Does Monetary Policy Shape the Path to Carbon Neutrality?

Robin Döttling[†] Adrian Lam[‡]

September 2023

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, with greater climate risk exposures, or without climate abatement plans. 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 shapes the path to carbon neutrality irrespective of whether central banks embrace a climate target.

JEL Classification: G12, G38, E52

Keywords: Carbon transition risk, monetary policy, firm valuation

[†] Erasmus University Rotterdam. Correspondence: doettling@rsm.nl.

[‡] University of Pittsburgh and Amsterdam Center for Law & Economics. Correspondence: y.h.a.lam@pitt.edu.

For helpful comments and suggestions, we thank Paul Smeets, Theresa Spickers, Magdalena Rola-Janicka, and Mathijs van Dijk. 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.

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, and the diverging policy choices across central banks, there is little empirical evidence on how central banks shape the path to net-zero emissions.

In this paper, we empirically examine whether monetary policy shapes the transition pathway to a low-carbon economy. We elicit market-based, forward-looking perceptions of how monetary policy interacts with carbon transition risk by investigating 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. We provide evidence that this effect is driven primarily by climate-related policy and legal risks as well as technological risks, while the effect of pressure from shareholders and stakeholders is less stark. 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 the path to carbon neutrality, *irrespective of whether central banks embrace a climate target*.

Conceptually, a tighter monetary policy stance increases funding costs, which suppresses corporate investment and slows down the replacement of existing assets. This may affect the valuation of firms with higher carbon emissions relatively more for two reasons. First, firms with higher emissions may be more affected by tighter funding conditions because they have greater needs to replace polluting assets. Second, firms may decide to delay transitioning. With net-zero targets gaining traction, firms that de-

[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.

lay transitioning retain a greater exposure to climate-related technological risks, such as stranded asset risk.[3,4] In the presence of convex adjustment costs, speeding up capital replacement in the future may also be costlier. Alongside technological risk, slower capital replacement also means that firms will retain their current exposure to climate regulatory risks, such as emissions standards and carbon taxes, and climate-related market and reputation risks, such as changing preferences or increasing awareness about climate change by investors, consumers, and suppliers. As outlined in the TCFD (2017), these risks are likely to have a financially material impact.

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 affects carbon transition risk of firms.[5] 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 transition, 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 Federal Funds futures 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 in

[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

[4] We refer to stranded asset risk as the risk of assets suffering from unanticipated write-downs or devaluation prior to the end of their economic life. See, for example, KMPG Advisory: https://advisory.kpmg.us/blog/2022/considerations-for-climate-stranded-assets.html, the University of Oxford's Smith School of Enterprise and the Environment: https://www.smithschool.ox.ac.uk/sites/default/files/2022-04/Stranded-Assets-and-Scenarios-Discussion-Paper.pdf, and the Carbon Tracker Initiative: https://carbontracker.org/terms/unburnable-carbon/.

[5] Carbon transition risk moved up the agenda of investors (Krueger et al., 2020; Cosemans et al., 2022) and policy makers (TCFD, 2017), and is reflected in asset prices (e.g., see Pastor et al., 2022; Bolton and Kacperczyk, 2021).

Fed Funds futures rates but also affect longer-term rates at the 2–10 year horizons, which are relevant for firms' long-run investment decisions. To capture a firm's exposure to carbon transition risk, we use firm-level carbon emissions 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-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 25 basis points (bps) 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.

Consistent with a stronger stock price response of high-emission firms due to the effect of monetary policy on the cost of transitioning, we also find that our headline result is driven by the subsamples of firms that are (perceived to be) less equipped to transition. Using environmental, social, and governance (ESG) ratings from MSCI, we find that the higher stock price sensitivity to monetary policy shocks among high-emission firms is driven by firms with low ESG ratings, and especially those with low environmental ratings. We also find our headline result to be driven by firms that have not reported climate-related abatement plans to the Carbon Disclosure Project (CDP).

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 1-year Treasury rate as our main measure of the monetary policy stance, and instrument the 1-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 1-year Treasury rate results in a decline of up to 3% 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' emissions. We find that when the level of interest rates is high, emissions growth among high-emission firms increases relative to low-emission firms. To put this result in context, we also show that, on average, emissions growth is negatively associated with emissions levels. Taken together, these findings suggest that high-emission firms reduce emissions relative to low-emissions firms, but these emissions-reduction efforts are hampered by a tighter monetary policy stance.

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 the transition to a low-carbon economy, regardless of whether a central bank embraces a climate mandate.

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.[6] 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).[7] 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 advantage of our setting is that we can cleanly identify the effect of carbon transition risk on stock returns because preferences and climate awareness are plausibly constant within the intra-day window around FOMC announcements that we consider.[8]

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; Gürkaynak 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 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

[6]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). By contrast, we find very similar results whether we use emissions levels or intensity.

[7]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.

[8]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.

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 (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. Panel B reports summary statistics. Panel C reports the pairwise correlations among several of our key variables.

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.[9] 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 Fed Funds futures rates in the 30-minute window around the Federal 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, MPS_τ has a mean of -0.005% and a standard deviation of 0.029%. Consistent with rational expectations, the average monetary policy

[9]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.

surprise is not statistically different from zero.

[Insert Figure 1 Here]

While these monetary policy shocks are based on movements in interest rate futures of short-term Fed Funds, they also affect longer-term interest rates that may be more relevant for investment decisions. In the Internet Appendix (Table IA7), we regress changes in the yield on on-the-run Treasury bonds on our monetary policy shock measures, and confirm the shocks have a significant effect on the yields of Treasuries with 6 months to 10 years maturity.

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 shapes the path to net zero, 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.[10] In a robustness exercise, we also show our main results are robust to using scope 2 or scope 3 instead of scope 1.

There is an active debate in the literature on whether total emissions or emissions intensity better capture exposure to carbon transition risk. On the one hand, as discussed in Bolton and Kacperczyk (2021), Bolton and Kacperczyk (2022) and Bolton and Kacperczyk (2023), total emission levels are more appropriate as (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, a number of papers argue that carbon intensity, which scales carbon emissions by sales, is the more appropriate measure. Aswani et al. (2022) argue that carbon intensity better captures carbon transition risk because carbon intensity measures how carbon-efficient firms generate profits and accounts for size effects. Zhang (2023) develops a model showing that carbon intensity is the more appropriate measure in capturing exposure to carbon policy shocks, as carbon intensity reflects carbon transition risks stemming from adjusting the business model and technology.

As we are primarily concerned with the path to net zero, 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

[10] 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.

contain outliers, we construct the log-linearized variable $Log(Scope\ 1_{it-1})$, 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 65.2% of scope 1 emissions are estimated.[11] 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. (2020), and climate change exposures based on 10-K filings from Baz et al. (2023); climate change-related abatement plans 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 at the firm-patent level from Kogan et al. (2017); and product similarity scores from Hoberg and Phillips (2016).[12]

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

[11] We classify a firm's $Scope\ 1\ Intensity_{it-1}$ as "estimated" if Trucost mentions the data point as estimated (variable: `di_319403_text`).

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

that can have a material effect on firms' cash flows. 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]

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.[13]

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

[13]In the Internet Appendix (Table IA5), 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).

may induce some firms to delay the transition 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, this should be reflected in 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.[14]

3.2 Methodology

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

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

where $Ret_{i\tau}^{FOMC}$ is the intra-day stock return of firm i on event-day τ of the FOMC meeting, and MPS_τ is the high-frequency monetary policy shock from Jarociński and Karadi (2020), based on movements in interest rate futures 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}. Following Bolton and Kacperczyk (2021), 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

[14] The 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).

and firm fixed effects. These fixed effects absorb any differences between industries in a given event date, as well as time-invariant, unobserved firm heterogeneity.[15] 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. 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 capital intensity, ESG ratings, and the existence of climate change-related abatement plans, etc. We expect β_2 to be more significant in the subsamples of firms that are more exposed to carbon transition risk.

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 MPS_t. The coefficient of MPS_t 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 MPS_t captures only the unexpected component of a monetary policy shock, 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

[15] The coefficient of MPS_τ 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.

(2005)).[16]

[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 MPS_τ with $Log(Scope\ 1_{it-1})$ (β_2 in Eq. (1)). We also control for the interaction of monetary policy shocks with $Log(MV_{it-1})$, 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 $Log(Scope\ 1_{it-1})$ is standardized, this implies a one-standard deviation increase in $Log(Scope\ 1_{it-1})$ 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 MPS_τ, in order to control for the interactive effects between MPS_τ and the observable firm characteristics. The coefficient of $MPS_\tau \times Log(Scope\ 1_{it-1})$ 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 of $MPS_\tau \times Log(Scope\ 1_{it-1})$ becomes slightly smaller, at -1.948, but remains statistically significant at the 5% level.

In Column (5), we address the concern that there may be an estimation bias in Trucost's carbon emissions data. We include the variable $Estimated_{it-1}$, and interact it with $Log(Scope\ 1_{it-1})$, MPS_t and $MPS_t \times Log(Scope\ 1_{it-1})$. If our results are driven by firms with estimated emissions, then the triple interaction term $MPS_t \times Log(Scope$

[16] 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 responses as in Bernanke and Kuttner (2005) when we use non-decomposed FF4 shocks during the pre-2010 sample period.

$1_{it-1}) \times Estimated_{it-1}$ should be negative and statistically significant, while the double interaction term $MPS_t \times Log(Scope\ 1_{it-1})$ would become statistically insignificant. However, as shown in Column (5), the coefficient of $MPS_t \times Log(Scope\ 1_{it-1})$ is quantitatively and statistically similar to that in Column (4), and the triple interaction term is not statistically significant. This suggests that, at the 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 $MPS_t \times Log(Scope\ 1_{it-1})$ 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 instead of the level of log scope 1 emissions, i.e. $Log(Scope\ 1\ Intensity_{it-1})$ instead of $Log(Scope\ 1_{it-1})$. Depending on the specification of fixed effects, the coefficient of $MPS_\tau \times Log(Scope\ 1\ Intensity_{it-1})$ ranges from -2.075 to -1.261 and remains statistically significant. This means that, relative to the average firm, a firm with $Log(Scope\ 1\ Intensity_{it-1})$ 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 25 basis points 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 IA2), 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 $Log(Scope\ 1_{it-1})$ with emission quintile indicators, and find consistent results. This 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 IA3).

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 emissions firms to brown portfolios with high-emission firms. This approach also allows us to construct value-weighted portfolios, which have been shown to 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 the market value of their assets, and then sort firms into scope 1 emissions quintiles within each size quintile.

Table 3, panel 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 lowest- to the highest-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 IA4).

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 Capital Intensity

In Panel A, 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 the higher stock price sensitivity of high-emission firms is driven by firms that are more exposed to technological, stranded-asset risk, we should expect the higher sensitivity 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 $PPE_{it-1}/Assets_{it-1}$. 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). We split the sample by the median value of $\frac{PPE_{it-1}}{Assets_{it-1}+Off{-}BS\ Intangibles_{it-1}}$. 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 $CAPX_{it-1}/Assets_{it-1}$.

The coefficient of $MPS_\tau \times Log(Scope\ 1_{it-1})$ 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.

4.3.2 Rated Sustainability Performance

In Panel B, we report the results from sample splits based on MSCI ESG Ratings. MSCI 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 ($MSCI\ Score^{ESG}_{im-1}$). In Columns (3) and (4), we narrow down to the environmental pillar score ($MSCI\ Score^{ENV}_{im-1}$). In Columns (5) and (6), we further narrow down to the climate change theme score ($MSCI\ Score^{CCT}_{im-1}$). 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 $MPS_\tau \times Log(Scope\ 1_{it-1})$ is negative and statistically significant in the subsamples with a lower third party-assessed ESG performance. Depending on the splitting variable, the coefficient ranges from -3.301 to -4.319, and is at least statistically significant at the 5% level. In both Columns (1) and (2), the coefficient of $MPS_\tau \times Log(Scope\ 1_{it-1})$ is quantitatively smaller and statistically weaker in the subsample with a higher overall ESG score, although it remains significant in both subsamples. This likely reflects the lower climate-relevance of the overall ESG score. Remarkably, 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. In Columns (7) and (8), we split the sample by the median value of the social pillar score ($MSCI\ Score^{SOC}_{im-1}$). In Columns (9) and (10), we split the sample by the median value of the governance pillar score ($MSCI\ Score^{GOV}_{im-1}$).

These results are more ambiguous. In both instances, while the coefficient of $MPS_\tau \times Log(Scope\ 1_{it-1})$ is more significant among firms with a higher social or governance pillar score, 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 driven by firms with a poorer rated sustainability 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.

4.3.3 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. If the greater stock price sensitivity by high-emission firms is driven by carbon transition risk, it should be concentrated among firms with a greater exposure, perceived or self-assessed, to climate change. The measures also allow us to delineate the effects of regulatory risk by using measures that focus on mentions of regulatory risk in particular.

In the upper panel, we use climate change exposures constructed by Sautner et al. (2023). These measures 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 ($CCExposure_{it-1}$). The coefficient of $MPS_\tau \times Log(Scope\ 1_{it-1})$ 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 ($CCExposure^{Reg}_{it-1}$). Given $CCExposure^{Reg}_{it-1}$ 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 $MPS_\tau \times Log(Scope\ 1_{it-1})$ 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 while attention to overall climate change exposure is important, attention to regulatory exposure has a particularly pronounced effect.

In the lower panel, we use climate change exposures constructed by Baz et al. (2023). 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 (CCE_{it-1}). In Columns (7) and (8), we split the sample by the median value of climate regulatory exposure (CRE_{it-1}). The coefficient of $MPS_\tau \times Log(Scope\ 1_{it-1})$ 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 the higher stock price sensitivity to monetary policy shocks by high-emission firms is driven by firms that have a greater perceived and self-disclosed exposure to climate change risks, and in particular regulatory risks.

4.3.4 Climate Change-related Abatement Plans

In Panel D, we report the results from sample splits based on whether a firm has reported any climate change-related abatement plans to CDP. As firms that do not sign up to the CDP likely have no abatement plans in place, we assign a firm in our sample to the no-abatement group if it is not in the CDP dataset. Firms with abatement plans are better-prepared and have likely already made progress in transitioning to a low-carbon business model. If the higher stock price sensitivity of high-emission firms is driven by firms that are less prepared to transition, we should expect the higher sensitivity to be concentrated among firms without an abatement plan in place.

In Columns (1) and (2), we split the sample by whether a firm has any emissions target (CDP_{it-1}^{Target}). In Columns (3) and (4), we split the sample by whether a firm has dedicated personnel responsible for climate change ($CDP_{it-1}^{Personnel}$).

The coefficient of $MPS_\tau \times Log(Scope\ 1_{it-1})$ is negative and statistically significant only in the subsamples without a climate change-related abatement plan. Depending on the splitting variable, the coefficient ranges from -2.477 to -4.039, and is statistically significant at the 1% level. Collectively, the results in Panel D suggest that the higher stock price sensitivity to monetary policy shocks is driven by firms that do not actively abate climate change risk.

4.3.5 Stakeholder Pressure

In Panel E, 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 (IO_{it-1}^{PRI}). The coefficient of MPS_τ

$\times$ $Log(Scope\ 1_{it-1})$ 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 ($Market\ Share_{it-1}$). 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 $MPS_\tau \times Log(Scope\ 1_{it-1})$ is negative and marginally significant in the subsample with a lower market share. While the coefficient is insignificant in Column (4), it should be noted that the size of the coefficient is quite close to that in Column (3).

In Columns (5) and (6), we split the sample by whether a firm has economically valuable patent applications ($Patent^{Value}_{it-1}$), 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 $MPS_\tau \times Log(Scope\ 1_{it-1})$ 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 ($Total\ Similarity_{it-1}$). Firms with a higher product similarity sell products that are more substitutable, and are arguably more exposed to pressure from customers. The coefficient of $MPS_\tau \times Log(Scope\ 1_{it-1})$ 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 E 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 A.

Taken together, the sample splits in Table 4 based on capital intensity (Panel A), assessed sustainability performance (Panel B), perceived exposure to regulatory risks

(Panel C), and abatement plans (Panel D) indicate that the greater stock price sensitivity of high-emission firms to monetary policy is driven by the technological and regulatory components of carbon risk. By contrast, the splits based on proxies for stakeholder pressure in Panel E suggest a smaller role for this channel.

5 Real Effects

The results so far show that the stock prices of firms with high carbon emissions are more sensitive to high-frequency monetary policy shocks. 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 question of whether these real effects are different for high-emission firms.

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 1-year Treasury rate as the monetary policy measure and instrument it using the cumulative sum of high-frequency shocks while also controlling for key lagged macroeconomic controls.[17] To trace out the dynamic effect of monetary policy, we estimate the following specification for different quarterly horizons h:

$$y_{it+h} - y_{it-1} = \beta_1^h \cdot \hat{R}_t + \gamma_1^{h\prime} \cdot X_{t-1}^m + \gamma_2^{h\prime} \cdot X_{it-1}^f + \mu_i + \varepsilon_{it}. \tag{2}$$

[17] This level measure of shocks is a stronger instrument for the 1-year Treasury level compared to the quarterly shocks, also see Bu et al. (2021) and Döttling and Ratnovski (2023).

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 1-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 Zakrajšek (2012) to control for financial conditions, obtained from the author's website. The vector X_{it-1}^f collects the firm-level controls from the high-frequency stock return analysis.[18] Additionally, we include firm fixed effects μ_i to control for time-invariant unobservable characteristics.

5.2 The 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_1^h in Eq. (2) 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_1^h for horizons of 1–4 years (i.e. quarterly horizons $h = 4, 8, 12$ and 16).

Figure 3 plots the β_1^h estimates along with 95% confidence intervals, rescaled to represent the response to a 25bps increase in the instrumented 1-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

[18] Since the data is at quarterly frequency, we do not include variables at a higher 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.

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 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 higher emissions to begin with. 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-related 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 when interest rates are low. 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 (2) by adding an interaction term $\hat{R}_t \times Log(Scope\ 1_{it-1})$. 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.[19]

Table 5 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

[19]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 confirm in the Internet Appendix that the results are robust to using firm fixed effects, but that the coefficients blow up in size (see Table IA6).

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 13.3% lower growth in emissions over two years, and 18.9% lower growth over three years. Columns 2–3 and 5–6 additionally include interaction terms. The coefficient estimate on the interaction between the instrumented 1-year Treasury and log scope 1 emissions is between 0.038 and 0.164, and 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 5 shows similar results for emissions intensity. The estimates are again only consistently statistically significant at the longer, 3-year horizon. This is consistent with the interpretation that the attenuated decline in emissions by high-emission firms is driven by abatement investments, as such investments should impact emissions intensity with a lag.

6 Conclusion

Despite the striking divergence in how central banks address climate change-related risks, it is yet unclear how monetary policy affects the path to climate neutrality. By exploiting high-frequency movements in Fed Funds futures contracts 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 slow down emission-reduction efforts when monetary policy is tight.

Taken together, our results highlight the interactive effects of monetary policy and climate policy goals, which can be interpreted in two (non-mutually exclusive) ways. First, monetary policy affects the cost of transitioning to a low-carbon business model, which is reflected in company valuations. Second, carbon transition risk may have an amplification effect on monetary policy transmission. 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.

References

Ai, Hengjie, Leyla Jianyu Han, Xuhui Nick Pan, and Lai Xu, "The cross section of the monetary policy announcement premium," *Journal of Financial Economics*, 2022, *143* (1), 247–276.

Aswani, Jitendra, Aneesh Raghunandan, and Shivaram Rajgopal, "Are Carbon Emissions Associated with Stock Returns?," *Review of Finance (Forthcoming)*, 2022.

Baker, Malcolm P, Daniel Bergstresser, George Serafeim, and Jeffrey Wurgler, "Financing the Response to Climate Change: The Pricing and Ownership of US Green Bonds," *Working Paper*, 2018.

Baz, Salim, Lara Cathcart, Alexander Michaelides, and Yi Zhang, "Firm-Level Climate Regulatory Exposure," *Working Paper*, 2023.

Bernanke, Ben S and Kenneth N Kuttner, "What Explains the Stock Market's Reaction to Federal Reserve Policy?," *The Journal of Finance*, may 2005, *60* (3), 1221–1257.

Bolton, Patrick and Marcin Kacperczyk, "Do investors care about carbon risk?," *Journal of Financial Economics*, nov 2021, *142* (2), 517–549.

_ **and** _ , "Global Pricing of Carbon-Transition Risk," *The Journal of Finance (Forthcoming)*, 2022.

_ **and** _ , "Are Carbon Emissions Associated with Stock Returns? Comment," *Review of Finance*, may 2023.

Bu, Chunya, John Rogers, and Wenbin Wu, "A unified measure of Fed monetary policy shocks," *Journal of Monetary Economics*, 2021, *118*, 331–349.

Chava, Sudheer and Alex Hsu, "Financial Constraints, Monetary Policy Shocks, and the Cross-Section of Equity Returns," *The Review of Financial Studies*, nov 2020, *33* (9), 4367–4402.

Cloyne, James, Clodomiro Ferreira, Maren Froemel, and Paolo Surico, "Monetary Policy, Corporate Finance, and Investment," *Journal of the European Economic Association*, mar 2023.

Cosemans, Mathijs, Xander Hut, and Mathijs A Van Dijk, "Climate Change and Long-Horizon Portfolio Choice: Combining Insights from Theory and Empirics," *Working Paper*, 2022.

Delis, Manthos D, Kathrin De Greiff, and Steven Ongena, "Being stranded with fossil fuel reserves? Climate policy risk and the pricing of bank loans," *EBRD Working Paper*, 2019.

Döttling, Robin and Lev Ratnovski, "Monetary policy and intangible investment," *Journal of Monetary Economics*, 2023, *134*, 53–72.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, "Liquidity, risk premia, and the financial transmission of monetary policy," *Annual Review of Financial Economics*, 2018, *10*, 309–328.

_ , _ , and _ , "A model of monetary policy and risk premia," *The Journal of Finance*, 2018, *73* (1), 317–373.

Fama, Eugene F and Kenneth R French, "Disagreement, tastes, and asset prices," *Journal of Financial Economics*, 2007, *83* (3), 667–689.

Ferrari, Alessandro and Valerio Nispi Landi, "Whatever it takes to save the planet? Central banks and unconventional green policy," *Macroeconomic Dynamics*, 2023, pp. 1–26.

Financial Stability Board, "Proposal for a Disclosure Task Force on Climate-Related Risks," 2015.

Gertler, Mark and Peter Karadi, "Monetary policy surprises, credit costs, and economic activity," *American Economic Journal: Macroeconomics*, 2015, *7* (1), 44–76.

_ and Simon Gilchrist, "Monetary policy, business cycles, and the behavior of small manufacturing firms," *The Quarterly Journal of Economics*, 1994, *109* (2), 309–340.

Giglio, Stefano, Bryan Kelly, and Johannes Stroebel, "Climate finance," *Annual Reviews*, 2021.

_ , Matteo Maggiori, Krishna Rao, Johannes Stroebel, and Andreas Weber, "Climate change and long-run discount rates: Evidence from real estate," *The Review of Financial Studies*, 2021, *34* (8), 3527–3571.

Gilchrist, Simon and Egon Zakrajšek, "Credit spreads and business cycle fluctuations," *American economic review*, 2012, *102* (4), 1692–1720.

Giovanardi, Francesco, Matthias Kaldorf, Lucas Radke, and Florian Wicknig, "The preferential treatment of green bonds," *Review of Economic Dynamics*, 2023.

Gürkaynak, Refet, Hatice Gökçe Karasoy-Can, and Sang Seok Lee, "Stock market's assessment of monetary policy transmission: The cash flow effect," *The Journal of Finance*, 2022, *77* (4), 2375–2421.

Gürkaynak, Refet S, Brian Sack, and Eric T Swanson, "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements," *International Journal of Central Banking*, May 2005, *1* (1), 55–93.

Heinkel, Robert, Alan Kraus, and Josef Zechner, "The Effect of Green Investment on Corporate Behavior," *The Journal of Financial and Quantitative Analysis*, dec 2001, *36* (4), 431.

Hoberg, Gerard and Gordon Phillips, "Text-based network industries and endogenous product differentiation," *Journal of Political Economy*, 2016, *124* (5), 1423–1465.

Ilhan, Emirhan, Zacharias Sautner, and Grigory Vilkov, "Carbon tail risk," *The Review of Financial Studies*, 2021, *34* (3), 1540–1571.

Issler, Paulo, Richard Stanton, Carles Vergara-Alert, and Nancy Wallace, "Mortgage markets with climate-change risk: Evidence from wildfires in california," *Working Paper*, 2020.

Jarociński, Marek and Peter Karadi, "Deconstructing Monetary Policy Surprises—The Role of Information Shocks," *American Economic Journal: Macroeconomics*, apr 2020, *12* (2), 1–43.

Kashyap, Anil K, Owen A Lamont, and Jeremy C Stein, "Credit conditions and the cyclical behavior of inventories," *The Quarterly Journal of Economics*, 1994, *109* (3), 565–592.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, "Technological Innovation, Resource Allocation, and Growth," *The Quarterly Journal of Economics*, May 2017, *132* (2), 665–712.

Krueger, Philipp, Zacharias Sautner, and Laura T Starks, "The Importance of Climate Risks for Institutional Investors," *The Review of Financial Studies*, feb 2020, *33* (3), 1067–1111.

Kuttner, Kenneth N, "Monetary policy surprises and interest rates: Evidence from the Fed funds futures market," *Journal of Monetary Economics*, jun 2001, *47* (3), 523–544.

Lucca, David O and Emanuel Moench, "The pre-FOMC announcement drift," *The Journal of finance*, 2015, *70* (1), 329–371.

MSCI, "MSCI ESG Ratings: Key Differentiators," May 2020.

Nakamura, Emi and Jón Steinsson, "High-Frequency Identification of Monetary Non-Neutrality: The Information Effect," *The Quarterly Journal of Economics*, jan 2018, *133* (3), 1283–1330.

Ottonello, Pablo and Thomas Winberry, "Financial Heterogeneity and the Investment Channel of Monetary Policy," *Econometrica*, 2020, *88* (6), 2473–2502.

Ozdagli, Ali and Mihail Velikov, "Show me the money: The monetary policy risk premium," *Journal of Financial Economics*, 2020, *135* (2), 320–339.

Ozdagli, Ali K., "Financial Frictions and the Stock Price Reaction to Monetary Policy," *The Review of Financial Studies*, sep 2018.

Pastor, Lubos, Robert F Stambaugh, and Lucian A Taylor, "Sustainable Investing in Equilibrium," *Journal of Financial Economics*, nov 2021, *142* (2), 550–571.

_ , _ , and _ , "Dissecting green returns," *Journal of Financial Economics*, 2022, *146* (2), 403–424.

Pedersen, Lasse Heje, Shaun Fitzgibbons, and Lukasz Pomorski, "Responsible Investing: The ESG-Efficient Frontier," *Journal of Financial Economics*, nov 2021.

Peters, Ryan H and Lucian A Taylor, "Intangible Capital and the Investment-q Relation," *Journal of Financial Economics*, February 2017, *123* (2), 251–272.

Sautner, Zacharias, Laurence Van Lent, Grigory Vilkov, and Ruishen Zhang, "Firm-level Climate Change Exposure," 2020.

_ , _ , _ , and _ , "Firm-Level Climate Change Exposure," *The Journal of Finance*, mar 2023, *78* (3), 1449–1498.

Seltzer, Lee H, Laura Starks, and Qifei Zhu, "Climate regulatory risk and corporate bonds," *NBER Working Paper*, 2022.

TCFD, "Recommendations of the Task Force on Climate-related Financial Disclosures," Technical Report 2017.

Zhang, Shaojun, "Carbon Returns Around the Globe," *Working Paper*, 2023.

A Tables

Table 1: Descriptive Statistics

This table reports sample composition (Panel A), summary statistics (Panel B), correlations (Panel C).

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

	Mean	P50	SD	N
FOMC Day Return	-0.076	-0.085	1.94	59271
MP Shock	-0.0050	-0.0044	0.029	59277
Log Total 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 / (Assets + Off-BS Intangibles)	0.24	0.13	0.24	59277
CAPX / Assets 3-Year Moving Avg	0.049	0.035	0.048	58971
ESG Score	4.36	4.24	2.11	43706
Environmental Pillar Score	4.89	4.80	2.00	43704
Climate Chg Theme Score	6.10	6.30	2.58	36162
CO2 Emissions Score	6.40	6.33	2.42	40777
Climate Change Exposure	0.0014	0.00037	0.0035	54891
Regulatory Exposure	0.000065	0	0.00033	54891
Physical Exposure	0.000017	0	0.00012	54891
Operational Exposure	0.00044	0	0.0015	54891
Institutional Ownership	0.77	0.82	0.23	55696
PRI Ownership	0.31	0.31	0.15	55696

Table 1: Descriptive Statistics (Continued)

Panel C: Correlations	Log Total Scope 1	Log Scope 1 Intensity	Log Market Value	PPE / Assets	ESG Score	Climate Chg Exposure	Inst Ownership
Log Total Scope 1	1						
Log Scope 1 Intensity	0.722	1					
Log Market Value	0.629	0.0515	1				
PPE / Assets	0.526	0.628	0.139	1			
ESG Score	-0.028	-0.147	0.144	-0.103	1		
Climate Chg Exposure	0.215	0.352	-0.0228	0.262	0.0412	1	
Inst Ownership	0.0592	-0.0616	0.109	-0.0811	0.0164	-0.198	1

Table 2: Baseline Results

This table reports coefficient estimates from estimating Equation 1. The dependent variable is $Ret_{i\tau}^{FOMC}$, 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 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 4-digit NAICS industry 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 4-digit NAICS industry and FOMC announcement date levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: 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

Panel B: ESG Rating

	DV: Stock Return on FOMC Day					
	$\boldsymbol{MSCI\ Score^{ESG}_{im-1}}$		$\boldsymbol{MSCI\ Score^{ENV}_{im-1}}$		$\boldsymbol{MSCI\ Score^{CCT}_{im-1}}$	
	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			
	$\boldsymbol{MSCI\ Score^{SOC}_{im-1}}$		$\boldsymbol{MSCI\ Score^{GOV}_{im-1}}$	
	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

Table 4: Sample Splits (Continued)

Panel C: Climate Change Exposures				
	DV: Stock Return on FOMC Day			
	$\boldsymbol{CCExposure_{it-1}}$		$\boldsymbol{CCExposure^{Reg}_{it-1}}$	
	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			
	$\boldsymbol{CCE_{it-1}}$		$\boldsymbol{CRE_{it-1}}$	
	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: Climate Change-related Abatement Plans

	DV: Stock Return on FOMC Day			
	CDP^{Target}_{it-1}		$CDP^{Personnel}_{it-1}$	
	No	Yes	No	Yes
	(1)	(2)	(3)	(4)
MP Shock × Log Scope 1	-2.447***	-1.463	-3.038***	-1.160
	(0.871)	(0.942)	(0.859)	(1.140)
Observations	41,101	11,009	37,953	14,095
Adj R2	0.318	0.489	0.308	0.491
Firm FE	Y	Y	Y	Y
Event-Date-by-Industry FE	Y	Y	Y	Y

Panel E: Stakeholder Pressure

	DV: Stock Return on FOMC Day			
	IO^{PRI}_{it-1}		$Market\ Share_{t-1}$	
	High	Low	Low	High
	(1)	(2)	(5)	(6)
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			
	$Patent^{Value}_{it-1}$		$Total\ Similarity_{it-1}$	
	Zero	Positive	High	Low
	(3)	(4)	(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

Table 5: Local Projections with Interaction Terms

This table reports coefficient estimates from a modified version of Equation 2, with the addition of the interaction term $\hat{R} \times$ Log Scope 1. The 1-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. 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					
	$h = 2$			$h = 3$		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Scope 1	-0.133***	-0.152***	-0.323***	-0.189***	-0.256***	-0.479***
	(0.016)	(0.029)	(0.049)	(0.024)	(0.035)	(0.055)
$\hat{R} \times$ Log Scope 1		0.038	0.105		0.144***	0.164**
		(0.047)	(0.084)		(0.050)	(0.080)
Observations	32,250	32,250	30,010	25,760	25,760	23,555
Adj R2	0.0420	0.0436	0.0819	0.0450	0.0475	0.108
Uninteracted Controls	Y	Y	Y	Y	Y	Y
Interacted Controls	N	Y	Y	N	Y	Y
Firm FE	N	N	N	N	N	N
Time FE	Y	Y	N	Y	Y	N
Industry-by-Time FE	N	N	Y	N	N	Y

Panel B: Emissions Intensity

	DV: Δ^h Log Scope 1 Intensity					
	$h = 2$			$h = 3$		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Scope 1	-0.069***	-0.099***	-0.246***	-0.106***	-0.170***	-0.343***
	(0.014)	(0.026)	(0.040)	(0.020)	(0.032)	(0.050)
$\hat{R} \times$ Log Scope 1		0.060	0.147*		0.136***	0.162*
		(0.045)	(0.077)		(0.048)	(0.081)
Observations	32,246	32,246	30,006	25,759	25,759	23,554
Adj R2	0.0206	0.0210	0.0603	0.0294	0.0317	0.0846
Uninteracted Controls	Y	Y	Y	Y	Y	Y
Interacted Controls	N	Y	Y	N	Y	Y
Firm FE	N	N	N	N	N	N
Time FE	Y	Y	N	Y	Y	N
Industry-by-Time FE	N	N	Y	N	N	Y

B Figures

Figure 1: Monetary Policy Shocks

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

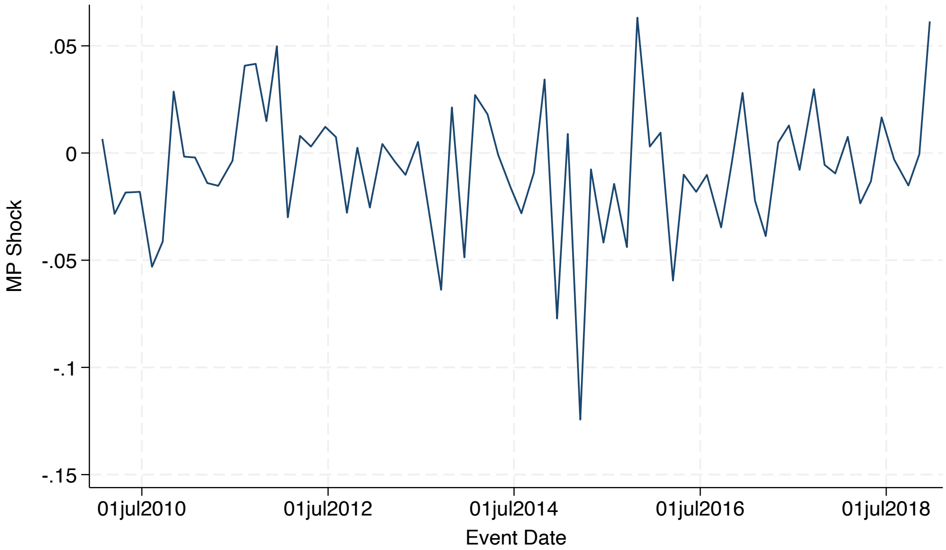
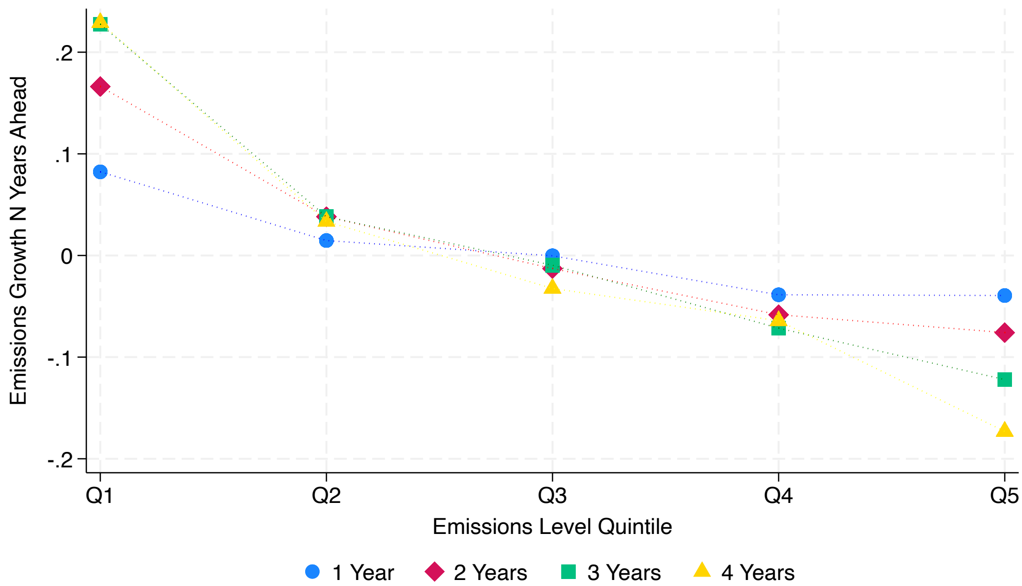


Figure 2: Emissions Level and Future Emissions Growth

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.

A: Main Sample



B: Entire Trucost Universe

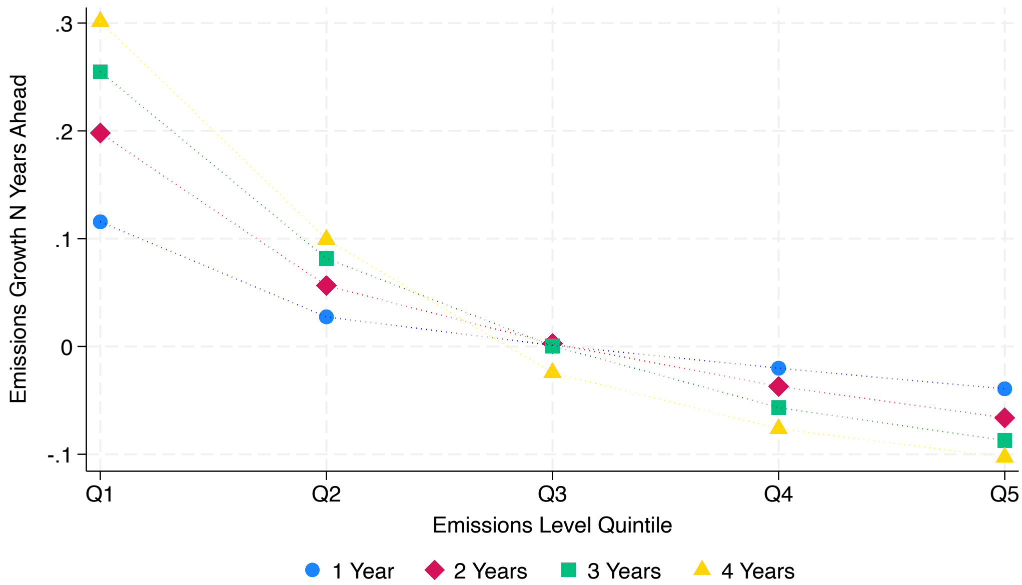
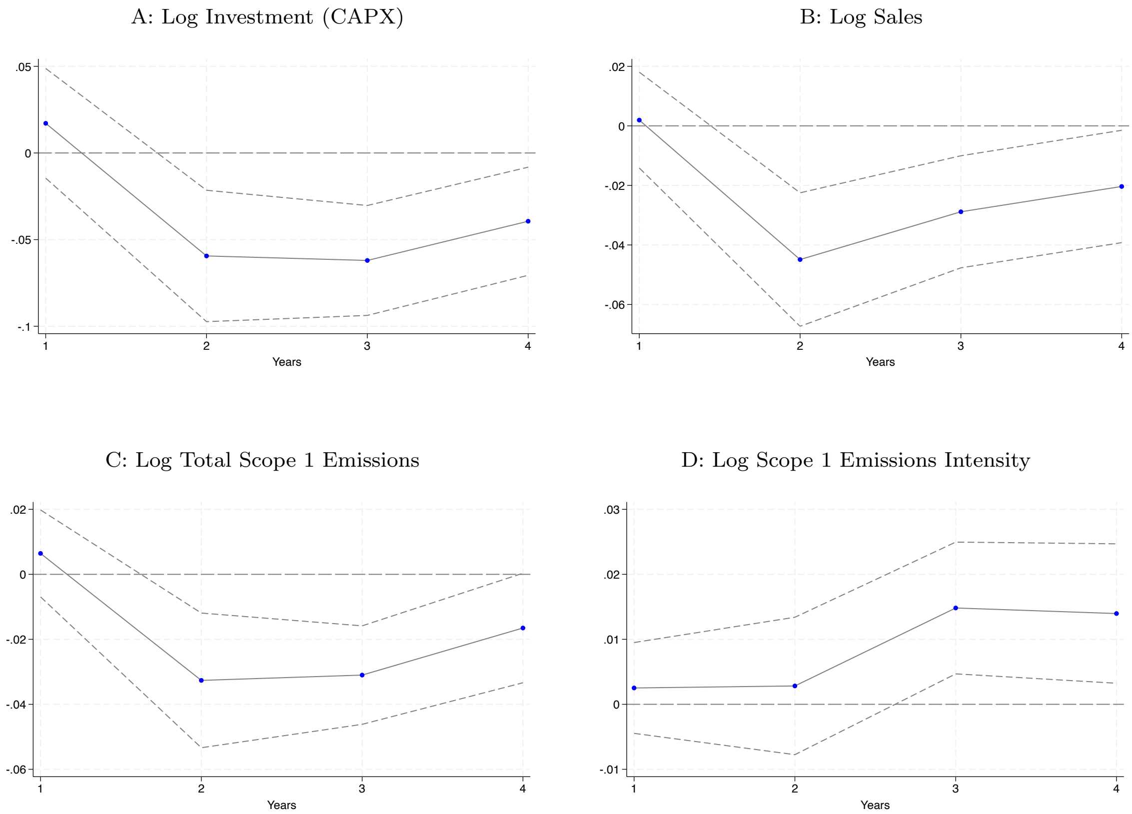


Figure 3: Response of Emissions, Sales, and Investment to Monetary Policy

This figure plots the dynamic response of investment to a 25bps higher 1-year Treasury rate, estimated using Eq. (2). The 1-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 1-year Treasury rate (β_1^h in Eq. (2)). 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.



Internet Appendix
for
Does Monetary Policy Shape the Path to Carbon Neutrality?

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.[20] 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.[21] In our sample, the average climate change theme score ($MSCI\ Score^{CCT}_{im-1}$) 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 ($MSCI\ Score^{ENV}_{im-1}$) is 4.89, with a standard deviation of 2.00. At the most aggregated level, there is the final industry-adjusted score ($MSCI\ Score^{ESG}_{im-1}$), ranging from 0 (worst) to 10 (best). These are the weighted average scores normalized relative to the industry peer set.[22] 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. (2020) and 10-K filings from Baz et al. (2023).[23]

[20] 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)).

[21] 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.

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

[23] 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 ($CCExposure_{it-1}$), 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 ($CCExposure^{Reg}_{it-1}$), 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 (CRE_{it-1}), 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 (CCE_{it-1}), which captures a firm's disclosed exposure to climate change (without restricting to climate change *regulations* only). The average of CCE_{it-1} 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 Climate Change-related Abatement Plans

We obtain data on climate change-related abatement plans 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 has certain abatement policies in place. As firms that do not have any climate change-related abatement plan are not likely to respond to the CDP questionnaires, we set the abatement indicators to 0 for firms that never participated in the CDP.

In our sample, the proportion of firms that have set an emissions reduction target (CDP^{Target}_{it-1}) is 21.13%. The proportion of firms that have personnel directly responsible for climate change ($CDP_i^{Personnel}$) is 27.10%.

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 (IO_{it-1}^{PRI}) 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 ($Market\ Share_{it-1}$) 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 ($Total\ Similarity_{it-1}$) from Hoberg and Phillips (2016). Hoberg and Phillips (2016) construct $Total\ Similarity_{it-1}$ 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 $Total\ Similarity_{it-1}$ 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 total economic value of patents for a firm in a given year ($Patent_{it-1}^{Value}$) is \$952.11M, with a standard deviation of \$5248.05M. The median firm has a total economic value of patents of 0.

IA.2 Variable Definitions

Table IA1: Variable Definitions

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

Variable	Definition	Source
$Ret_{i\tau}^{FOMC}$	Realized open-to-close stock return of firm i on FOMC announcement date τ.	CRSP
MPS_t	Monetary policy shock on day tau, as constructed by Jarociński and Karadi (2020).	Jarociński and Karadi (2020)
$Estimated_{it-1}$	Indicator variable that is equal to 1 if firm i's scope 1 carbon emissions are estimated in year $t-1$. (Variable: Derived from `di_319403_text`)	Trucost
$Log(Scope\ 1_{it-1})$	Log of firm i's scope 1 carbon emissions in year $t-1$. (Variable: Log(`di_319413`))	Trucost
$Log(Scope\ 1\ Intensity_{it-1})$	Log of firm i's scope 1 carbon emission intensity in year $t-1$. (Variable: Log(`di_319407`))	Trucost
$Log(MV_{it-1})$	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_{it-1}	Book-to-market ratio of firm i on day $\tau-1$.	Compustat
$Investment_{it-1}$	Capital expenditures of firm i in year t divided by total assets in year $t-1$.	Compustat
$Leverage_{it-1}$	Book leverage of firm i in year $t-1$.	Compustat
$Log(PPE_{it-1}$	Log of firm i's net property, plant and equipment in year $t-1$.	Compustat
$PPE_{it-1}/Assets_{it-1}$	Net property, plant and equipment of firm i in year $t-1$ divided by total assets in year $t-1$.	Compustat
$\frac{PPE_{it-1}}{Assets+Off-BS\ Intangibles_{it-1}}$	Net property, plant and equipment of firm i in year $t-1$ divided by total assets and off-balance sheet intangible assets in year $t-1$.	Compustat
ROE_{it-1}	Return on book equity of firm i in year $t-1$.	Compustat
$Sales\ Growth_{it-1}$	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
$Institutional\ Ownership_{it-1}$	Total institutional ownership by 13-F institutions. (Variable: `InstOwn_Perc`)	Thomson Reuters s34/WRDS Web Application
$CCExposure_{it-1}$	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. (Variable: `cc_expo_ew`)	Sautner et al. (2020)
$CCExposure^{Reg}_{it-1}$	Relative frequency with which bigrams that capture regulatory shocks 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. (Variable: `rg_expo_ew`)	Sautner et al. (2020)
$CCExposure^{Phy}_{it-1}$	Relative frequency with which bigrams that capture physical shocks 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. (Variable: `ph_expo_ew`)	Sautner et al. (2020)
$MSCI\ Score^{ESG}_{im-1}$	MSCI's industry-adjusted overall ESG score of firm i in month $m - 1$. (Variable: `INDUSTRY_ADJUSTED_SCORE`)	MSCI ESG
$MSCI\ Score^{ENV}_{im-1}$	MSCI's industry-adjusted overall ESG score of firm i in month $m - 1$. (Variable: `ENVIRONMENTAL_PILLAR_SCORE`)	MSCI ESG
$MSCI\ Score^{CCT}_{im-1}$	MSCI's industry-adjusted overall ESG score of firm i in month $m - 1$. (Variable: `CLIMATE_CHANGE_THEME_SCORE`)	MSCI ESG

IA.3 Additional Tables

Table IA2: 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 IA3: 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 IA4: 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 IA5: 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 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 IA6: Local Projections with Interaction Terms with Firm Fixed Effects

This table reports coefficient estimates from a modified version of Equation 2, with the addition of the interaction term $\hat{R} \times$ Log Scope 1 and firm fixed effects. The 1-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. 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					
	$h = 2$			$h = 3$		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Scope 1	-1.059***	-1.088***	-1.098***	-1.410***	-1.501***	-1.499***
	(0.082)	(0.084)	(0.101)	(0.085)	(0.091)	(0.099)
$\hat{R} \times$ Log Scope 1		0.062	0.150*		0.193***	0.287***
		(0.046)	(0.079)		(0.056)	(0.094)
Observations	32,141	32,141	29,901	25,641	25,641	23,438
Adj R2	0.441	0.442	0.466	0.554	0.557	0.591
Uninteracted Controls	Y	Y	Y	Y	Y	Y
Interacted Controls	N	Y	Y	N	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	N	Y	Y	N
Industry-by-Time FE	N	N	Y	N	N	Y

Panel B: Emissions Intensity

	DV: Δ^h Log Scope 1 Intensity					
	$h = 2$			$h = 3$		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Scope 1	-0.873***	-0.917***	-0.950***	-1.177***	-1.275***	-1.282***
	(0.071)	(0.074)	(0.080)	(0.081)	(0.087)	(0.097)
$\hat{R} \times$ Log Scope 1		0.089*	0.208***		0.203***	0.302***
		(0.045)	(0.075)		(0.053)	(0.094)
Observations	32,137	32,137	29,897	25,640	25,640	23,437
Adj R2	0.352	0.353	0.390	0.475	0.479	0.522
Uninteracted Controls	Y	Y	Y	Y	Y	Y
Interacted Controls	N	Y	Y	N	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	N	Y	Y	N
Industry-by-Time FE	N	N	Y	N	N	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	0.444***	0.563***	0.459***	0.298**	0.052
	(0.070)	(0.119)	(0.139)	(0.130)	(0.112)
Observations	165	165	165	165	165
R-squared	0.517	0.420	0.251	0.119	0.005