 to -1.261 and remains statistically significant. This means that, relative to the average firm, a firm with scope 1 intensity that is one standard deviation above the mean has an additional 0.32–0.52% decrease (increase) in realized stock returns in response to a 25bps unexpected increase (decrease) in the policy rate. This shows that, regardless of whether we use scope 1 emission levels or emission intensity to capture carbon transition risk, there is a higher stock price sensitivity to monetary policy shocks among large polluters.

Additional Robustness. In the Internet Appendix (Table IA3), we show that the main results in Table 2 are robust to replacing scope 1 emissions with scope 2 or scope 3 emissions. We also show that the results are robust to replacing scope 1 emissions with quintile indicators. We find the results are largely driven by the top two quintiles, consistent with a high skewness in emissions. This also indicates that our results are unlikely to be affected by data release lags because firms sorting into emissions quintiles are relatively stable over time. The Internet Appendix also shows that the results are robust to using raw Fed Funds future changes instead of monetary policy shocks (often referred to as "FF4" in the literature), and to controlling for central bank information shocks (see Table IA4).

4.2 Portfolio-Level Evidence

To further corroborate our main results, we complement the stock-level analysis with portfolio-level analysis, where we compare the monetary policy response of green portfolios with low-emission firms to brown portfolios with high-emission firms. This approach also allows us to construct value-weighted portfolios, which may affect the finding of evidence for a carbon premium (see Zhang, 2023).

In portfolio-level analysis we cannot control for firm size. To avoid capturing size effects, we first sort firms into size quintiles based on firm market value, and then sort firms into scope 1 emissions quintiles within each size quintile.

[Insert Table 3 Here]

Table 3, Pabel A, presents the results from firm-level regressions estimating the response of a firm's stock return to monetary policy shocks within each emissions quintile. This exercise reveals a monotonically decreasing pattern in coefficient estimates going from the bottom- to the top-emissions quintile. While the stock prices of the greenest firms in the bottom quintile drop by 3.6% in response to a 25bps surprise monetary tightening ($\approx 14.377 \times 0.25$), the stock price of the brownest firms in the top quintile drop by 5% ($\approx 20.018 \times 0.25$).

Panel B of Table 3 presents estimates from portfolio-level regressions. We construct a brown-minus-green (BMG) portfolio that goes long in the top emissions quintile and short in the bottom emissions quintile. Columns (1)–(2) present results using an equal-weighted portfolio, and columns (3)–(4) use a value-weighted portfolio. The results indicate that the BMG portfolio loses between 1.4% ($\approx 5.519 \times 0.25$) and 2.27% ($\approx 9.087 \times 0.25$) in response to a 25bps tightening, consistent with our headline results in Table 2. In the Internet Appendix, we replicate these results replacing total scope 1 emissions by scope 1 intensity, and find very similar results (see Table IA5).

4.3 Cross-sectional Heterogeneity

Next, we conduct a number of cross-sectional tests to examine whether the higher stock price sensitivity to monetary policy shocks for firms with higher carbon emissions is driven by sub-samples of firms that are more exposed to different aspects of carbon transition risk. Conceptually, we follow the TCFD framework and break carbon transition risk into (1) policy and legal risks, (2) technological risks, and (3) market and reputational risks. While there are no proxies that can map one-for-one to each of these conceptual carbon risk categories, we can nevertheless examine a range of different measures that capture different sets of transition risk categories. This also helps corroborate our interpretation that the greater stock price sensitivity of high-emission firms to monetary policy is driven by carbon transition risk. Table 4 reports the results.

[Insert Table 4 Here]

4.3.1 Rated Sustainability Performance

Before using proxies for specific dimensions of carbon transition risk, we report results from sample splits based on MSCI ESG Ratings in Panel A. ESG Ratings provide third party assessments of a firm's sustainability performance, and are used by the largest global asset managers, investment consultants and wealth managers (MSCI (2020)). Firms with lower ESG scores are assessed to perform worse in sustainability-related issues, and may reflect a lack of ability in managing transition risks. If the higher stock price sensitivity of high-emission firms is driven by poorer sustainability performance as assessed by MSCI, we should expect the higher sensitivity to be concentrated among firms with lower ESG scores, especially scores that relate to climate change and the environment.

We first examine the overall ESG score and environmental score. In Columns (1) and (2), we split the sample by the median value of the overall ESG score. In Columns (3) and (4), we narrow down to the environmental pillar score. In Columns (5) and (6), we further narrow down to the climate change theme score. Given not all our observations in the sample are tracked by MSCI, we have a smaller number of total observations in this set of analyses.

The coefficient of $MP\ Sshock \times Log\ Scope\ 1$ is negative and statistically significant in the subsamples with a lower third party-assessed environmental performance. Depending on the splitting variable, the coefficient ranges from -2.625 to -3.572, and is at least statistically significant at the 5% level. The coefficient estimate remains significant also in the subsample of firms with lower overall ESG scores. This likely reflects the lower climate-relevance of the overall ESG score. As the splitting variables become more climate-relevant, the size of the coefficients increases monotonically.

We also examine the role of social and governance performance separately. In Columns (7) and (8), we split the sample by the median value of the social pillar score. In Columns (9) and (10), we split the sample by the median value of the governance pillar score. These results are more ambiguous. In both instances the coefficient estimate is more significant among firms with a higher social or governance pillar score, but the size of the coefficient is smaller compared to their lower-scoring counterparts.

Collectively, the results in Panel B indicate that the higher stock price sensitivity to monetary policy shocks is concentrated among firms with a poorer rated environmental performance. The more ambiguous results on the social and governance pillars are consistent with the fact that carbon risk is closely related to climate change and the environment.

4.3.2 Capital Intensity

In Panel B, we report the results from sample splits using different measures of capital intensity. Given scope 1 emissions are direct emissions that are physically generated on-site, firms with more fixed assets are more exposed to technological, stranded-asset risk. If technological risk is an important component explaining our headline results, we should expect the higher stock price sensitivity of high-emission to be concentrated among firms with higher physical capital intensity.

In Columns (1) and (2), we examine the role of asset tangibility, splitting the sample by the median value of property, plant, and equipment (PPE) over assets. In Columns (3) and (4), we take intangible assets into account, by adding the value of off-balance sheet intangible assets to the denominator, using the intangible capital measure from Peters and Taylor (2017). In Columns (5) and (6), we examine the role of investment levels, splitting the sample by the median value of the three-year moving average of CAPX over assets.

The coefficient on the interaction between the monetary policy shock and log scope

1 emissions is negative and statistically significant only in the subsamples with a higher level of capital intensity. Depending on the splitting variable, the coefficient ranges from −2.57 to −3.9 (twice the baseline estimate in Table 2), and is statistically significant at the 1% level. Panel A provides evidence that the higher stock price sensitivity to monetary policy shocks is driven by firms that are more capital intensive.

4.3.3 Climate Change Exposures

In Panel C, we report the results from sample splits based on a firm's perceived and self-assessed exposure to climate change, constructed using transcripts on earnings conference calls and risk disclosures in annual reports, respectively. The measures also allow us to delineate the effects of regulatory risk by using measures that focus on mentions of regulatory risk in particular.

First, we use climate change exposures constructed by Sautner et al. (2023) (SLVZ), which capture the attention to climate change-related topics by participants in earnings conference calls. In Columns (1) and (2), we split the sample by the median value of the overall climate change exposure. The coefficient of $MP\ Shock \times Log\ Scope\ 1$ is −2.117 and is statistically significant at the 5% level in the subsample of firms with overall exposure above the median, but insignificant in the subsample of firms below the median.

In Columns (3) and (4), we examine a firm's regulatory exposure to climate change according to the measure by Sautner et al. (2023). Given the regulatory exposure measure has a value of zero at the 75$^{\text{th}}$ percentile, we split the sample by whether a firm has a positive regulatory exposure to climate change. The coefficient of the interaction between the monetary policy shock and log scope 1 emissions is −4.170 and is statistically significant at the 5% level in the subsample of firms with a positive value of climate regulatory exposure, but insignificant in the subsample of firms with a zero value of climate regulatory exposure. Remarkably, the stock price sensitivity to monetary policy shocks in Column (3) is close to double that in Column (1). This suggests that regulatory exposure is a particularly relevant dimension of climate transition risk behind our headline results.

In the lower panel, we use climate change exposures constructed by Baz et al. (2023) (BCMZ). These measures capture a firm's self-assessment of its exposure to climate change, based on 10-K filings. In Columns (5) and (6), we split the sample by the median value of the overall climate change exposure. In Columns (7) and (8), we split the sample by the median value of climate regulatory exposure. The coefficient of *MP Shock* $\times$ *Log Scope* 1 is negative and statistically significant only among the subsample with a higher climate change exposure, ranging from -2.684 to -2.700. While the increase in the size of the coefficient is modest when the splitting variable changes from the overall climate change exposure to climate regulatory exposure, there is an increase in statistical significance in the latter group.

Collectively, the results in Panel C suggest that regulatory risks are an important component explaining the higher stock price sensitivity to monetary policy shocks by high-emission firms.

4.3.4 Stakeholder Pressure

In Panel D, we report results from sample splits based on a firm's exposure to stakeholder pressure. The TCFD has articulated that market risks (climate-related risks and opportunities that are being taken into account) and reputational risks (changing customer and community perceptions) constitute part of the overall carbon transition risk. Stakeholders — shareholders, suppliers, and customers, etc — with green preferences may switch away from firms that are less likely to successfully transition. If the higher stock price sensitivity of high-emission firms is driven by market and reputational risks, we should expect the higher sensitivity to be concentrated among firms with greater exposure to stakeholder pressure.

In Columns (1) and (2), we analyze the role of shareholder pressure and split the sample by the median value of ownership by socially responsible investors that are signatory of the Principles for Responsible Investment (PRI). The coefficient of *MP Shock* $\times$ *Log Scope* 1 is negative and marginally significant in the subsample with a higher proportion of socially responsible investors. While the coefficient is insignificant in Column (2), it should be noted that the size of the coefficient is quite close to that in Column (1).

In Columns (3) and (4), we split the sample by the median value of sales-based market share. Firms with a higher market share likely have greater market power, and are arguably less exposed to pressure from suppliers and customers. The coefficient of MP *Shock* $\times$ *Log Scope* 1 is negative and marginally significant in the subsample with a lower market share. While the coefficient is statistically insignificant in Column (4), the point estimate is slightly larger than in Column (3).

In Columns (5) and (6), we split the sample by whether a firm has economically valuable patent applications, constructed using data from Kogan et al. (2017). Firms with valuable patents produce goods that are less substitutable, and are arguably less exposed to pressure from customers. The coefficient of MP *Shock* $\times$ *Log Scope* 1 is negative and statistically significant in the subsample with fewer successful patent applications, but insignificant in the subsample with more successful patent applications.

In Columns (7) and (8), we split the sample by the median value of product similarity score from Hoberg and Phillips (2016). Firms with a higher product similarity sell products that are more substitutable, and are arguably more exposed to pressure from customers. The coefficient of MP *Shock* $\times$ *Log Scope* 1 is negative and marginally significant in the subsample with higher product similarity. While the coefficient is insignificant in Column (8), it should be noted that the size of the coefficient is quite close to that in Column (7).

The results in Panel D provide no clear evidence that the higher stock price sensitivity is driven by firms with a greater exposure to stakeholder pressure. The only sample split that displays a clear difference is the one based on patents. But firms with more productive patents may also be less exposed to technological risks, consistent with a key role for technological risk and the evidence based on splits by capital intensity in Panel B.

4.3.5 CDP Respondents

In Panel E, we report the results from one additional set of sample splits based on whether a firm has responded to the survey on climate disclosures by the Carbon Disclosure Project (CDP). Firms that voluntarily participate in the CDP have likely made more progress in transitioning to a low-carbon business model and may therefore be better prepared to tackle carbon transition risk. If the greater stock price sensitivity of high-emission firms is related to carbon transition risk, we should expect the higher sensitivity to be concentrated among firms that do not respond to the CDP.

In Columns (1) and (2), we split the sample by whether a firm participates in the CDP. Among firms that do not respond to the CDP, the coefficient estimate on the interaction between the monetary policy shock and a firm's log scope 1 emissions is -3.948 and statistically significant at the 1% level. By contrast, the coefficient estimate is -1.104 and statistically insignificant among firms that respond to the CDP.

In Columns (3) and (4), we additionally use information on whether firms reported to the CDP that they have an emissions reduction target in place. As firms that do not participate in the CDP likely have no climate target in place, we assign a firm in our sample to the no-abatement group if it is not in the CDP dataset. In Columns (5) and (6), we split the sample by whether a firm reported that it has dedicated personnel responsible for climate change. In both these exercises, the coefficient of $MP\ Shock \times Log\ Scope\ 1$ is negative and statistically significant only in the subsamples without a climate target or without climate personnel.

Collectively, the results in Panel E lend support to the interpretation that the higher stock price sensitivity to monetary policy shocks is attenuated by firms' commitments to decarbonization. This is consistent with evidence in Altavilla et al. (2023), who find that, in the Eurozone, monetary policy tightening induces banks to increase credit spreads to high-emission firms, but less so for firms that commit to decarbonization.

4.3.6 Discussion

Taken together, the sample splits in Table 4 based on assessed sustainability performance (Panel A), capital intensity (Panel B), perceived exposure to regulatory risks (Panel C), and CDP respondents (Panel E) indicate that the technological and regulatory components of carbon transition risk are a key driver explaining the greater stock price sensitivity of high-emission firms to monetary policy shocks. By contrast, the splits based on proxies for stakeholder pressure in Panel D suggest a smaller role for this channel.

4.4 Cash Flow Effects vs Discount Rate Effects

The results so far show that the stock prices of firms with high carbon emissions are more sensitive monetary policy shocks, especially among firms that are more exposed to technological and regulatory carbon transition risk. However, it is yet unclear whether these effects operate via a cash flow or a discount rate channel. While disentangling these effects is inherently challenging, we use the corporate bond market as our laboratory and perform two tests as best-effort attempts to isolate discount rate effects from cash flow effects.

4.4.1 Bond Returns

The first test attempts to isolate discount rate effects from cash flow effects by exploiting the lower performance sensitivity of bonds relative to stocks, especially for investment-grade bonds (similar to Elenev et al., 2024). As bond prices are less sensitive to cash flow news, we hypothesize that differences in bond price reactions to monetary policy shocks between high- and low-emission firms can be primarily attributed to changes in discount rates.

We construct a bond-event date level sample that consists of 4,488 investment grade bonds issued by 363 firms in linked Trucost and CRSP/Compustat sample. Section IA.1.5 provides a detailed discussion of the data construction process. We estimate the following regression:

$$
\begin{aligned}
Bond\ Ret_{b\tau}^{FOMC} = {} & \beta_1 \cdot Log(Scope\ 1_{it-1}) + \beta_2 \cdot MPShock_\tau \times Log(Scope\ 1_{it-1}) \\
& + \gamma_1^{'} \cdot X_{it-1}^{f} + \gamma_2^{'} \cdot MPShock_\tau \times X_{it-1}^{f} \\
& + \gamma_3^{'} \cdot X_{bm-1}^{b} + \gamma_4^{'} \cdot MPShock_\tau \times X_{bm-1}^{b} \\
& + \mu_b + \eta_{i\tau} + \varepsilon_{b\tau}
\end{aligned}
\qquad (2)
$$

where $Log(Scope\ 1_{it-1})$, $MPShock_{\tau}$, and X^{f}_{it-1} are as defined in Equation 1. *Bond* $Ret^{FOMC}_{b\tau}$ is the intra-day bond return of bond b on event-day τ of the FOMC meeting. We further include the following bond characteristics in the prior month (and their interactions with monetary policy shocks) in the vector X^{b}_{bm-1}: log of remaining time-to-maturity, log of bond age, log of amount outstanding, log of end-of-month bond price, end-of-month realized bond return, accrued coupons, and bond yield. We include bond fixed effects to control for unobserved, time-invariant bond heterogeneity. In the most stringent specification, we include event date-by-firm fixed effects to control for unobserved, time-varying shocks to a firm on each FOMC date. Standard errors are clustered at the firm and event-date levels.

[Insert Table 5 Here]

Table 5 reports the results using Equation 1, but with realized intra-day bond returns on FOMC dates as the dependent variable. This bond-event date level sample consists of 4,488 investment grade bonds issued by 363 firms in the linked Trucost and CRSP/Compustat sample. Section IA.1.5 provides a detailed discussion of the data construction process. We further include the following bond characteristics in the prior month (and their interactions with monetary policy shocks) as control variables: log of remaining time-to-maturity, log of bond age, log of amount outstanding, log of end-of-month bond price, end-of-month realized bond return, accrued coupons, and bond yield.

In Column (1), we only include uninteracted control variables and bond fixed effects to estimate the average bond price reaction to monetary policy shocks. The coefficient of *MP Shock* is -3.433, and is statistically significant at the 1% level. This indicates that bond prices fall by 3.433% in response to a 1% surprise monetary tightening.

In Columns (2)–(4), we investigate whether the bond price reactions to monetary policy shocks depend on a firm's scope 1 emission levels. As our sample only includes investment grade-bonds, the impact of a surprise monetary policy tightening on bond cash flows is likely to be minimal. As a result, a statistically significant coefficient of the interaction between *MP Shock* and *Log Scope* 1 will lend support to a differential change in discount rates in response to monetary policy shocks that varies by a firms' emission levels. In our estimations, while the coefficient of *MP Shock* $\times$ *Log Scope* 1 *Intensity* is negative, it is statistically insignificant across columns. In Columns (5)–(6), we replace emission levels with emission intensity. The coefficient of *MP Shock* $\times$ *Log Scope* 1 remains statistically insignificant. In sum, there is limited evidence to suggest that bond price reactions to monetary policy shocks depend on a firm's carbon emission levels or emission intensity.

4.4.2 Green Bond Returns

The second test attempts to isolate preference-based discount rate effects by comparing returns on green bonds and non-green bonds issued by the same issuer. This within-firm comparison can elicit the response of the greenium that bond investors are willing to pay due to their taste for environmentally-friendly investments (Pastor et al., 2022).

In this set of analyses, we retain bonds from firms that have issued a green bond over the sample period. As a result of this restriction, the sample size shrinks to 1,286, with 127 unique bonds, of which eight are green bonds.

To evaluate whether the prices of green bonds respond differently, we re-estimate Eq. (2) but we include the variable *Green Bond*, which is the sustainable debt instrument indicator assigned by Bloomberg, as well as the interaction term *MP Shock* $\times$ *Green Bond*. The coefficient on this interaction term identifies differences in realized returns between green and non-green bonds issued by the same firm. Since this coefficient can be identified from variation in bonds issued by the same firm, we can include firm-by-event date fixed effects to control for unobserved, time-varying shocks to a firm on each FOMC date.

[Insert Table 6 Here]

Table 6 reports the results. If monetary policy shocks affect bond investors' preference for sustainability, then the coefficient of *MP Shock* $\times$ *Green Bond* will be statistically significant. However, it is not statistically significant in any column and changes sign between specifications. Importantly, in Column (4), we include firm-by-event date fixed effects, which explicitly control for cash flow news at the firm-date level.

4.4.3 Discussion

In summary, we use the bond market as a best-effort attempt to empirically isolate discount rate effects from cash flows effects. The results in Table 5 show that, unlike stock prices, bond price reactions to monetary policy shocks do not statistically significantly depend on a firm's emissions level. Additionally, the results in Table 6 show that the bond price reactions to monetary policy shocks between green and non-green bonds issued by the same issuer are not statistically different.

There are a number of key caveats in interpreting these results. First, bonds are less liquid than stocks, and bond prices are less informationally sensitive than stock prices. This concern is somewhat alleviated by the fact that the Trucost sample covers relatively large firms with relatively liquid bonds. Additionally, we use intra-day bond returns as the dependent variable, which requires multiple transactions on an FOMC day. Nevertheless, the lack of depth of bond markets and segmentation of the equity and debt markets may limit the power of the test. Second, while Table 6 compares returns between green and non-green bonds issued by the same firm, and explicitly controls for cash flow effects via the inclusion of firm-by-event-date fixed effects, the reduction in sample size may lower the power of the test.

While these results do not disprove the existence of a discount rate effect, our preferred interpretation is that the higher stock price sensitivity to monetary policy shocks among high-emission firms is primarily driven by a differential cash flow effect rather than a discounting effect.

5 Real Effects

The results in the previous section are based on high-frequency financial market responses to FOMC announcements. We now turn to evaluating the real effects of monetary policy at a lower frequency. In a first step, we evaluate the average effect of monetary policy on emissions. Then, we turn to the cross-section to evaluate whether these real effects depend on the level of a firm's scope 1 emissions.

5.1 Methodology

The high-frequency shocks are well-suited to identify the effect of monetary policy shocks on stock prices and other variables that can be observed at high frequency. By contrast, identifying the causal effect of monetary policy on slow-moving variables such as emissions or investment is difficult (Nakamura and Steinsson, 2018). We follow recent literature and estimate the effect using instrumental variable local projections (Gertler and Karadi, 2015; Ottonello and Winberry, 2020; Bu et al., 2021; Cloyne et al., 2023). We transform the data to the quarterly level by summing up the monetary policy shocks that occur in a given quarter. We use the 2-year Treasury rate as a measure of the monetary policy stance, which captures the effects of conventional and unconventional monetary policy. We instrument the 2-year Treasury rate using the cumulative sum of high-frequency shocks over time, while also controlling for key lagged macroeconomic controls.[16] To trace out the dynamic effect of monetary policy, we estimate the following specification for different quarterly horizons h:

$$y_{it+h-1} - y_{it-1} = \beta_1^h \cdot \hat{R}_t + \gamma_1^{h\prime} \cdot X_{t-1}^m + \gamma_2^{h\prime} \cdot X_{it-1}^f + \mu_i + \varepsilon_{it}. \tag{3}$$

The dependent variable is the h-quarter change in log emissions or other variable of interest. The coefficient β_1^h is the key coefficient of interest, which measures the response of the dependent variable to an increase in the instrumented 2-year Treasury $\hat{R}_t$. The vector X_{t-1}^m contains lagged macroeconomic controls: real GDP growth, the employment-to-population ratio, and the log of the Consumer Price Index, all obtained from FRED Economic Data, as well as the Excess Bond Premium from Gilchrist and

[16] This "level measure" of shocks is a stronger instrument for the Treasury rate level compared to the quarterly shocks, also see Bu et al. (2021) and Döttling and Ratnovski (2023). Alternatively, we could instrument changes in the 2-year Treasury using the quarterly shocks directly.

Zakrajšek (2012) to control for financial conditions, obtained from the author's website. The vector X^f_{it-1} collects the firm-level controls from the high-frequency stock return analysis, as well as the lagged dependent variable y_{it-1} to condition on the level of the dependent variable.[17] Additionally, we include firm fixed effects μ_i to control for time-invariant unobservable characteristics.

5.2 The Average Effect of Monetary Policy on Emissions

How monetary policy affects emissions is a priori unclear. On one hand, monetary policy has an effect on output, and higher output tends to result in higher emissions. On the other hand, monetary easing may allow firms to make investments in green technologies, which may bring down emissions down the line. To estimate the average effect of monetary policy, we estimate the coefficient β^h_1 in Eq. (3) for different horizons. Since emissions are reported at the fiscal-year level, we estimate the year-on-year response rather than the quarterly response, i.e., we estimate β^h_1 for horizons of 1–4 years (i.e. quarterly horizons $h = 4, 8, 12$ and 16).

Figure 3 plots the β^h_1 estimates along with 95% confidence intervals, rescaled to represent the response to a 25bps increase in the instrumented 2-year Treasury rate. Panels A and B plot the response of log investment (CAPX) and log sales. The biggest effects occur after two years, where investment falls by just over 5% and sales by just over 4%, consistent with monetary policy operating with a lag. Panel C shows that total scope 1 emissions drop by around 3% on average, indicating that monetary policy tightening results in lower emissions. By contrast, in Panel D emissions intensity does not respond at 1–2 year horizons. This indicates that the emissions reduction in response to monetary tightening is driven by a reduction in output rather than improved efficiency. At the longer 3 and 4-year horizons, emissions intensity even slightly increases. This is consistent with firms forgoing investments in low-carbon technologies when monetary

[17] We do not include variables at a higher-than-quarterly frequency. We exclude the momentum control variable, which is measured as the return between two FOMC meetings, and control for firm size using the log of book assets instead of the log of the market value of the firm's assets, which is measured on the day before the FOMC meeting.

policy is restrictive, resulting in a deterioration in carbon efficiency at longer horizons.

5.3 Heterogeneity

We now ask whether the effect of monetary policy is stronger for firms that have a higher level of emissions. Our stock return results indicate that monetary policy is amplified for high-emission firms due to the effect of monetary policy on the cost of carbon transition risk. A priori, it is not clear whether this implies a stronger or weaker response in emissions to monetary policy for high-emission firms. High-emission firms may take advantage of accommodative funding conditions and reduce their emissions by investing in low-carbon technologies. This would attenuate the response of emissions to monetary policy. Alternatively, monetary tightening (easing) may aggravate (ease) the pressure on high-emission firms to reduce emissions, resulting in an amplified response by high-emission firms.

To assess whether high-emission firms respond more or less, we amend Specification (3) by adding an interaction term $\hat{R} \times$ *Log Scope* 1. Since we are interested in estimating an interactive effect, we can saturate the model with time fixed effects or industry-by-time fixed effects. We also control for the interaction of monetary policy with other firm-level controls.[18]

Table 7 presents the results for horizons of 2 and 3 years, at which the effect of monetary policy is the strongest. In Panel A, the dependent variable is the change in the log of total scope 1 emissions. Columns 1 and 4 report results from regressions without interaction terms, which show that firms with higher emissions tend to decrease their emissions relative to low-emission firms. Unconditionally, a one standard deviation increase in log scope 1 emissions is associated with a 28.8% lower growth in emissions over two years, and 42.5% lower growth over three years, confirming the pattern shown in Figure 2. Columns 2–3 and 5–6 additionally include interaction terms. The coefficient

[18] We do not include firm fixed effects because the dependent variable is *changes* in emissions between t and $t + h$, while the key independent variable is the log *level* of emissions at $t - 1$. With firm fixed effects, the coefficient on log emissions would mechanically be highly negative because it would measure the reduction in emissions within a firm given a high current level. We also confirm the results are robust to including firm fixed effects in Columns (3) and (6) of Table 7.

estimate on the interaction between the instrumented 2-year Treasury and log scope 1 emissions is between 0.123 and 0.315, and consistently statistically significant at the three-year horizon. This indicates that, while high-emission firms on average reduce their emissions relative to other firms, they reduce emissions less when interest rates are higher and monetary policy is tight. Vice versa, high-emission firms reduce their emissions by more when funding conditions are accommodative. This suggests that the abatement activities of highly polluting firms are more responsive to monetary policy compared to other firms, resulting in an attenuated response in emissions at longer horizons. Consistent with this interpretation, Panel B of Table 7 shows similar results for emissions intensity. The estimates are consistently statistically significant at both the 2-year and 3-year horizons.

We note that these results are based on relative reductions in emissions. If we were to evaluate changes in absolute emissions, the differences in responses between high- and low-emission firms would be even larger because firms with a higher level of emissions on average undergo larger absolute changes in emissions (see Hartzmark and Shue, 2023).

5.4 Discussion

Taken together, the real effects results paint a picture consistent with the high-frequency stock market responses. Monetary policy has a relatively stronger effect on the performance of firms with greater exposure to carbon transition risk. Such firms need to replace polluting assets to transition to a low-carbon business model. This transition is cheaper when funding conditions are accommodative, but costlier when monetary policy is restrictive. As high-emission firms disproportionately slow down emissions reductions efforts when monetary policy tightens, they retain a greater exposure to carbon transition risk. These effects are reflected in stock prices on FOMC announcement dates, resulting in an amplified response among high-emission firms.

6 Conclusion

Despite the striking divergence in how central banks address climate change-related risks, it is yet unclear how monetary policy affects firms' path to climate neutrality. By exploiting high-frequency monetary policy shocks around FOMC announcements, this paper documents that — in the US — stock prices of firms with relatively higher carbon emissions are more sensitive to monetary policy shocks. Consistent with the valuation results, we find that high-emission firms reduce their emissions relative to low-emission firms, but disproportionately slow down emissions-reduction efforts when monetary policy is tight.

Our results suggest that regardless of whether a central bank embraces a climate mandate, there may still be a need to incorporate carbon transition risk in monetary policymaking. Our results also caution against impact investing strategies aimed at increasing high-emission firms' cost of capital, as firms with the highest emission levels may respond by slowing down emissions reductions the most.

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A Tables

Table 1: Descriptive Statistics

This table reports sample composition (Panel A) and summary statistics (Panel B). Variables definitions are reported in Table IA1 the Internet Appendix.

Panel A: Number of Firms and Emissions per Industry

	N Firms	Percent	Mean Emissions	
			Total	Intensity
11: Agriculture, Forestry, Fishing, Hunting	3	0.17%	10.83	5.75
21: Mining, Quarrying, Oil, Gas Extraction	87	4.91%	13.08	5.50
22: Utilities	69	3.89%	14.81	6.70
23: Construction	41	2.31%	10.95	3.05
31-33: Manufacturing	846	47.74%	12.06	3.41
42: Wholesale Trade	65	3.67%	11.64	2.90
44-45: Retail Trade	107	6.04%	11.48	2.18
48-49: Transportation and Warehousing	57	3.22%	14.15	5.79
51: Information	207	11.68%	8.75	1.21
53: Real Estate, Rental, Leasing	67	3.78%	9.70	2.51
54: Professional, Scientific, Tech. Services	67	3.78%	9.33	1.76
56: Administrative, Support, Waste Mgmt., Remediation Services	41	2.31%	10.64	2.80
61: Educational Services	12	0.68%	10.08	3.01
62: Health Care and Social Assistance	37	2.09%	10.88	2.60
71: Arts, Entertainment, Recreation	11	0.62%	10.06	2.74
72: Accommodation and Food Services	46	2.60%	11.17	3.21
81: Other Services (except Public Administration)	6	0.34%	10.92	3.26
99: Unclassified	3	0.17%	16.02	5.22
Total	1772	100%	11.09	3.27

Table 1: Descriptive Statistics (Continued)

Panel B: Summary Statistics

	All Firms			
	Mean	P50	SD	N
Stock Return on FOMC Day	-0.076	-0.085	1.94	59271
Log Scope 1	11.1	10.9	2.64	59277
Log Scope 1 Intensity	3.27	2.99	1.84	59277
Log Market Value	8.85	8.90	1.68	59277
Leverage	0.27	0.26	0.21	59277
ROE	9.49	12.3	76.7	59277
BM	0.40	0.35	0.39	59277
Log PPE	6.39	6.49	2.35	59277
Investment	0.052	0.035	0.060	59277
Sales Growth	0.064	0.050	0.26	59277
Momentum	0.98	1.15	11.6	59277
PPE / Assets	0.28	0.19	0.25	59277
PPE / (Tot Assets)	0.24	0.13	0.24	59277
ESG Score	4.36	4.24	2.11	43706
E(nvironmental) Score	4.89	4.80	2.00	43704
S(ocial) Score	4.43	4.40	1.65	43706
G(overnance) Score	5.35	5.20	1.93	43700
CC Exposure (SLVZ)	0.0014	0.00037	0.0035	54891
Reg Exposure (SLVZ)	0.000065	0	0.00033	54891
CC Exposure (BCMZ)	0.0045	0.00099	0.0089	56891
Reg Exposure (BCMZ)	0.0028	0.00057	0.0051	56891
CDP Respondent	0.44	0	0.50	59277
Climate Target	0.23	0	0.42	59277
Climate Personnel	0.29	0	0.45	59277
PRI Ownership	0.31	0.31	0.15	55696
Market Share	0.16	0.055	0.23	59277
Patent Value	844.4	0	4440.5	59277
Product Similarity	4.43	1.55	9.24	58723

Table 2: Baseline Results

This table reports coefficient estimates from estimating Equation 1. The dependent variable is $Ret^{FOMC}_{i\tau}$, the stock return of firm i on FOMC announcement date τ. MP Shock is the monetary policy shock on day τ, as constructed by Jarociński and Karadi (2020). Log Scope 1 is the log of firm i's scope 1 emissions in year $t-1$ (standardized z-score). Log Market Value is the log of firm i's market value of assets on day $\tau-1$. Leverage is book leverage of firm i in year $t-1$. ROE is the return on book equity of firm i in year $t-1$. BM is the book-to-market ratio of firm i on day $\tau-1$. Log PPE is the log of firm i's net property, plant and equipment in year $t-1$. Investment is capital expenditures of firm i in year t divided by total assets in year $t-1$. Sales Growth is the percentage change in sales of firm i from year $t-1$ to year t. Momentum is the realized stock return of firm i between the day after the previous announcement and day $\tau-1$. We suppress the coefficients of the non-interacted control variables due to space constraints. The sample includes all FOMC meetings in between 2010 and 2018, and covers all firms in the matched CRSP-Compustat-Trucost sample, excluding financial firms, utilities and government. Standard errors are two-way clustered at the firm and FOMC announcement date levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: Stock Return on FOMC Day							
	Total Emissions						**Emissions Intensity**	
	Baseline Full Sample				Estimated Emissions	Ex Utilities		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MP Shock	-16.580***							
	(4.235)							
MP Shock × Log Scope 1		-2.514***	-2.531***	-1.948**	-2.190**	-1.692**		
		(0.945)	(0.863)	(0.761)	(0.870)	(0.782)		
MP Shock × Log Scope 1 × Estimated					0.442			
					(0.869)			
MP Shock × Log Scope 1 Intensity							-2.075***	-1.264**
							(0.727)	(0.499)
MP Shock × Log Market Value		1.289*	0.410	-0.527	-0.431	-0.492	-0.286	-0.962
		(0.653)	(0.697)	(0.585)	(0.568)	(0.589)	(0.823)	(0.644)
MP Shock × Leverage			-3.266	-0.302	-0.491	-0.533	-2.902	-0.362
			(2.508)	(2.493)	(2.520)	(2.481)	(2.457)	(2.485)
MP Shock × ROE			-0.000	-0.003	-0.003	-0.003	-0.002	-0.004
			(0.006)	(0.005)	(0.005)	(0.005)	(0.007)	(0.005)
MP Shock × BM			-2.954	-2.616*	-2.582*	-2.853*	-3.024	-2.779*
			(2.009)	(1.539)	(1.513)	(1.598)	(2.018)	(1.558)
MP Shock × Log PPE			0.806*	0.946**	0.968**	0.877**	0.653	0.712*
			(0.416)	(0.428)	(0.439)	(0.421)	(0.435)	(0.405)
MP Shock × Investment			-26.301**	-22.554***	-23.308***	-21.814***	-21.892**	-20.585***
			(10.338)	(6.583)	(6.548)	(6.722)	(10.576)	(6.810)
MP Shock × Sales Growth			-4.085**	-1.733	-1.876	-2.216	-3.762*	-1.549
			(1.971)	(1.528)	(1.564)	(1.689)	(1.954)	(1.516)
MP Shock × Momentum			0.101	0.033	0.031	0.041	0.104	0.036
			(0.082)	(0.053)	(0.054)	(0.050)	(0.082)	(0.053)
Observations	59,271	59,271	59,271	54,971	54,971	51,534	59,271	54,971
Adjusted R-squared	0.067	0.253	0.254	0.343	0.343	0.329	0.254	0.343
Uninteracted Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Event-Date FE	N	Y	Y	N	N	N	Y	N
Event-Date-by-Industry FE	N	N	N	Y	Y	Y	N	Y

Table 3: Brown-Minus-Green (BMG) Portfolios

This table reports evidence on brown-minus-green portfolio returns in response to monetary policy shocks. In Panel A, we sort firms into quintiles by scope 1 emissions and regress $Ret_{i\tau}^{FOMC}$, the stock return of firm i on FOMC announcement date τ, on MP Shock, the monetary policy shock on day τ, as constructed by Jarociński and Karadi (2020). In Panel B, we form equal-weighted and value-weighted portfolios by double-sorting on size and emissions. Standard errors are two-way clustered at the 4-digit NAICS industry and FOMC announcement date levels in Panel A. Standard errors are heteroskedasticity-robust in Panel B. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Split by Emissions Quintiles

	DV: Stock Return on FOMC Day				
	Q1	Q2	Q3	Q4	Q5
	(1)	(2)	(3)	(4)	(5)
MP Shock	-14.377***	-14.415***	-15.836***	-17.856***	-20.018***
	(4.205)	(4.303)	(4.419)	(4.296)	(4.188)
Observations	12,004	11,761	11,811	11,784	11,747
Adjusted R-squared	0.047	0.060	0.075	0.080	0.084
Controls	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y

Panel B: Brown-Minus-Green Porfolio Return

	DV: BMG Portfolio Return on FOMC Day			
	Equal-weighted		Value-weighted	
	(1)	(2)	(3)	(4)
MP Shock	-5.519**	-7.486***	-5.943**	-9.087***
	(2.202)	(2.544)	(2.304)	(2.861)
Observations	72	71	72	71
R-squared	0.079	0.356	0.059	0.235
Year FE	N	Y	N	Y
Month FE	N	Y	N	Y

Table 4: Sample Splits

This table reports coefficient estimates from estimating Equation 1, using subsamples split by variables that capture different dimensions of carbon transition risk. The dependent variable is $Ret_{i\tau}$, the stock return of firm i on FOMC announcement date τ. Control variables are the same as in Table 2. We suppress the coefficients of other variables due to space constraints. We suppress the coefficients of the non-interacted control variables due to space constraints. The sample includes all FOMC meetings in between 2010 and 2018, and covers all firms in the matched CRSP-Compustat-Trucost sample, excluding financial firms, utilities and government. Standard errors are two-way clustered at the firm and FOMC announcement date levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: ESG Rating

	DV: Stock Return on FOMC Day					
	ESG Score		**E Score**		**Cl Chg Theme**	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
MP Shock × Log Scope 1	-2.625*	-1.709*	-3.164***	-0.735	-3.572**	-1.191
	(1.533)	(0.858)	(1.044)	(1.163)	(1.637)	(1.160)
Observations	18,591	17,404	18,789	17,936	15,460	15,206
Adj R2	0.400	0.369	0.417	0.357	0.402	0.327
(Interacted) Firm Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Event-Date-by-Industry FE	Y	Y	Y	Y	Y	Y

	DV: Stock Return on FOMC Day			
	S Score		**G Score**	
	Low	High	Low	High
	(7)	(8)	(9)	(10)
MP Shock × Log Scope 1	-1.702	-1.364*	-2.605*	-2.044**
	(1.340)	(0.793)	(1.337)	(0.836)
Observations	18,602	17,410	18,196	17,832
Adj R2	0.396	0.372	0.379	0.397
(Interacted) Firm Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Event-Date-by-Industry FE	Y	Y	Y	Y

Panel B: Capital Intensity

	DV: Stock Return on FOMC Day					
	PPE / Assets		**PPE / (Tot Assets)**		**CAPX / Assets**	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
MP Shock × Log Scope 1	-3.900***	-0.476	-3.847***	-0.397	-2.570***	-0.601
	(0.911)	(1.114)	(0.970)	(1.134)	(0.952)	(1.078)
Observations	25,582	26,046	25,589	25,961	25,030	25,590
Adj R2	0.413	0.282	0.416	0.279	0.399	0.285
Firm FE	Y	Y	Y	Y	Y	Y
Event-Date-by-Industry FE	Y	Y	Y	Y	Y	Y

Table 4: Sample Splits (Continued)

Panel C: Climate Change Exposures

	DV: Stock Return on FOMC Day			
	CC Exposure (SLVZ)		**Reg Exposure (SLVZ)**	
	High	Low	High	Low
	(1)	(2)	(3)	(4)
MP Shock × Log Scope 1	-2.117**	-0.534	-4.170**	-0.859
	(0.872)	(0.994)	(1.644)	(0.758)
Observations	23,582	23,726	10,338	41,727
Adj R2	0.391	0.308	0.388	0.332
Firm FE	Y	Y	Y	Y
Event-Date-by-Industry FE	Y	Y	Y	Y

	DV: Stock Return on FOMC Day			
	CC Exposure (BCMZ)		**Reg Exposure (BCMZ)**	
	High	Low	High	Low
	(5)	(6)	(7)	(8)
MP Shock × Log Scope 1	-2.684**	-0.992	-2.700***	-0.733
	(1.159)	(1.207)	(0.901)	(1.339)
Observations	24,892	24,346	24,593	24,057
Adj R2	0.407	0.267	0.396	0.267
Firm FE	Y	Y	Y	Y
Event-Date-by-Industry FE	Y	Y	Y	Y

Table 4: Sample Splits (Continued)

Panel D: Stakeholder Pressure

	DV: Stock Return on FOMC Day			
	PRI Ownership		**Market Share**	
	High	Low	Low	High
	(1)	(2)	(3)	(4)
MP Shock × Log Scope 1	-1.695*	-1.645	-1.789*	-1.903
	(0.981)	(1.198)	(0.903)	(1.515)
Observations	23,832	23,192	27,059	25,126
Adj R2	0.420	0.269	0.333	0.403
Firm FE	Y	Y	Y	Y
Event-Date-by-Industry FE	Y	Y	Y	Y

	DV: Stock Return on FOMC Day			
	Patent Value		**Product Similarity**	
	Zero	Positive	High	Low
	(5)	(6)	(7)	(8)
MP Shock × Log Scope 1	-2.570***	-1.444	-1.730*	-1.533
	(0.896)	(1.105)	(1.004)	(1.104)
Observations	29,991	21,502	26,314	25,296
Adj R2	0.351	0.329	0.360	0.322
Firm FE	Y	Y	Y	Y
Event-Date-by-Industry FE	Y	Y	Y	Y

Panel E: Carbon Disclosure Project (CDP)

	DV: Stock Return on FOMC Day					
	CDP Respondent		**Climate Target**		**Climate Personnel**	
	No	Yes	No	Yes	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)
MP Shock × Log Scope 1	-3.948***	-1.104	-2.447***	-1.463	-3.038***	-1.160
	(0.950)	(0.992)	(0.871)	(0.942)	(0.859)	(1.140)
Observations	29,082	23,259	41,101	11,009	37,953	14,095
Adj R2	0.277	0.486	0.318	0.489	0.308	0.491
(Interacted) Firm Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Event-Date-by-Industry FE	Y	Y	Y	Y	Y	Y

Table 5: Bond Price Responses

This table reports coefficient estimates from estimating Equation 2. The dependent variable is *Bond* $Ret_{i\tau}^{FOMC}$, the return of bond b on FOMC announcement date τ. MP Shock is the monetary policy shock on day τ, as constructed by Jarociński and Karadi (2020). Log Scope 1 is the log of firm i's scope 1 emissions in year $t-1$ (standardized z-score). Log Market Value is the log of firm i's market value of assets on day $\tau-1$. Leverage is book leverage of firm i in year $t-1$. ROE is the return on book equity of firm i in year $t-1$. BM is the book-to-market ratio of firm i on day $\tau-1$. Log PPE is the log of firm i's net property, plant and equipment in year $t-1$. Investment is capital expenditures of firm i in year t divided by total assets in year $t-1$. Sales Growth is the percentage change in sales of firm i from year $t-1$ to year t. Momentum is the realized stock return of firm i between the day after the previous announcement and day $\tau-1$. Due to space constraints, we suppress the coefficients of the uninteracted control variables as well as the bond-level control variables interacted with the monetary policy shock. The sample includes all FOMC meetings in between 2010 and 2018, and covers bonds issued by firms in the matched CRSP-Compustat-Trucost sample, excluding financial firms, utilities and government. Standard errors are two-way clustered at the firm and FOMC announcement date levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: Bond Return on FOMC Day					
	Total Emissions				**Emissions Intensity**	
	(1)	(2)	(3)	(4)	(5)	(6)
MP Shock	-3.675***					
	(0.971)					
MP Shock × Log Scope 1		-0.100	-0.309	-0.348		
		(0.166)	(0.266)	(0.509)		
MP Shock × Log Scope 1 Intensity					-0.114	-0.360
					(0.171)	(0.420)
MP Shock × Log Market Value		-0.106	0.132	0.134	0.145	0.047
		(0.181)	(0.310)	(0.605)	(0.321)	(0.623)
MP Shock × Leverage			-0.287	-0.628	-0.172	-0.586
			(1.181)	(1.525)	(1.229)	(1.521)
MP Shock × ROE			0.001	0.002	0.001	0.002
			(0.002)	(0.003)	(0.002)	(0.003)
MP Shock × BM			-0.480	-2.003	-0.453	-2.010
			(0.863)	(1.246)	(0.866)	(1.248)
MP Shock × Log PPE			0.070	-0.154	-0.016	-0.169
			(0.198)	(0.421)	(0.186)	(0.423)
MP Shock × Investment			1.079	-4.051	1.338	-3.789
			(3.880)	(8.906)	(3.888)	(8.919)
MP Shock × Sales Growth			0.699	1.261	0.748	1.252
			(1.041)	(1.771)	(1.032)	(1.776)
MP Shock × Momentum			0.009	0.017	0.009	0.017
			(0.020)	(0.034)	(0.019)	(0.034)
Observations	60,734	60,734	60,734	59,401	60,734	59,401
Adjusted R-squared	0.021	0.064	0.068	0.083	0.067	0.083
Uninteracted Controls	Y	Y	Y	Y	Y	Y
MP Shock × Bond Controls	N	N	Y	Y	Y	Y
Bond FE	Y	Y	Y	Y	Y	Y
Event-Date FE	N	Y	Y	N	Y	N
Event-Date-by-Industry FE	N	N	N	Y	N	Y

Table 6: Green Bonds

This table reports coefficient estimates from estimating Equation 2. The dependent variable is *Bond* $Ret^{FOMC}_{i\tau}$, the return of bond b on FOMC announcement date τ. MP Shock is the monetary policy shock on day τ, as constructed by Jarociński and Karadi (2020). Green bond is an indicator variable that is equal to 1 if Bloomberg has assigned the sustainable debt instrument flag to bond b. Log Bond Age is the log of bond b's age in month $m-1$. Log Amount Outstanding is the log of bond b's amount outstanding in month $m-1$. Log Bond Price EoM is the log of the end-of-month price of bond b in month $m-1$. Log Time to Maturity is the log of bond b's remaining time to maturity in month $m-1$. Bond Return EoM is bond b's end-of-month return in month $m-1$. Coupon Accrued is the coupon accrued on bond b from the last coupon payment date to month $m-1$. Bond Yield is the yield on bond b in month $m-1$. We suppress the coefficients of the all firm-level control variables and uninteracted bond-level control variables due to space constraints. The sample includes all FOMC meetings in between 2010 and 2018, and covers bonds issued by firms that have issued a green bond in the matched CRSP-Compustat-Trucost sample, excluding financial firms, utilities and government. Standard errors are two-way clustered at the firm and FOMC announcement date levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: Bond Return on FOMC Day			
	(1)	(2)	(3)	(4)
MP Shock × Green Bond	-1.325	-0.635	0.126	0.262
	(2.522)	(2.185)	(2.345)	(1.882)
MP Shock × Log Bond Age		1.993	1.756	1.648
		(1.551)	(2.637)	(1.355)
MP Shock × Log Amount Outstanding		-2.644	-2.413	-2.254
		(1.943)	(2.238)	(2.179)
MP Shock × Log Bond Price EoM		14.646	7.214	2.833
		(28.152)	(26.508)	(26.671)
MP Shock × Log Time to Maturity		-3.062	-3.277	-2.942
		(2.199)	(2.347)	(2.211)
MP Shock × Bond Return EoM		1.626	1.461	1.605
		(1.117)	(1.317)	(1.009)
MP Shock × Coupon Accrued		-2.212	-2.086	-2.530
		(2.661)	(3.304)	(2.471)
MP Shock × Bond Yield		3.941*	3.923*	3.614*
		(2.020)	(2.260)	(2.134)
Observations	1,946	1,946	1,946	1,946
Adjusted R-squared	0.167	0.170	0.175	0.202
Uninteracted Controls	Y	Y	Y	Y
MP Shock × Firm Controls	N	N	Y	N
Bond FE	Y	Y	Y	Y
Event-Date FE	Y	Y	Y	N
Event-Date-by-Firm FE	N	N	N	Y

Table 7: Local Projections with Interaction Terms

This table reports coefficient estimates from a modified version of Equation 3, with the addition of the interaction term $\hat{R} \times$ Log Scope 1. $\hat{R}$ is the 2-year Treasury rate instrumented by cumulative high-frequency monetary policy shocks. Log Scope 1 is the log of firm i's scope 1 emissions in fiscal year $t-1$ (standardized z-score). The sample begins in 2010 and ends in 2018, and covers all firms in the matched CRSP-Compustat-Trucost sample, excluding financial firms, utilities and government. Heteroscedasticity and autocorrelation robust Driscoll-Kraay standard errors are used. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Total Emissions

	DV: Δ^h Log Scope 1					
	$h = 2$ years			$h = 3$ years		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Scope 1	-0.288***	-0.379***	-1.190***	-0.425***	-0.564***	-1.616***
	(0.027)	(0.064)	(0.109)	(0.046)	(0.079)	(0.114)
$\hat{R} \times$ Log Scope 1		0.123	0.208**		0.190**	0.315***
		(0.079)	(0.081)		(0.093)	(0.111)
Observations	30,010	30,010	29,901	23,555	23,555	23,438
Adj R2	0.0671	0.0682	0.462	0.0991	0.101	0.593
Uninteracted Controls	Y	Y	Y	Y	Y	Y
Interacted Controls	N	Y	Y	N	Y	Y
Firm FE	N	N	Y	N	N	Y
Industry-by-Time FE	Y	Y	Y	Y	Y	Y

Panel B: Emissions Intensity

	DV: Δ^h Log Scope 1 Intensity					
	$h = 2$ years			$h = 3$ years		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Scope 1	-0.179***	-0.176***	-0.256**	-0.274***	-0.202**	-0.282*
	(0.023)	(0.062)	(0.098)	(0.037)	(0.087)	(0.151)
$\hat{R} \times$ Log Scope 1		0.147**	0.229***		0.165*	0.283**
		(0.070)	(0.075)		(0.086)	(0.109)
Observations	30,006	30,006	29,897	23,554	23,554	23,437
Adj R2	0.197	0.201	0.533	0.233	0.239	0.645
Uninteracted Controls	Y	Y	Y	Y	Y	Y
Interacted Controls	N	Y	Y	N	Y	Y
Firm FE	N	N	Y	N	N	Y
Industry-by-Time FE	Y	Y	Y	Y	Y	Y

B Figures

Figure 1: Monetary Policy Shocks

This figure plots the high-frequency monetary policy shocks in our sample.

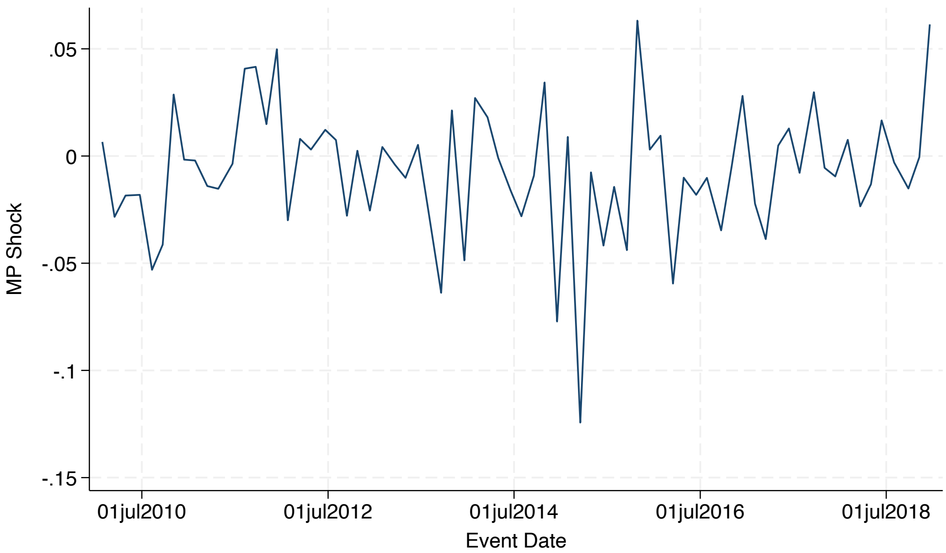


Figure 2: Emissions Level and Future Emissions Growth

This figure plots the relationship between a firm's current emissions and cumulative emissions growth over horizons of 1–4 year, by plotting the average emissions growth by emissions quintile. Each point represents the average cumulative emissions growth between year t and $t+n$ among firms sorted into quintiles of emissions levels in year t. Panel A uses the main sample, which begins in 2010 and ends in 2018, and covers all firms in the matched CRSP-Compustat-Trucost sample, excluding financial firms and government. Panel B is based on the the entire Trucost universe of firms between 2002 and 2021.

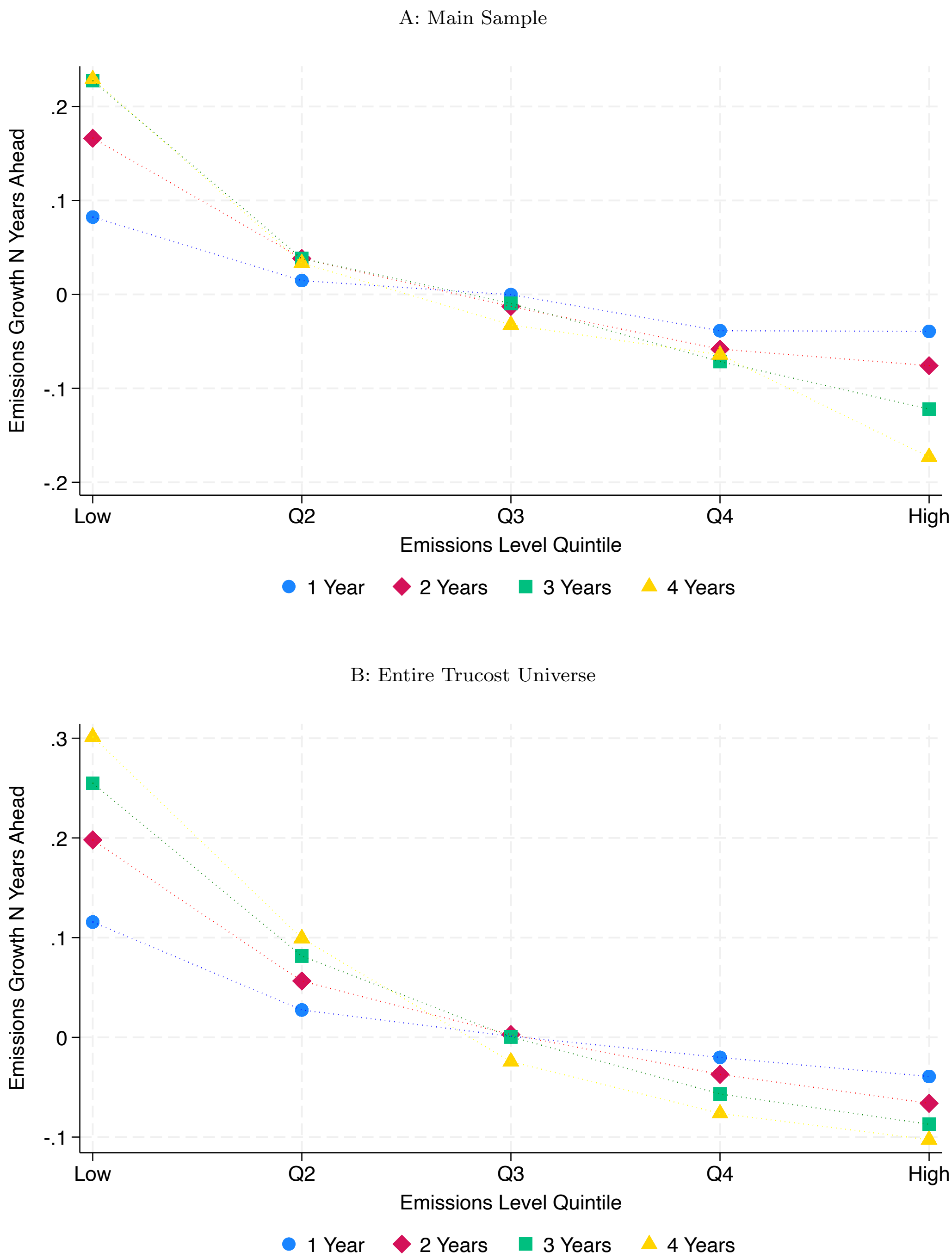
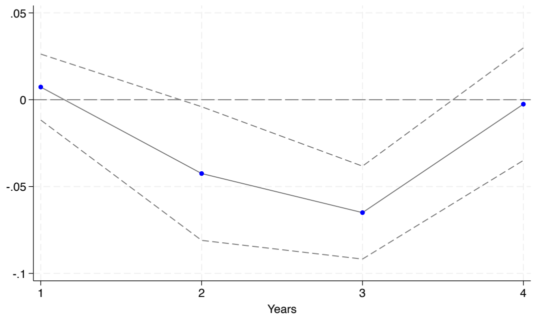


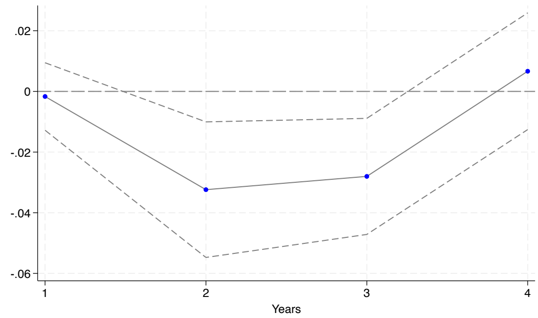
Figure 3: Response of Emissions, Sales, and Investment to Monetary Policy

This figure plots the dynamic response of investment to a 25bps higher 2-year Treasury rate, estimated using Eq. (3). The 2-year Treasury rate is instrumented by cumulative high-frequency monetary policy shocks. The sample begins in 2010 and ends in 2018, and covers all firms in the matched CRSP-Compustat-Trucost sample, excluding financial firms, utilities and government. Each point represents the point estimate of the coefficient of instrumented the 2-year Treasury rate (β_1^h in Eq. (3)). All regressions include firm and macro controls, as well as firm and fiscal quarter fixed effects. The dashed line represents 95% confidence intervals using heteroscedasticity and autocorrelation robust Driscoll-Kraay standard errors.

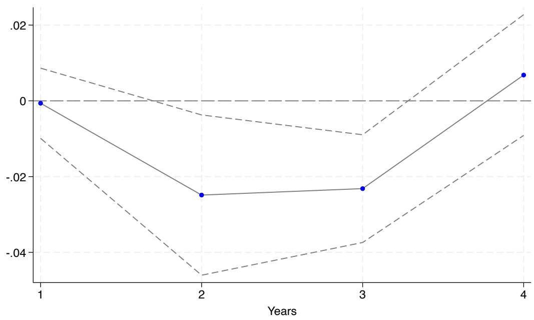
A: Log Investment (CAPX)



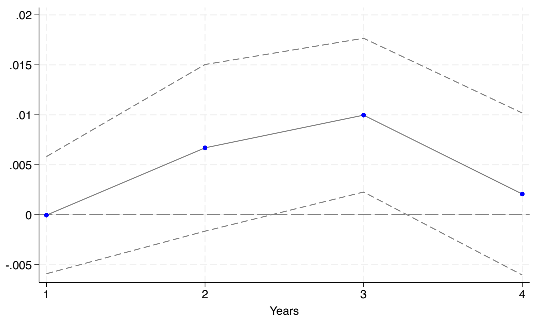
B: Log Sales



C: Log Total Scope 1 Emissions



D: Log Scope 1 Emissions Intensity



Internet Appendix
for
Monetary Policy, Carbon Transition Risk, and Firm Valuation

Robin Döttling and Adrian Lam

IA Internet Appendix

IA.1 Database Description

IA.1.1 ESG Ratings Data

We obtain firm level environmental, social and governance (ESG) ratings from MSCI ESG Ratings. The MSCI ESG Ratings are used by asset owners, consultants and wealth managers to evaluate corporate ESG performance.[19] The ESG ratings follow a four-level hierarchy, from the most granular to the most aggregate: (1) Key issues, (2) macro themes, (3) ESG pillars, and (4) the overall company rating.

At the most granular level, MSCI monitors 37 key ESG issues (e.g. carbon emissions, climate change vulnerability, and labor management, etc). For each company in an industry that generates large environmental or social externalities, MSCI identifies six to 10 key ESG issues that may result in large unanticipated costs, and evaluates the company's track record in managing these risks or opportunities. MSCI then assigns a score in between 0 (worst) and 10 (best) to a company for each rated issue.

At the second-most granular level, there are 10 theme scores (e.g. the climate change theme and the human capital theme), ranging from 0 (worst) to 10 (best). These are weighted-averages of key issue scores under a theme, normalized by the industry weights.[20] In our sample, the average climate change theme score is 6.10, with a standard deviation of 2.58.

The environmental, social or governance pillar scores range from 0 (worst) to 10 (best). These are the weighted average key issue scores under each pillar, normalized by the weights for each key issue underlying each pillar. In our sample, the average environmental pillar score (E Score) is 4.89, with a standard deviation of 2.00. At the most aggregated level, there is the final industry-adjusted score (ESG Score), ranging from 0 (worst) to 10 (best). These are the weighted average scores normalized relative to the industry peer set.[21] In our sample, the average industry adjusted score is 4.36, with a standard deviation of 2.11.

IA.1.2 Firm-level Climate Change Exposures

We obtain firm-level climate change exposures based on transcripts of earnings conference calls from Sautner et al. (2023) and 10-K filings from Baz et al. (2023).[22]

[19] As of 2018, 47 out of the 50 largest global asset managers, four out of the six largest investment consultants, and the five largest wealth managers (MSCI (2020)).

[20] For example, the key issues carbon emissions and climate change vulnerability are mapped to the climate change theme, and the key issue labor management is mapped to the human capital theme.

[21] The numerical score is also mapped to an alphabetic score ranging from CCC to AAA.

[22] We thank Salim Baz, Lara Cathcart, Alexander Michalelides and Yi Zhang for sharing the data with us.

Climate Change Exposures Based on Earnings Conference Calls

Sautner et al. (2023) construct measures for firm-level climate change exposures using transcripts of quarterly earnings conference calls from 2002 to 2020 by capturing the share of conversation devoted to climate change related topics. These exposure measures are relative frequency measures, where the count of certain climate change bi-grams in a transcript is divided by the total number of bi-grams in that transcript. They capture "soft information" originating from information exchanges between managers and analysts and reflect call participants' attention to these topics (Sautner et al. (2023)). These quarterly measures are annualized by averaging across quarters.

In our sample, the average climate change exposure (CC Exposure (SLVZ)), which captures exposure to broadly defined aspects of climate change, is 0.0014, with a standard deviation of 0.0034. The average regulatory climate exposure (Reg Exposure (SLVZ)), which captures exposure to climate change-related regulatory shocks, is 0.00007, with firms below the 75$^{\text{th}}$ percentile having a climate regulatory exposure of 0.

Climate Change Exposures Based on 10-K Filings

Baz et al. (2023) construct a measure for firm-level climate regulatory exposures using 10-K filings from 2006 to 2018, based on the share of climate change and regulation-related words in the Business (Item 1) and Risk Factors (Item 1A) sections. Listed firms are legally required to disclose financially material information to the public regularly. The comprehensive nature of 10-K filings provide a firm's own assessment on its business outlook and risk exposures. Baz et al. (2023) use a dictionary approach and compute a firm's evaluation of risks arising from climate change regulations based on n-gram searching.

In our sample, the average climate regulatory exposure (Reg Exposure (BCMZ)), which captures a firm's disclosed exposure to climate change *regulations*, is 0.0028, and has a standard deviation of 0.0051. Firms below the 25$^{\text{th}}$ percentile has a climate regulatory exposure of 0. Baz et al. (2023) also construct the broader climate change exposure (CC Exposure (BCMZ)), which captures a firm's disclosed exposure to climate change (without restricting to climate change *regulations* only). The average of regulatory exposure is 0.0045 and has a standard deviation of 0.0089. Firms below the 10$^{\text{th}}$ percentile having a value of 0.

IA.1.3 Carbon Disclosure Project

We obtain data from Carbon Disclosure Project's (CDP) Climate Change dataset. CDP uses an annual questionnaire to collect climate-related information from large companies, with both standardized and qualitative questions. We construct indicator variables to identify whether a firm participates in the CDP. We also construct a variable for whether a firm has reported an emissions reduction target to CDP and a variables for whether a firm has reported that it has dedicated climate personnel. We set these indicators to 0 for firms that never participated in the CDP. In our sample, the proportion of firms that participate in the CDP is 44.1%, the proportion of fimrs that participate and have set an emissions reduction target is 23.3%, and the proportion of firms that have personnel directly responsible for climate change is 28.8%.

IA.1.4 Stakeholder Pressure

Institutional Investors

We obtain institutional ownership data from WRDS Thomson Reuters Institutional (13f) Holdings. WRDS Thomson Reuters Institutional (13f) Holdings provides quarter-end institutional ownership data at the stock-level, adjusted for corporate actions and differences in filing dates. In our sample, the average institutional ownership (IO_{it-1}) is 76.7%, with a standard deviation of 23.1%.

We identify ownership by "socially responsible investors" if an investor is a signatory of the Principles for Responsible Investment (PRI). We perform a fuzzy name-matching exercise between PRI signatories and Thomson Reuters Institutional (13f) Holdings (S34), and aggregate socially responsible ownership to the firm-quarter level. In our sample, ownership by socially responsible investors is 30.9%, with a standard deviation of 15.1%.

Product Market Competition and Innovation

We use a number of measures that capture a firm's exposure to product market competition. Based on Compustat data, we compute market shares (*Market Share*) as a firm's sale divided by the sum of sales in a 4-digit SIC industry. In our sample, the average market share is 6.88%, with a standard deviation of 15.85%.

We obtain firm level total similarity scores (*Product Similarity*) from Hoberg and Phillips (2016). Hoberg and Phillips (2016) construct *Product Similarity* by parsing a firm's product description in 10-K filings, then summing the pairwise similarities between the firm and all other firms in a given year. In our sample, the average of *Product Similarity* is 4.43, with a standard deviation of 9.24.

We also obtain data on the economic value of innovations at the firm-patent level from Kogan et al. (2017). Kogan et al. (2017) construct a database of the economic value of patents that are granted to firms by exploiting stock market reaction around patent grant dates. In our sample, the average total economic value of patents for a firm in a given year is $952.11M, with a standard deviation of $5248.05M. The median firm has a total economic value of patents of 0.

IA.1.5 Corporate Bond

Bond Prices

We obtain transaction-level bond prices from the Trade Reporting and Compliance Engine (TRACE) Enhanced dataset. All broker-dealers who are members of the Financial Industry Regulatory Authority are required to report transactions of TRACE-eligible fixed income securities. The Enhanced dataset provides data on all historical transactions reported to TRACE. We follow the documentation on WRDS Bond Returns to clean the data, including addressing trade cancellations, corrections, reversals and double counting, as well as the change in the TRACE system on February 6th, 2012.

We use a multi-step procedure to compute intra-day bond returns on FOMC announcement dates. First, we compute the volume-weighted transaction price for each bond based on execution time. Second, on each FOMC announcement date, we compute the intra-day announcement return using the the first and the last volume-weighted transaction price on the day. We further require that the first transaction to take place before 14:00 Eastern time, and the last transaction to take place after 14:00 Eastern time.

Bond Characteristics

We obtain bond issue and issuer characteristics from WRDS Bond Returns. WRDS Bond Returns provides data on bond issue and issuer characteristics based on data from Mergent FISD. We construct a sample of investment grade bonds issued by firms in the linked Trucost and CRSP/Compustat sample. There are 4,488 bonds issued by 363 firms. The average intra-day bond return on an FOMC date is 0.07%, with a standard deviation of 0.83%.

We identify green bonds using Bloomberg. Bloomberg provides information on whether a bond is identified as a "Sustainable Debt Instrument". We construct a sample of bonds issued by green bond-issuing firms. In this sample, 5.6% of the observations are green bonds.

IA.2 Variable Definitions

Table IA1: Variable Definitions

This table provides detailed variable definitions and the relevant data sources.

Variable	Definition	Source
Ret^{FOMC}	Realized open-to-close stock return of firm i on FOMC announcement date τ.	CRSP
MP Shock	Monetary policy shock on day tau, as constructed by Jarociński and Karadi (2020).	Jarociński and Karadi (2020)
Estimated	Indicator variable that is equal to 1 if firm i's scope 1 carbon emissions are estimated in year $t-1$.	Trucost
Log Scope 1	Log of firm i's scope 1 carbon emissions in year $t-1$.	Trucost
Log Scope 1 Intensity	Log of firm i's scope 1 carbon emission intensity in year $t-1$.	Trucost
Log Market Value	Log of firm i's market value of assets on day $\tau-1$, measured as firm i's market value of equity on day $\tau-1$ plus book value of assets net of book value of equity in year $t-1$	Compustat and CRSP
BM	Book-to-market ratio of firm i on day $\tau-1$.	Compustat
Investment	Capital expenditures of firm i in year t divided by total assets in year $t-1$.	Compustat
Leverage	Book leverage of firm i in year $t-1$.	Compustat
Log PPE	Log of firm i's net property, plant and equipment in year $t-1$.	Compustat
PPE / Assets	Net property, plant and equipment of firm i in year $t-1$ divided by total assets in year $t-1$.	Compustat
PPE / (Tot Assets)	Net property, plant and equipment of firm i in year $t-1$ divided by total assets and off-balance sheet intangible assets from Peters and Taylor (2017) in year $t-1$.	Compustat
ROE	Net income of firm i in year $t-1$ divided by lagged book equity.	Compustat
Sales Growth	Percentage change in sales of firm i from year $t-1$ to year t.	Compustat

Table IA1: Variable Definitions

This table provides detailed variable definitions and the relevant data sources.

Variable	Definition	Source
Momentum	Realized stock return of firm i between the day after the previous announcement and day $\tau - 1$.	CRSP
CC Exposure (SLVZ)	Relative frequency with which bigrams related to climate change occur in the transcripts of earnings conference calls. Sautner et al. (2023) count the number of such bigrams and divide by the total number of bigrams in the transcripts.	Sautner et al. (2023)
Reg Exposure (SLVZ)	Relative frequency with which bigrams that capture regulatory risk related to climate change occur in the transcripts of earnings conference calls. Sautner et al. (2023) count the number of such bigrams and divide by the total number of bigrams in the transcripts.	Sautner et al. (2023)
CC Exposure (BCMZ)	Relative frequency with which bigrams related to climate change occur in the transcripts of earnings conference calls. Baz et al. (2023) count the number of such bigrams and divide by the total number of bigrams in the transcripts.	Baz et al. (2023)
Reg Exposure (BCMZ)	Relative frequency with which bigrams that capture regulatory risk related to climate change occur in the transcripts of earnings conference calls. Baz et al. (2023)count the number of such bigrams and divide by the total number of bigrams in the transcripts.	Baz et al. (2023)
ESG Score	MSCI's industry-adjusted overall ESG score of firm i in month $m - 1$.	MSCI ESG
E Score	MSCI's industry-adjusted overall environmental score of firm i in month $m - 1$.	MSCI ESG
Cl Chg Theme Score	MSCI's industry-adjusted overall climate change theme score of firm i in month $m - 1$.	MSCI ESG

Table IA1: Variable Definitions

This table provides detailed variable definitions and the relevant data sources.

Variable	Definition	Source
Bond Ret^{FOMC}	Realized open-to-close return on bond b on FOMC announcement date τ.	TRACE
Green Bond	Indicator variable that is equal to 1 if Bloomberg has assigned the sustainable debt instrument flag to bond b.	Bloomberg
Log Bond Age	The log of bond b's age in month $m-1$.	WRDS Bond Returns
Log Amount Outstanding	The log of bond b's amount outstanding in month $m-1$.	WRDS Bond Returns
Log Bond Price EoM	The log of the price of bond b in month $m-1$.	WRDS Bond Returns
Log Time to Maturity	The log of bond b's remaining time to maturity in month $m-1$.	WRDS Bond Returns
Bond Return EoM	Bond b's end-of-month return in month $m-1$.	WRDS Bond Returns
Coupon Accrued	Coupon accrued on bond b from the last coupon payment date to month $m-1$.	WRDS Bond Returns
Bond Yield	The yield on bond b in month $m-1$.	WRDS Bond Returns
CDP Respondent	Indicator variable that is equal to 1 if firm i has ever responded to the CDP Questionnaires.	Carbon Disclosure Project
Climate Target	Indicator variable that is equal to 1 if firm i has an emission reduction target (absolute or intensity) in year $t-1$.	Carbon Disclosure Project
Climate Personnel	Indicator variable that is equal to 1 if firm i has personnel that is responsible for climate change issues in year $t-1$.	Carbon Disclosure Project
Patent Value	Total value of patents granted to firm i in year $t-1$, computed by Kogan et al. (2017).	Kogan et al. (2017)
Product Similarity	Firm i's TNIC-3 score in year $t-1$, as computed by Hoberg and Phillips (2016).	Hoberg and Phillips (2016)
Market Share	Firm i's sales divided by the sum of sales within the same 4-digit SIC code.	Compustat
PRI Ownership	Firm i's ownership by institutional investors that are signatories of the Principles of Responsible Investment (PRI) in year $t-1$.	Thomson Reuters s34/PRI

IA.3 Additional Tables

Table IA2: Descriptive Statistics

This table reports additional summary statistics. Variables definitions are reported in Table IA1 the Internet Appendix.

	Bonds Issued by Firms in Regression Sample			
	Mean	P50	SD	N
Log Bond Age	0.93	1.08	1.05	50472
Log Amount Outstanding	13.6	13.5	0.67	50472
Log Bond Price EoM	4.65	4.63	0.082	50472
Log Time to Maturity	1.72	1.77	1.04	50472
Bond Return EoM	0.20	0.16	1.72	50472
Coupon Accrued	1.03	0.85	0.85	50472
Bond Yield	3.14	3.08	1.50	50472
Green Bond	0.056	0	0.23	1286

Table IA3: Alternative Emissions Measures

This table reports coefficient estimates from estimating a modified version of Equation 1, where we replace Log Scope 1 with other measures of carbon emissions. The dependent variable is $Ret_{i\tau}^{FOMC}$, the stock return of firm i on FOMC announcement date τ. Control variables are the same as in Table 2. We suppress the coefficients of the non-interacted control variables due to space constraints. The sample includes all FOMC meetings in between 2010 and 2018, and covers all firms in the matched CRSP-Compustat-Trucost sample, excluding financial firms, utilities and government. Standard errors are two-way clustered at the 4-digit NAICS industry and FOMC announcement date levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	DV: Stock Return on FOMC Day							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MP Shock × Log Scope 2	-1.357	-1.692**						
	(0.929)	(0.708)						
MP Shock × Log Scope 3			-2.060**	-2.481*				
			(0.925)	(1.474)				
MP Shock × Scope 1 Q5					-2.899**	-3.124***	-4.902***	-4.532***
					(1.446)	(0.939)	(1.782)	(1.507)
MP Shock × Scope 1 Q4							-3.387***	-1.873
							(1.259)	(1.459)
MP Shock × Scope 1 Q3							-1.775	-0.504
							(1.222)	(1.429)
MP Shock × Scope 1 Q2							-0.290	-0.603
							(0.885)	(1.148)
Observations	59,223	54,923	59,271	54,971	59,271	54,971	59,271	54,971
Adjusted R-squared	0.254	0.343	0.254	0.343	0.254	0.343	0.254	0.343
(Interacted) Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Event-Date FE	Y	N	Y	N	Y	N	Y	N
Event-Date-by-Industry FE	N	Y	N	Y	N	Y	N	Y

Table IA4: Alternative Monetary Policy Measures

This table reports coefficient estimates from estimating a modified version of Equation 1, where we replace MP Shock with other versions of monetary policy shocks. The dependent variable is $Ret_{i\tau}^{FOMC}$, the stock return of firm i on FOMC announcement date τ. In Columns (1)-(2), we replace MP Shock with FF4, the change in the 3-months ahead Fed Funds futures rate in the 30 min around the FOMC announcement. In Columns (3)-(4), we include CBI Shock, the central bank information shock constructed by Jarociński and Karadi (2020). Control variables are the same as in Table 2. We suppress the coefficients of the non-interacted control variables due to space constraints. The sample includes all FOMC meetings in between 2010 and 2018, and covers all firms in the matched CRSP-Compustat-Trucost sample, excluding financial firms, utilities and government. Standard errors are two-way clustered at the 4-digit NAICS industry and FOMC announcement date levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	DV: Stock Return on FOMC Day			
	FF4		**Information Shocks**	
	(1)	(2)	(3)	(4)
FF4 × Log Scope 1	-3.641**	-2.955*		
	(1.645)	(1.583)		
MP Shock × Log Scope 1			-3.122***	-2.191**
			(0.813)	(0.892)
CBI Shock × Log Scope 1			-1.557	-0.716
			(1.497)	(1.908)
Observations	59,271	54,971	59,271	54,971
Adjusted R-squared	0.253	0.343	0.254	0.343
Firm FE	Y	Y	Y	Y
(Interacted) Controls	Y	Y	Y	Y
Event-Date FE	Y	N	Y	N
Event-Date-by-Industry FE	N	Y	N	Y

Table IA5: Brown-Minus-Green (BMG) Portfolios Using Emissions Intensity

This table reports evidence on brown-minus-green portfolio returns in response to monetary policy shocks. In Panel A, we sort firms into quintiles by scope 1 emissions intensity and regress $Ret_{i\tau}^{FOMC}$, the stock return of firm i on FOMC announcement date τ, on MP Shock, the monetary policy shock on day τ, as constructed by Jarociński and Karadi (2020). In Panel B, we form equal-weighted and value-weighted portfolios by double-sorting on size and emissions intensity. Standard errors are two-way clustered at the 4-digit NAICS industry and FOMC announcement date levels in Panel A. Standard errors are heteroskedasticity-robust in Panel B. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Split by Emissions Intensity Quintiles

	DV: Stock Return on FOMC Day				
	Q1	Q2	Q3	Q4	Q5
	(1)	(2)	(3)	(4)	(5)
MP Shock	-13.075***	-15.610***	-16.388***	-16.323***	-21.011***
	(4.127)	(4.208)	(4.761)	(4.014)	(4.448)
Observations	12,069	11,928	11,756	11,708	11,716
Adjusted R-squared	0.044	0.072	0.067	0.080	0.088
Firm FE	Y	Y	Y	Y	Y

Panel B: Brown-Minus-Green Intensity Porfolio Return

	DV: BMG Portfolio Return on FOMC Day			
	Equal-weighted		Value-weighted	
	(1)	(2)	(3)	(4)
MP Shock	-7.739***	-9.232***	-7.678***	-9.584***
	(1.900)	(2.312)	(2.393)	(3.299)
Observations	72	71	72	71
R-squared	0.152	0.384	0.094	0.254
Year FE	N	Y	N	Y
Month FE	N	Y	N	Y

Table IA6: Changes in Future Emissions Using Full Trucost Sample

This table reports coefficient estimates from regression changes in future emissions on current emission levels. The dependent variable is the h-period ahead change in annual scope 1 emissions. Log Scope 1 is the log of scope 1 carbon emissions of firm i in year t. In contrast to the main paper, Log Scope 1 is not a z-score (normalized within our regression sample), because Panel B is based on the entire Trucost universe. In Panel A, the sample begins in 2010 and ends in 2018, and covers all firms in the matched CRSP-Compustat-Trucost sample, excluding financial firms, utilities and government. In Panel B, the sample beings in 2002 and ends in 2020, and covers all observations in the Trucost dataset. Standard errors are two-way clustered at the Trucost industry and financial year levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Regression Sample

	DV: Δ^h Log Scope 1			
	$h=1$	$h=2$	$h=3$	$h=4$
	(1)	(2)	(3)	(4)
Log Scope 1	-0.054***	-0.111***	-0.162***	-0.205***
	(0.005)	(0.009)	(0.013)	(0.019)
Observations	53,975	46,233	39,036	32,341
Adj R2	0.0252	0.0682	0.0999	0.119
Controls	Y	Y	Y	Y
Firm FE	N	N	N	N
Industry-by-Time FE	Y	Y	Y	Y

Panel B: Trucost Sample

	DV: Δ^h Log Scope 1			
	$h=1$	$h=2$	$h=3$	$h=4$
	(1)	(2)	(3)	(4)
Log Scope 1	-0.029***	-0.056***	-0.081***	-0.103***
	(0.002)	(0.003)	(0.004)	(0.006)
Observations	104,343	88,096	73,479	60,083
Adj R2	0.056	0.071	0.082	0.097
Controls	N	N	N	N
Firm FE	N	N	N	N
Industry-by-Time FE	Y	Y	Y	Y

Table IA7: Yield Curve Response to Monetary Policy Shocks

This table reports the high-frequency response of on-the-run Treasury bonds around FOMC meetings. The dependent variable is the change in the yield on the 6 months, 2 years, 5 years, 10 years, and 30 year maturity bond, respectively. Standard errors are clustered at the event date level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	DV: Δ Treasury Yield				
	6m	2y	5y	10y	30y
	(1)	(2)	(3)	(4)	(5)
MP Shock	0.218***	0.651***	0.763***	0.488***	0.093
	(0.050)	(0.130)	(0.185)	(0.140)	(0.168)
Observations	72	72	72	72	72
R-squared	0.354	0.353	0.283	0.210	0.008

Table IA8: Correlations between Log Scope 1 Emissions and Splitting Variables

This table reports the pairwise correlations between the log of scope 1 emissions and variables used in sub-sample splits.

Panel A: ESG Ratings

	Log Scope 1	ESG Score	E Score	Cl Chg Theme	S Score	G Score
Log Scope 1	1					
ESG Score	-0.0280***	1				
E Score	-0.122***	0.422***	1			
Cl Chg Theme	-0.135***	0.389***	0.645***	1		
S Score	-0.0136**	0.521***	0.0545***	0.0721***	1	
G Score	0.138***	0.232***	-0.0501***	0.00442	0.0343***	1

Panel B: Capital Intensity

	Log Scope 1	PPE / Assets	PPE / (Tot Assets)	CAPX / Assets
Log Scope 1	1			
PPE / Assets	0.526***	1		
PPE / (Tot Assets)	0.542***	0.982***	1	
CAPX / Assets	0.268***	0.667***	0.644***	1

Panel C: Climate Change Exposures

	Log Scope 1	CC Exposure (SLVZ)	Reg Exposure (SLVZ)	CC Exposure (BCMZ)	Reg Exposure (BCMZ)
Log Scope 1	1				
CC Exposure (SLVZ)	0.215***	1			
Reg Exposure (SLVZ)	0.138***	0.626***	1		
CC Exposure (BCMZ)	0.401***	0.262***	0.204***	1	
Reg Exposure (BCMZ)	0.413***	0.245***	0.185***	0.858***	1

Panel D: Stakeholder Pressure

	Log Scope 1	PRI Ownership	Market Share	Market Share	Product Similarity
Log Scope 1	1				
PRI Ownership	0.0567***	1			
Market Share	0.234***	0.0448***	1		
Patent Value	0.0877***	-0.000518	0.125***	1	
Product Similarity	-0.252***	-0.0276***	-0.176***	-0.0147***	1

Panel E: Carbon Disclosure Project

	Log Scope 1	CDP Non-Respondent	No Climate Target	No Climate Personnel
Log Scope 1	1			
CDP Non-Respondent	-0.434***	1		
No Climate Target	-0.327***	0.621***	1	
No Climate Personnel	-0.359***	0.716***	0.864***	1