Measuring the Effect of Green Monetary Policy Surprises*

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Central banks are under increasing pressure to integrate green monetary policies–measures that support the transition to a low-carbon economy–into their mandates. We leverage central bank announcements of participation in the Network for Greening the Financial System (NGFS) as a quasi-natural experiment to assess financial market reactions to unexpected central bank actions signaling a shift toward climate objectives–green monetary policy surprises. Using high-frequency event studies, we find significant positive abnormal returns for clean energy stocks in the days following NGFS participation announcements, with impacts comparable to those observed following the Paris Agreement and the strongest effects concentrated in low-carbon firms. A difference-in-differences (DiD) analysis further shows a sustained increase in green bond issuance following these surprises, highlighting the role of central bank signaling in catalyzing capital flows toward sustainable finance. Our findings suggest that central banks continue to prioritize their primary mandates of price stability and economic growth over climate objectives.

JEL: E58, E61, G1, Q54, Q58

Keywords: Climate finance, green central bank policy, stock market reaction, sustainable finance

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1. Introduction

> *"The ECB's Governing Council is strongly committed [...] to further incorporating climate change considerations into its monetary policy framework."*
>
> — ECB Press Release 8. July 2021[1]

On 17 January 2025 at 13:30, the Federal Reserve (Fed) unexpectedly announced its withdrawal from the Network for Greening the Financial System (NGFS)– a global coalition of central banks dedicated to greening the financial system. The market's reaction was immediate: returns on green stocks fell by around 50 basis points, causing a substantial wedge between green and brown stocks within few hours (see Figure 1). Explaining the decision, Fed Chair Jerome Powell emphasized that the NGFS's focus—particularly its aim to *"mobilize mainstream finance to support the transition toward a sustainable economy"*—fell *"just way beyond any plausible mandate that you could attribute to the Fed [. . .] it's not right for the Fed."*[2]

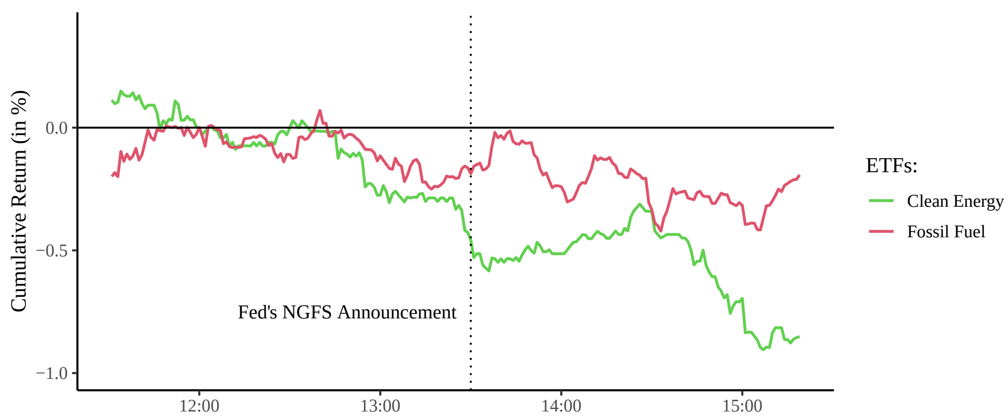


Figure 1 : Caption

Notes: This graph presents the market response to the Fed exiting the NGFS on January 17, 2025. The dotted line represents the time when the Fed announced to leave the NGFS at 13:30 (eastern time). Clean energy and fossil fuel cumulative returns are calculated by aggregating average minute-by-minute returns from sector-specific ETFs as illustrated within Table A5. Further information on the construction of the dataset in Chapter 4.1.

Notwithstanding the Fed's withdrawal from the NGFS, the urgent challenge posed

[1]ECB Press release from 8 July 2021 with title "ECB presents action plan to include climate change considerations in its monetary policy strategy". Available at https://www.ecb.europa.eu/press/pr/date/2021/html/ecb.pr210708_1~f104919225.en.html (accessed: September 1, 2023).

[2]Fed press conference from January 29, 2025. Available at https://www.federalreserve.gov/mediacenter/files/FOMCpresconf20250129.pdf(accessed:February2,2025).

by climate change and the resulting need for a green transition to a sustainable economy are becoming increasingly pressing (Allen et al., 2022). Given this context, policymakers and scholars have increasingly questioned whether, and how, central banks should facilitate a low-carbon transition. For instance, Mark Carney, the Governor of the Bank of England, emphasized in a speech on 29th September 2015 that central banks have *"a clear interest in ensuring the financial system is resilient to any transition [...] and that it can finance the transition efficiently"* (Carney, 2015). The European Central Bank (ECB) echoed a similar reasoning on July 8, 2021, when announcing the institution would *"incorporating climate change considerations into its monetary policy framework"* (as stated in the opening quote of this paper).

Despite a growing body of literature examining legal and institutional constraints to green monetary policy actions, relatively little is known about how financial markets would respond to shifts in central bank climate objectives. Empirical research in this area faces significant identification challenges, as in green policy actions and announcements are potentially endogenous to the wider macroeconomic environment and widely anticipated by financial markets. Take the expansion of the European Central Bank (ECB) mandate to include climate change considerations at the beginning of this paper. This policy shift was largely expected, partly due to remarks made by Jens Weidmann about a month earlier at the Green Swan 2021 Global Virtual Conference, where he suggested that the ECB *"should only purchase securities [...] if their issuers meet certain climate-related reporting obligations"*.[3] Given Weidmann's prior reputation to oppose such measures, his statement was picked up by several news sources, such as the Financial Times (Arnold, 2021) and Reuters (Canepa, 2021), as a clear signal that the ECB would adopt a stronger stance on climate change in its upcoming strategy review.

To address the identification problem, we introduce the concept of green monetary policy surprises–unexpected policy actions that signal a central bank's commitment to environmental objectives. We operationalize this concept using announcements of central bank participation in the NGFS, a global coalition of central banks dedicated to promoting sustainable finance. Established in 2017, the NGFS serves as a platform for central banks to coordinate on climate-related financial risks, and its membership has grown steadily as institutions increasingly align with green finance goals. Because NGFS membership announcements are unanticipated by financial markets, they serve as a quasi-natural experiment, providing a unique opportunity to isolate the effects of green policy signals on financial markets.

Our analysis yields three main findings. First, we show that the propensity to join the NGFS is a function in the country's economic development (e.g., GDP per capita), national institutions (e.g., central bank independence), and the fulfillment

[3] Speech-Transcript from June 7, 2021 with title "Enhance transparency of climate related financial risks". Available at https://www.bundesbank.de/en/tasks/topics/weidmann-enhance-transparency-of-climate-related-financial-risks-867492 (accessed: September 1, 2023).

of primary mandates (e.g., price stability and economic growth). These results suggest that policy makers view greening the financial sector to be subordinate to their remaining mandates.

Second, by treating NGFS expansion as a green monetary policy surprise in a high-frequency event study, we estimate its causal impact of green monetary policy on stock markets. We find that green monetary policy significantly fuels the valuation of clean energy. In economic terms, assuming a scenario, where only the US Federal Reserve joins the NGFS, our results suggests that a difference portfolio that is long in clean energy stocks and short in fossil fuel stocks earns a return of 8.4 percent over the following three days – around twice the abnormal return of clean energy stocks following the announcement of the Paris Agreement. We substantiate these results with a firm-level event study on the US-market (e.g., Bauer et al., 2024), where we show that predominantly low carbon firms experienced higher stock market returns.

Finally, we assess the medium-term impact of green monetary policy surprises on the green transition, employing a Difference-in-Difference regression to examine shifts in green bond issuance. Our results indicate a significant increase in green bond issuance in countries following a green monetary policy surprise, suggesting the potential of green monetary policy to influence not only immediate market valuations but also longer-term capital allocation. The remainder of this paper is structured as follows: The next section discusses the role of central banks for the green transformation and develops our hypotheses. Section 3 describes and examines the development of the network. Section 4 examines the consequences in capital markets, before the last section concludes the paper.

2. Central banks, NGFS, and the green transition

The existing literature on green monetary policy primarily focuses on three main dimensions: legal constraints (e.g., Skinner, 2021; Schnabel, 2021; Bartholomew and Diggle, 2021), implementation constraints (e.g., Brunnermeier and Landau, 2020; Campiglio et al., 2018; Ferrari and Landi, 2024; Ilzetzki and Jia, 2021; Papoutsi et al., 2021; Schoenmaker, 2021), and central bank preferences and communication (e.g., Arseneau and Osada, 2023; Azanbayev and Rülke, 2024; Campiglio et al., 2023; Deyris, 2023). Our paper builds on and extends these strands by introducing the concept of green monetary policy surprises–unexpected policy actions that signal a central bank's commitment to environmental objectives. Specifically, a green monetary policy surprise must meet two criteria: (1) being a surprise it must unanticipated by market participants, and (2) it signals the central bank's commitment to green objectives. We operationalize this concept by using announcements of central bank participation in the NGFS as quasi-natural experiments, as these announcements meet both criteria. In Section 3, we will provide evidence that NGFS announcements were indeed unexpected by market participants, fulfilling the first criterion. Next, we focus on the second criterion, showing that NGFS membership announcements explicitly convey central banks'

intentions to integrate environmental considerations.
The NGFS, founded in December 2017 during the One Planet Summit in Paris, represent a coalition of central banks and supervisory authorities dedicated to analyze the implications of climate change for the financial system and to redirect global financial flows toward enabling low-carbon economic growth. The Deutsche Bundesbank, one of the founding members, articulates the network's mission as "a global network of central banks and supervisory authorities advocating for a more sustainable financial system".[4] In terms of identification, our green monetary policy surprises offer distinct advantages over traditional policy announcements. First, as we will show, these surprises are unexpected to market participant, thereby reducing anticipation bias in the estimates. Second, NGFS participation membership signals a central banks commitment to green objectives. Third, the signal is purely informative, helping markets update their understanding of central banks' positions on climate policy rather than as a signal of binding commitment, as NGFS membership signals interest in sustainable finance but lacks immediate policy implications. Finally, NGFS entry announcements convey information that is unrelated to central banks' conventional objectives, such as price stability.
Due to this separation, we are able to effectively attribute observed market reactions to the climate-related component of central banks' objectives, without the confounding influence of conventional monetary policy concerns. To formalize, consider a central bank loss function (e.g., Galí, 2015), extended to include a climate damage term (e.g., Chen et al., 2021):

$$L_t = \Delta\beta_1\pi_t^2 + \Delta\beta_2 y_t^2 + \Delta\beta_3 C_t^2 \tag{1}$$

where, $\Delta\pi_t$ and Δy_t represent deviations in inflation and output, respectively, and ΔC_t denotes damages to the environment. The inclusion of ΔC_t implies that central banks now face an additional consideration alongside traditional objectives like price stability and output stabilization. The β's determine the relative weight of inflation, output, and climate damages. The majority of the literature on green monetary policy adopt a traditional loss function model, wherein the response to climate concerns operates through macro prudential policies, financial stability objectives or heightened inflation expectations, thereby positing $\beta_3 = 0$ (Abiry et al., 2022; Darracq Paries et al., 2023; Dietrich et al., 2021; Diluiso et al., 2021; Masciandaro and Russo, 2024; Kara and Thakoor, 2023).[5] This stance is echoed by the majority of surveyed finance academics and public-sector regulators, who argue that the payoffs to projects addressing climate risks are orthogonal to economic fluctuations (Stroebel and Wurgler, 2021).
In practice, however, policymakers appear to hold a different perspective. Following the Fed's withdrawal from the NGFS, Chair Jerome Powell remarked that

[4]See https://www.bundesbank.de/en/bundesbank/green-finance/-/network-for-greening-the-financial-system-808978 (accessed September 1, 2023).
[5]An alternative view, such as posed by Del Negro et al., 2023 is that the green transition can generally be regarded inflationary due to prices being stickier in the brown sector.

"the activities of the NGFS are not a good fit for the Fed, given our current mandate,"[6] adding that *"other central banks have different mandates and belong to the NGFS,"* explicitly linking NGFS membership with a broader green mandate. To the best of our knowledge, Chen et al. (2021) provide the only explicit model with a climate-adjusted central bank loss function. The authors incorporate the variance of the emissions gap (i.e., the difference between actual and potential emissions) as an additional term. The loss function motivates our hypotheses. The weighting of β_3 serves as an indicator of the central bank's green preference: a higher β_3 would suggest a greater willingness to accept trade-offs in favor of environmental objectives. Consider a scenario where an energy price shock raises inflation ($\Delta\pi_t$) but lower environmental damages (ΔC_t). In this case, central banks must balance inflation stability against climate goals, guided by the relative magnitudes of the β's. This trade-off illustrates how green monetary policy shifts might influence market expectations and signals regarding central bank commitment to climate objectives. In this context, NGFS participation can be interpreted as a signal that a central bank has chosen to emphasize climate considerations alongside traditional objectives. If the timing (or nature) of this decision was not anticipated by financial markets, this unexpected action that signals or strengthens the banks' climate commitment would be a green monetary policy surprise. Our first hypothesis examines the conditions influencing NGFS participation. Specifically, we posit that developed countries are more likely to join NGFS, given their regulatory capacity and institutional readiness to address climate risks:

> **H1.a:** Central banks of developed economies are more likely to join the NGFS.

In addition, central banks may prioritize NGFS participation only when primary mandates, such as price stability and economic growth, are fulfilled. For instance, Dikau and Volz (2023) highlight how the People's Bank of China reversed its longstanding practice of discouraging loans to high-pollution sectors in response to low growth rates in 2015. This is consistent with studies highlighting the tradeoffs central banks face when incorporating climate concerns into policy objectives (Dikau and Volz, 2021; Azanbayev and Rülke, 2024):

> **H1.b:** Central banks are more likely to join the NGFS when their primary and secondary objectives are fulfilled.

Next, we analyze the effects of green monetary policy surprises on capital markets. As noted in the introduction, the Fed's withdrawal from the NGFS adversely affected green stocks while benefiting brown stocks, in line with similar results for green news (e.g., Ardia et al., 2023), green political announcements (e.g., Antoniuk and Leirvik, 2024; Bauer et al. 2024) or green QE (e.g., Diluiso et al.,

[6] Fed press conference from January 29, 2025. Available at https://www.federalreserve.gov/mediacenter/files/FOMCpresconf20250129.pdf (accessed: February 2, 2025).

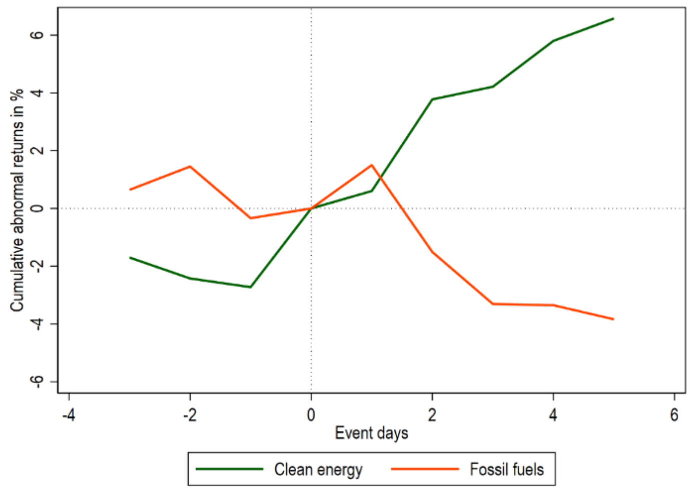
2021). As a results, we expect segments most exposed to climate regulation to be most sensitive to a green monetary policy surprise. Specifically, we expect that clean energy stocks (fossil fuel stocks) benefit (suffer). To lend further anecdotal evidence to this hypothesis, Figure 2 documents the development of green (clean) energy stocks and fossil fuel stocks around the announcement of the Paris Agreement (United Nations, 2015) on December 12, 2015. Following the announcement fossil fuel stocks fell, while (clean) energy stocks gained in value. In quantitative terms: clean stocks gained almost 4 percent over the next three days. Given the (anecdotal) evidence from Figure 1, we conjecture:

> **H2:** Green monetary policy surprises lead benefit clean energy stocks and hurt fossil fuel stocks.

Our final hypothesis is motivated by recent work examining that examines how green policy shifts influence financial markets and corporate behavior. Studies such as Xiao et al. (2024), Diluiso et al. (2021), and Känzig (2023) show that unexpected green policy announcements can lead firms to improve ESG ratings and prompt financial markets to reallocate capital toward sustainable investments. As a result, we expect that green monetary policy surprises will foster increased investment in clean energy sectors and green bonds. Specifically, we anticipate that green monetary policy surprises will lead to an increase in the issuance of green bonds - fixed-income instruments dedicated to financing environmentally sustainable projects (e.g., Guter-Sandu et al., 2024):

> **H3:** Green monetary policy surprises lead to an increase in the issuance of green bonds.

Figure 2 : Market response to the Paris Agreement (Dec 12, 2015)



Notes: This graph illustrates the market response to the signing of the Paris Agreement on Dec 12, 2015. Cumulative abnormal returns over event days -3 to 5, normalized to the event date for both categories, clean energy and fossil fuel stocks, are shown. With December 12, 2015 being a non-trading day, the event day (announcement date) is set to the next trading day, December 14, 2015.

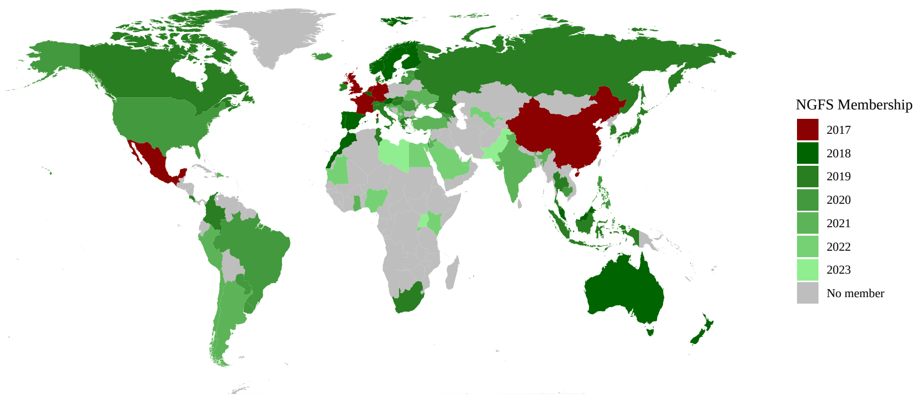
3. Network development

In the first step, we analyze the growth of the Network for Greening the Financial System (NGFS), exploring both cross-sectional and time-varying determinants of central bank participation at the country level.

3.1. Network development over time

To date, 84 central banks from all continents have joined the NGFS. We illustrate the network's global reach in Figure 3, highlighting founding members (Table A1) in red and non-founding members in shades of green based on their entry date. A detailed overview of network expansion is presented in Table A2, which documents the network's annual expansion from its establishment in December 2017 to April 2023, alongside average GDP per capita of NGFS and non-NGFS members, size of incoming members, and overall network size. It shows that NGFS members are covering over 91% of global GDP by 2022.
In addition, Table A2 shows that central banks from large, developed economies led early participation. The average GDP of new members decreased substantially, from 3.4 trillion USD (founding members) to 0.2 trillion USD in 2022 – supporting H1.a. We confirm this pattern with a traditional empirical test below. Nevertheless, we find notable temporal variation in network size, most pronounced in 2020 when the Federal Reserve joined the network.

Figure 3 : World-map of NGFS member



Notes: This table illustrates the evolution of global membership in the NGFS. Founding members are highlighted in red, while non-founding members are shown in varying shades of green, reflecting their respective entry dates. Non-members are represented in gray. Detailed data can be found in Table A2.

3.2. Cross-sectional determinants of central bank's NGFS membership

To examine cross-sectional factors influencing NGFS participation, we conduct a cross-sectional logit regression using a confidential dataset from the Deutsche Bundesbank, which includes the exact joining dates for each member. We complement the data-set with macroeconomic data from the World Bank (Development Indicators) and other sources, covering up to 217 countries.[7] Our logit model is specified as follows:

$$NGFS\ member_{i,2021} = \alpha + \beta_1 y_i + \beta_2 X_i + \beta_3 b_i + \epsilon_i \tag{2}$$

where the dependent is binary indictor being 1 if central bank i was an NGFS member as of 2021, the year NGFS announced its first Climate Scenarios. y_i represents GDP per capita, X_i social, economic, and institutional variables, and b_i geographic proximity to NGFS members. All covariates stem from pre-2021, to address potential endogeneity concerns and have been demeaned and standardized to facilitate the interpretation of the coefficients. Table A3 and Table A4 provide an overview as well the respective descriptive statistics.[8]

Our results can be found in Table 1. Column 1 shows a strong positive relationship between GDP per capita and NGFS membership, controlling for adjacent

[7]We focus on national central banks that join the network, as macroeconomic variables are measured on country-level. Thus, we exclude central banks at the supranational level (e.g., the European Central Bank) and non-central bank financial supervisory institutions.

[8]We describe our approach for building this first dataset in detail in the Online Appendix.

NGFS members. A one-standard-deviation increase in GDP per capita (for instance from the Czech Republic to Germany) more than quadruples the likelihood of joining the NGFS by 2021. Column 2 introduces proxies for national green production and consumption, specifically the share of renewable energy, energy use per capita, and CO2 emissions per capita, showing that countries with lower CO2 emissions are more likely to join. Column 3 examines economic and population vulnerabilities to climate change (e.g., the share of agriculture and coastal populations), finding that countries with larger agricultural sectors are significantly less likely to participate in the NGFS. Column 4 examines the role of national institutions, focusing on central bank independence (CBI) as measured by Romelli (2022). A one-standard-deviation increase in CBI (for instance from the Bank of Albania to the Banca D'Italia) doubles the probability of NGFS membership, suggesting central bank independence to be crucial from green monetary policy. Finally, we assess multicollinearity in Column 5, confirming the robustness of our results. Overall, our findings indicate that high-income countries with green preferences and strong institutions are the most likely to join the NGFS.

3.3. The Role of Primary and Secondary Objectives

Building on the discussion of central banks' loss functions, where climate concerns are hypothesized to play a tertiary role, we now empirically examine the relationship between central banks' primary (price stability) and secondary (economic slack) objectives and their decisions to join the NGFS.[9]
Specifically, we test whether the weighting of climate objectives (β_3 in Equation (1)) is relatively low compared to the weights assigned to inflation (β_1) and output (β_2), suggesting that central banks prioritize traditional mandates before committing to climate initiatives like the NGFS. To test this hypothesis, we estimate the following panel regression:

$$NGFS : join_{i,t} = \alpha + \beta_1 |\pi_t - \hat{\pi} + \beta_2 (x_t - \hat{x}) + \beta_3 u_t + f_{i,t} + \epsilon_{i,t} \tag{3}$$

where $NGFS : join_{i,t}$ is a binary variable equal to 1 if central bank i joined the NGFS in year t, and 0 otherwise. The key independent variables are the absolute deviation from trend inflation $|\pi_t - \hat{\pi}|$, the output gap $(x_t - \hat{x})$, and the unemployment rate u_t.[10] We also include a set of fixed effects f to capture unobservable factors specific to each central bank and year. The coefficients of interest are the β's. We expect greater inflation deviations to reduce the likelihood of joining the NGFS. Conversely, a positive (negative) output gap should increase (decrease) the likelihood of joining.

[9]We recognize that not all central banks have de jure objectives related to price stability and economic activity. Nevertheless, the work of Cobham (2021) highlights that most central banks worldwide have de facto mandates relating to at least one of the three.

[10]To estimate deviation in inflation and output from trend, we employ an HP filter on the annualized inflation rate and real output spanning from 1980 to 2023 sourced from the WDI. We describe our approach for building our second dataset in detail in the Online Appendix

Table 1: Cross-sectional determinants of central bank's NGFS membership

	Dependent variable:				
	Membership in 2021				
	(1)	(2)	(3)	(4)	(5)
GDP per capita	1.51***	4.39***	1.20***	1.62***	2.84***
	(4.50)	(4.01)	(2.88)	(4.24)	(3.38)
NGFS Border	1.13***	0.82	1.04**	0.83*	0.91*
	(2.81)	(1.64)	(2.36)	(1.93)	(1.89)
Renewable Production		-0.20			
		(-0.75)			
Energy use		0.65			
		(1.02)			
CO2 emissions		-2.55***			-1.46***
		(-3.14)			(-3.29)
Urban population in coastal zone			-0.30		
			(-1.31)		
Agriculture, forestry, and fishing			-0.65*		-1.00**
			(-1.80)		(-2.54)
Central bank independence index				0.69***	0.58**
				(3.09)	(2.23)
Constant	-0.76**	0.57	-0.81**	-0.40	-0.36
	(-2.38)	(1.19)	(-2.27)	(-0.42)	(-0.90)
Observations	151	123	143	151	148
Log Likelihood	−79.03	−56.40	−70.40	−73.69	−61.32
Akaike Inf. Crit.	164.06	124.79	150.79	155.37	134.63

Note: This table reports the results of logistic regressions of NGFS membership on different categories of determinants. Specifically, these categories refer to: National green preferences (specification 1), national constraints (specification 2), impact of national institutions (specification 3), and to the relevance of regional institutions (specification 4). Most of the independent variables are standardized and demeaned. T-statistics are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels. A detailed description of the variables used is provided in Table A4.

The regression results, presented in Table 2, confirm our hypotheses. Column 1 indicates that an increase in inflation deviation by one standard deviation significantly reduces the probability of NGFS entry in that year by around 75%. Column 2 shows that the same relationship holds for the output gap. Interestingly, we find we find no significant relationship between the unemployment rate (column 3). To ensure robustness, we assess multicollinearity in Column 4, finding no significant issues, indicating that central banks prioritize price stability and above-trend economic activity to NGFS membership.

Finally, in Column 5 we examine whether our findings are driven by developed countries, as there may be unobserved confounding factors, such as stronger inflation-targeting mandates. To test this, we exclude countries with a real income below $10,000, finding that the results remain consistent, which supports the generalizability of our findings across income levels.

In summary, central banks tend to commit to climate-related objectives once

Table 2: More on central bank's decision to join the NGFS

	Dependent variable:				
	Joining NGFS				
	(1)	(2)	(3)	(4)	(5)
Inflation Gap	-1.400***			-1.390***	-1.243**
	(-3.680)			(-3.588)	(-2.340)
Output Gap		0.404***		0.418***	0.450*
		(2.587)		(2.618)	(1.884)
Unemployment Rate			0.143	0.201	0.292
			(1.087)	(1.405)	(1.330)
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Countries > 10k Dollar	No	No	No	No	Yes
Observations	590	590	590	590	352
Log Likelihood	-187.838	-192.54	-195.521	-183.641	-105.467
Akaike Inf. Crit.	539.676	549.081	555.042	535.283	318.934

*Note:*This table reports the results of logistic panel regressions of Joining the NGFS on several objectives of central banks. Inflation gap is the deviation from the long-term inflation trend (specification 1). Output gap is the deviation from the long-term Output-trend (specification 2). Deviations from long term trends are estimated using HP-filtered time series. Unemployment rate is measured as % of total labor force (specification 3). Specification (5) excludes countries with a real income below 10,000 US-Dollars. All specifications account for time- and individual-specific fixed effects. T-statistics are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels. A detailed description of the variables used is provided in Table A4.

their primary and secondary objectives are fulfilled. Thus, our results suggest that policy makers perceive climate change concerns as subordinate to addressing price stability and output deviations.

4. Financial market response to green monetary policy surprise

We next examine the reaction of market participant to a NGFS network expansions (a green monetary policy surprise). Our analysis focuses on three key dimensions: (i) the aggregate global financial market response, (ii) U.S. firm-level response following the Federal Reserve's entry, and (iii) the medium-term transmission through green bond issuance.

The use of NGFS network expansions as a proxy for green monetary policy surprises should raise endogeneity concerns, as we established in the previous section that these surprises are not entirely random and may be somewhat predictable. If market participants engage in anticipatory behaviors–often referred to as a "green paradox"–in response to an expected NGFS announcement, we risk observing biased estimates of the policy's impact.[11]

[11]For instance, Lemoine (2017) find that the legislative process surrounding the U.S. Senate's 2010 climate initiative resulted in an overall increase in CO2 emissions. Structural factors, such as the decline in equilibrium real interest rates and the resulting effects on social discount rates (e.g., Bauer and Rudebusch, 2023), further complicate the accurate evaluation of climate policies.

To address the endogeneity concerns, we adopt a high-frequency event study design to isolate the causal effects of green policy surprises on stock market evaluations. Event studies, widely used in green policy research (e.g., Antoniuk and Leirvik, 2024; Bauer et al., 2024; Ramiah et al., 2013; Wallace and McIver, 2019), allow us to disentangle immediate market responses from broader structural trends. By using event windows of one to three days around the announcement, we exploit the largely random timing of daily policy events, minimizing anticipation bias to isolate the short-term effects from long-term predictable trends. We support this assumption in two ways. First, we conduct a review of newspaper articles published around each event, finding no evidence of media coverage anticipating a single NGFS announcements in advance. Second, we perform a back-of-the-envelope calculation: Our sample period spans 5.5 years, from January 2018 to June 2023, during which we identify 17 distinct events. Given an average of 252 trading days per year, the unconditional probability of an event occurring on any single day in our sample period is roughly 1.2%. Even within a four-day window, this probability remains below 5%, suggesting that such events are relatively infrequent and their specific timing unpredictable.

4.1. Event Study I: Global financial market reaction

To identify the precise dates on which financial markets became aware of new NGFS members, we manually gathered information from press releases available on the NGFS website. Specifically, we collected the dates of press releases announcing network expansions. This process yielded 17 distinct announcements (excluding the founding event, and the Fed's withdrawal[12]) involving 76 central banks. We complemented this dataset with daily market data on "brown" and "green" stock prices obtained from Refinitiv Datastream. An overview and definitions of variables are presented in Table A3, and Table A4 provides the corresponding descriptive statistics. To identify the exact dates of green monetary surprises – specifically, when markets became aware of the addition of new NGFS members – we manually collect the dates of the press releases announcing the expansion of the network on the NGFS website. We find these press releases for 76 central banks and 17 distinct events (after the foundation event). We complement this dataset with data on daily market, "brown" and "green" stock price data from Refinitiv Datastream. Table A3 provides an overview and definitions of the variables, and Table A4 the corresponding descriptive statistics.[13]
To proxy the global stock market performance of climate-sensitive industries, we

[12]While NGFS membership announcements have been isolated events, the Fed's withdrawal announcement was not. It took place on Friday, January 17, 2025, at 13:30, just before the Martin Luther King Jr. Day holiday (Monday, January 20) and the public ceremony for Donald Trump's inauguration, during which President Trump declared the United States' withdrawal from the Paris Agreement—a significant climate policy shift that could confound our analysis. Consequently, we exclude the Fed's withdrawal announcement from our main sample. Nevertheless, as demonstrated in the introduction, intraday data from January 17 indicate that the effect aligns with our broader expectations.

[13]Again, we describe the approach of building our third dataset in detail in the Online Appendix.

utilize the performance of thematically consistent ETFs in line with the literature (e.g., Antoniuk and Leirvik, 2024; Bauer et al. 2024; Wallace and McIver, 2019). We focus on two key industries: clean energy and fossil fuels.[14] Our analysis centers on cumulative abnormal returns (CAR) for these ETFs around each public announcement. We estimate the stock market reaction to our green monetary policy surprises using the following specification:

$$CAR_{[t_1,t_2]} = \alpha + \beta_1 GreenMPSurprise + \epsilon_i \tag{4}$$

where the dependent variable is the average CAR (in percentage) for the thematically sorted ETFs (i.e., "green" and "brown" ETFs) over the event window $[t_1, t_2]$ and $GreenMPSurprise$ is measured in terms of GDP contribution of new NGFS members. We expect the coefficient of interest, β_1, to be positive for clean energy stocks as well as the difference between clean energy- and fossil fuel stocks (difference portfolio), indicating a positive stock market response to green monetary policy.

Table 3: Event study I results – global financial market reaction

	Dependent variable CAR:				
	clean energy - fossil fuel				clean energy
	(1)	(2)	(3)	(4)	(5)
$GreenMPSurprise$	34.10***	37.00**	35.23***	26.75***	26.13***
	(4.18)	(2.17)	(3.44)	(4.60)	(3.79)
Abnormal Network size			-1.913	-1.05	-1.75
			(-0.89)	(-0.69)	(-1.01)
Constant	-1.00	-0.48	-1.04	-1.28	-0.98
	(-1.08)	(-0.34)	(-1.10)	(-1.61)	(-0.92)
Observations	17	17	17	17	17
R-squared	0.30	0.30	0.33	0.32	0.24
Method	OLS	Median	OLS	OLS	OLS
Event window	[-1;+3]	[-1;+3]	[-1;+3]	[-1;+1]	[-1;+3]

Note: This table reports the results of OLS- and median regressions of the cumulative (average) abnormal returns (CAR) of clean energy stocks and a difference portfolio on the respective network enlargements by national banks joining the Network for Greening the Financial System. The difference portfolio is computed as the difference in cumulative returns between clean energy and fossil fuel stocks, mimicking a portfolio that is long in clean energy- and short in fossil fuel stocks. $GreenMPSurprise$ is defined as the network enlargement, and calculated as the relative GDP contribution per joining date, in relation to the world-wide year end GDP in the respective joining year. Abnormal network size is calculated as the demeaned size of the network measured as the sum of each members' GDP after the respective announcement date (Specifications 3 to 5). Robust t-statistics are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels. A detailed description of the variables used is provided in Table A4.

[14]The clean energy ETFs cover firms operating in clean energy and wind industries, fossil fuel ETFs invest in stocks of firms in certain industries which are considered to be polluting and thus harmful to the environment (e.g., Wallace and McIver, 2019). Technically, we proxy the stock market performance of clean energy stocks and fossil fuel stocks as the equal-weighted average performance of the ETFs reported in Table A5.

Our findings are presented in Table 3. First, we observe a significantly positive market response in climate-sensitive segments during the $[-1, +3]$ window following a green monetary policy surprise. The intensity of this reaction increases with the magnitude of the surprise, indicating that announcements involving countries with substantial GDP contributions to the network elicit a stronger response. The coefficient is economically meaningful: a one-standard-deviation surprise is associated with an average CAR increase of 2.24 percent for the difference portfolio. Additionally, we account for approximately one-third of the explained variance, highlighting the substantial impact of our surprise on returns during these days. Column two to four report that the results are not dependent on specific model specifications. Specifically, we estimate the base model using a median regression (column 2), controlling for the post-enlargement size of the network (column 3), and by narrowing the cumulative abnormal return window down to a three-day window around the respective announcement dates (column 4). In Column 5, we exclusively re-estimate the model for clean energy stocks' CARs only over the $[-1, +3]$ interval. The results suggest that the returns of the clean energy stocks are the main driver behind the formerly observed difference portfolio returns. When comparing our findings to the market reaction to the Paris Agreement (see Figure 1), we observe that a one-standard-deviation green monetary policy surprise yields approximately half the impact of the Paris Agreement announcement. To illustrate, consider the Federal Reserve's entry into the NGFS on December 15, 2020, which represents a green monetary policy surprise corresponding to 23.9 percent of global GDP. The surprise on that day is projected to generate an estimated abnormal return of 8.4 percent in the difference portfolio over the [-1,+3] window, an effect that is nearly 2.5 times greater than the market response observed following the Paris Agreement announcement.

Overall, our results indicate that financial markets react to climate-related central bank surprises. More specifically, the difference portfolio, which is long in clean energy stocks and short in fossil fuel stocks, substantially benefit from such green surprises. We show that this effect is primarily driven by the clean energy stocks.

4.2. Event study II: US firm-level reaction

Next, we substantiate our findings on global level with firm-level response to green monetary policy surprises, focusing on the Federal Reserve's announcement of NGFS membership on December 15, 2020.[15] Following Bauer et al. (2024), we conduct an event study to assess the reaction of US firm returns to this announcement, using a dataset that links observed firm-level returns to the green monetary policy surprise to cross-sectional characteristics, including three distinct measures of firms' environmental performance.[16] Specifically, we run the

[15]The FED has officially announced that it joined the NGFS formally on December 15, 2020 before trading starts at 09:00 am. See https://www.federalreserve.gov/newsevents/pressreleases/bcreg20201215a.htm (accessed: September 1, 2023)

[16]We construct our sample by retrieving all available U.S. securities included in the Refinitiv U.S. ESG-Universe as of December 9, 2024 (Bauer et al., 2024). Our initial dataset consists of 3,649 individual

following regression:

$$Return_i = \alpha + \beta_1 E + \beta_2 X_i + \epsilon_i \tag{5}$$

where *Return* is the raw return of firm i on the announcement day, while E denotes a firm-specific environmental performance indicator. We follow Bauer, Offner, and Rudebusch, 2023 using (i) the Environmental Score, (ii) the Emissions Score, and (iii) Emission Intensity. The first two are industry-adjusted measures provided by Refinitiv. The Environmental Score aggregates over 60 metrics to capture firms' overall environmental performance, while the Emissions Score focuses on emissions-related themes such as carbon output, waste management, and biodiversity impact. Given recent criticism on these scores (e.g., Gourier and Mathurin, 2024), we also use is a direct measure, Emission Intensity, that scales a firm's CO2-equivalent emissions relative to its market capitalization, thereby accounting for firm size. Notably, data availability constraints on CO2 emissions reduce the sample size for the Emission Intensity analysis.

In all empirical specifications, we add a set of firm-specific control variables X_i for size (log of market capitalization), sales growth (annual change in net sales), book leverage (total debt to total assets), profitability (net income to total assets), and the effective tax rate (ETR, calculated as the ratio of total income taxes paid to pretax income). We further incorporate industry controls based on the FamaFrench classification scheme, which categorizes firms into 17 industries using SIC codes. To mitigate the influence of outliers, all variables are winsorized at the 1% level.

The average company in our sample has an environmental and an emission score of 0.28, with higher scores reflecting more environmentally friendly practices. In terms of emissions intensity, the average firms report an average of 0.29 kilotons per million US dollars of market capitalization, where lower values signify better environmental performance. The average raw return from 14 December to 15 December 2020 was 1.88 percent. Table A3 and Table A4 provide an overview of the variables and further descriptive statistics.[17]

securities. We then exclude securities with missing emissions score data for 2020, reducing the sample to 3,130 securities. In line with established practices, we further refine our sample by excluding non-equity and non-primary security types (e.g., Ince and Porter, 2006). As we focus on U.S. firms, we also exclude all firms not listed on either the NYSE, NASDAQ, or AMEX, following the approach of Bauer et al. (2024). Next, we exclude firms with earnings announcements or closing prices below $1 on the event days (December 14 to December 15, 2020), and require non-missing firm-level control covariates as per 2020. This refinement results in an intermediate sample of 2,693 firms. To encounter a survivorship bias (e.g., Hanauer, 2014), we supplement this sample with delisted or dead companies. By applying the same filtering criteria as above we account for additional 404 firms. In total, our fourth dataset covers a maximum of 3,097 firm observations. Given that the Federal Reserve announced to join the NGFS on December 15, 2020, and the announcement was made public at 9 a.m., we use market returns from December 14 to December 15 to capture the immediate market reaction. For the firm-level environmental and accounting data, we utilize data from the end of 2020. We opt for this approach, because the event occurred in mid-December, making end-of-year data the most relevant for capturing the firms' status close to the event date.

[17] Please refer to the Online Appendix for additional explanations with regard to the sample construction process for our US firm-level sample.

The regression results can be found in Table 4. We find a statistically significant coefficient for all three environmental performance indicators in the expected direction. The magnitudes of the effects are substantial, a one-standard deviation increase in the Environmental Score is associated with an additional return of approximately 0.37%, equivalent to about one-seventh of a standard deviation of raw returns. Comparing our coefficients to those of Bauer et al. (2024). we find that the effect size is roughly half the magnitude of their findings, indicating that the Federal Reserve's announcement of NGFS membership has a significant, albeit somewhat smaller, influence on asset markets than the $1 trillion Inflation Reduction Act of 2022.[18]

In conclusion, our firm-level event study corroborates the insights from the previous section. At a more granular level of analysis, our results indicate that, on average, low-carbon firms experienced higher stock market returns on December 15, 2020. In conjunction with the previous findings, our results suggest strong market reactions to green monetary policy surprises. They also suggest that market participants believe in the associated central bank commitments to green and sustainable finance are perceived as a credible signal by market participants.

We find that, on average, low-carbon firms experienced significantly higher stock market returns on 15 December 2020. In conjunction with the findings from the previous section, our results indicate a robust market response to green monetary policy surprises. Moreover, our results suggest that market participants view green central bank commitments to sustainable finance as credible signals that shape investor behavior.

4.3. Green bond issuance reaction

Next, we focus on the implications of green monetary policy surprises, specifically examining whether our surprises can persistently stimulate capital flows to green projects, rather than just having immediate or short-term impacts (e.g., Diluiso et al., 2021). To analyze this medium-term relationship, we merge our dataset of green monetary policy surprises with the IMF's Climate Change Green Bonds database (Mertzanis, 2024). The database compiles fixed-income instruments designed to finance or refinance sustainability projects, commonly referred to as "green bonds." It encompasses green bond issuance across 75 countries from 2010 to 2022. A statistical summary of this dataset is provided in Table A4, showing that, on average, approximately US$2.12 billion were issued annually per country within the sample.

To empirically assess the causal impact of green monetary policy surprises on green bond issuance, we adopt a difference-in-differences (DiD) and a panel-

[18] In additional unreported analyses of our baseline results using decile-portfolio regressions, we document that the observed correlations are primarily driven by the "greenest" and most "brown" firms. These results hold across all measures of greenness. Furthermore, we find that emissions directly "controlled" by firms (i.e., Scope 1 emissions)—which are more directly attributable to them by investors and the stock market—drive the negative correlation between emission intensity and equity returns on the event day. We provide these analyses as well as several robustness checks within the Online Appendix.

Table 4: Event study II results – US firm-level reaction

	Dependent variable CAR:		
	Raw Return (Dec 14-15, 2020)		
	(1)	(2)	(3)
E (of ESG)	1.369***		
	(3.36)		
Emission score		0.905**	
		(2.92)	
Emission intensity			-0.280***
			(-2.94)
Size	-0.238***	-0.219***	-0.268***
	(-3.97)	(-3.55)	(-4.97)
Sales growth	-0.250***	-0.280***	-0.591
	(-3.30)	(-3.68)	(-1.32)
Leverage	0.264	0.256	0.208
	(1.22)	(1.12)	(0.78)
Profitability	1.718***	1.843***	-0.234
	(5.65)	(5.96)	(-0.31)
Effective tax rate	0.053	0.082	-0.201**
	(0.67)	(0.96)	(-2.73)
Constant	4.998***	4.851***	
	(7.95)	(7.61)	
Observations	3,097	3,097	1,034
Adjusted R^2	0.041	0.036	0.124
Industry fixed effects	No	No	Yes

Note: This table reports the results of regressions of the (individual) raw returns of US firms on three environmental measures and a set of firm controls. While specifications (1) and (2) employ the environmental and emissions score as proxies for measuring firms' greenness, specification (3) uses firms' emission intensity. All models include controls for firm size, sales growth, leverage, profitability, and effective tax rate. Additionally, specification (3) incorporates industry fixed effects based on the Fama-French classification (17 industries). Robust T-statistics are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels. A detailed description of variables used is provided in Table A4.

regression approach, where we compare changes in green bond issuance between treated countries (those whose central banks joined the NGFS) and control countries (those that have not joined the NGFS), before and after NGFS participation. Specifically, we start by estimating the following panel regression model:

$$Green\ Bond_{i,t} = \alpha + \beta_1(Post \times NGFS_{i,t}) + \beta_2 X_{i,t} + \epsilon_{i,t} \tag{6}$$

where *Green Bond* denotes green bond issuance (in billions of US dollars) for country i at time t. Our variable of interest, $Post \times NGFS_{i,t}$, is equal to 1 if a country's central bank has joined the NGFS by time i and 0 otherwise. To account for unobserved time-specific and country-specific variations, we include time and country fixed effects. Further information on the variables can be found in Table A3 and Table A4.

The results are presented in Table 5, columns (1) to (3). The first column shows a difference-in-means comparison, suggesting that NGFS membership is associated with an increase in green bond issuance of about US$7 billion. Qualitatively, the effect remains robust when controlling for country-specific and time-specific variations (column 2), and country size (column 3). Quantitatively, across various model specifications, NGFS membership is associated with an additional annual green bond issuance of US$2.7 billion to US$4 billion, which corresponds to about half a standard deviation of annual issuance levels.

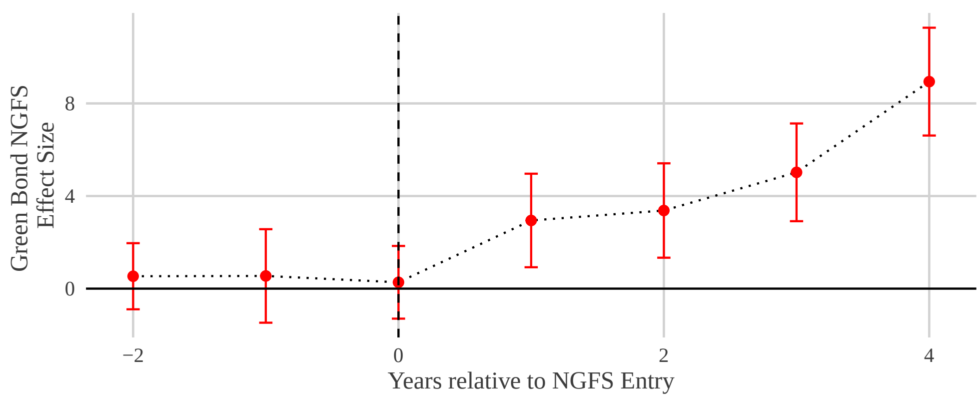
Table 5: Regression results - green bond issuance reaction

	Dependent variable:				
	Green Bond Issuance				
	(1)	(2)	(3)	(4)	(5)
NGFS	6.94***	3.42***	2.65***	4.05***	
	(12.82)	(4.48)	(4.06)	(3.04)	
$NGFS_{t=-1}$				0.55	-0.07
				(0.53)	(-0.11)
$NGFS_{t=0}$				0.27	0.41
				(0.34)	(0.59)
$NGFS_{t=1}$				2.94***	1.67**
				(2.86)	(2.28)
$NGFS_{t=2}$				3.37***	1.46*
				(3.25)	(1.83)
$NGFS_{t=3}$				5.02***	2.97***
				(4.66)	(3.34)
$NGFS_{t=4}$				8.94***	6.46***
				(7.53)	(6.31)
GDP			5.58***		4.66***
			(18.37)		(8.91)
Constant	0.48*	-0.83	-2.13	-2.76	-2.08
	(1.82)	(-0.46)	(-1.38)	(-0.62)	(-1.44)
Observations	975	975	975	593	593
Adjusted R^2	0.14	0.40	0.57	0.15	0.68
Regression Type	Panel	Panel	Panel	DiD	DiD
Year effects	No	Yes	Yes	No	Yes
Country effects	No	Yes	Yes	No	Yes

Note: RT-statistics are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels. A detailed description of the variables used is provided in Table A4.

To further assess anticipation effects and the persistence of the effect of green monetary policy surprises on green bond issuance, we turn to a DiD-approach with two-way fixed effects in columns (4) to (5). We find the following. We find the following. First, the pre-treatment coefficients are insignificant, suggesting that treated and control units followed parallel trends prior to NGFS membership¬–an important condition for the causal interpretation of our estimates. Second, in the announcement year, we detect no significant effect, which is unsurprising given that announcements may occur late in the calendar year and which suggests that capital allocation does not adjust immediately. Third, we observe a steadily increasing and statistically significant coefficient in each subsequent year following the announcement. This effect remains robust when controlling for country- and time-specific variation (column 5). Quantitatively, the estimated effect rises from approximately US$ 1.6 billion in the first year to US$ 6.5 billion by the fourth year, indicating substantial capital movement. Figure 4 provides a visual summary of these findings, suggesting that monetary policymakers can effectively foster a sustained transition towards green finance through their commitments to sustainability.

Figure 4 : Green bond analysis - Evolution of $NGFS$ coefficient



Notes: This graph illustrates the coefficients in equation (5) from Table 5. The error bars show the 95% confidence intervals for the coefficients.

5. Alternative explanations and robustness checks

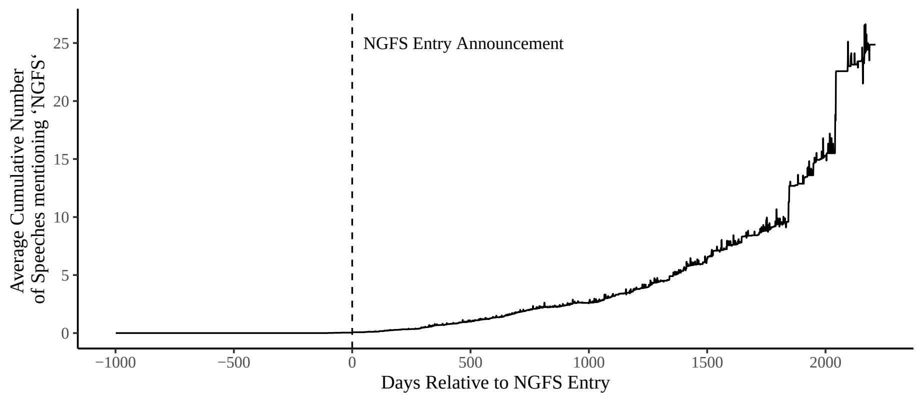
5.1. Anticipation through speeches

A potential concern is the possibility that central bankers may have provided advance signals regarding their NGFS membership through public speeches. If market participants then anticipated the central bank's decision to join the NGFS based on prior statements, the observed market reactions might be partially or fully endogenous to expectations rather than true surprises. To address this issue, we systematically investigate the presence of anticipatory signals in central bank speeches.

To assess whether central banks signalled their NGFS membership before official announcements, we rely on the central bank speech datasets compiled by

Baumgärtner and Zahner (2023) and Campiglio et al. (2025). These datasets contain transcriptions of speeches delivered by central bank officials across various institutions. We systematically search for mentions of "NGFS" within these speech databases, and count references to NGFS over time, examining whether central banks mentioned the NGFS before becoming members and whether speech frequency changes post-membership. The results of this exercise are presented within Figure 5.

Figure 5 : Mentioning of NGFS in central banks speeches over time



Notes: This graph depicts the frequency of "NGFS" mentions in central bank speech databases. Specifically, it tracks NGFS references over time and plots the average cumulative number of speeches against the days relative to NGFS membership entry.

We find that, with rare exceptions, central banks did not publicly discuss the NGFS before becoming members. Among the 83 central banks analyzed, only three instances of pre-membership mentions were identified: Banco Central de Chile (on November 18, 2020), the National Bank of Serbia (on April 16, 2021), and the Croatian National Bank (on April 29, 2021). These references, however, do not provide direct signals of impending membership but rather were generally framed as congratulatory statements toward existing members.

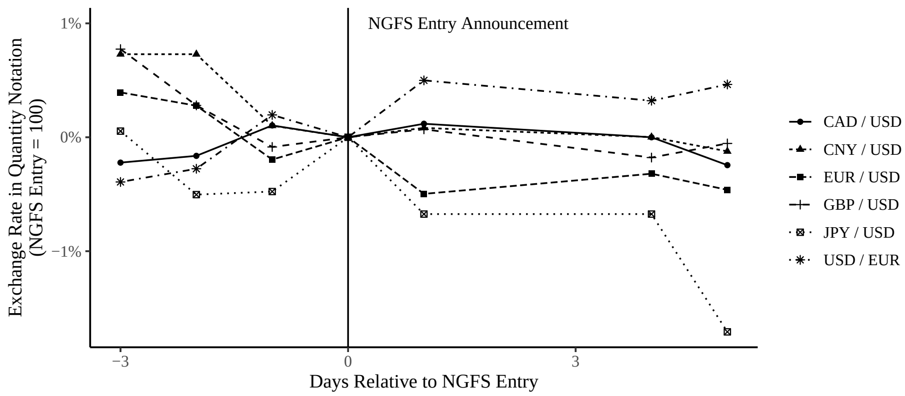
Figure 5 also shows significant increase in NGFS-mentions post-membership. On average, the term "NGFS" was used in approximately one speech in the first year after membership, rising to more than three speeches after three years, and reaching nearly ten speeches after five years, which suggests that NGFS participation significantly influences the discourse of central banks on sustainable finance.

5.2. Exchange Rate

A potential confounder is the possibility that exchange rate movements could distort our measured effects of NGFS announcements. If a currency systematically appreciates or depreciates following an announcement—perhaps due to speculation about future interest rate paths or capital flows—investor demand for domestic assets may shift for reasons unrelated to the central bank's climate policy stance. To assess this possibility, we collect high-frequency exchange rate data for major currencies around the relevant NGFS announcements by their issuing central banks.

Figure 6 presents our findings, revealing no systematic exchange rate response to NGFS announcements. The U.S. dollar, Canadian dollar, Chinese yuan, and British pound display appreciations, while the euro and Japanese yen depreciate, producing a mixed overall pattern. These inconclusive currency movements suggest that the observed market reactions are unlikely to be driven by exchange rate fluctuations.

Figure 6 : Exchange rates around NGFS entries



Notes: This graph depicts selected exchange rates relative to the respective NGFS entry announcements of the Bank of Canada, the Central Bank of the People's Republic of China, the ECB, the Bank of England, the Bank of Japan, and the Fed. The exchange rates are sourced from the FRED database in quantity notation. The base currency is the USD, for the Fed it is the EUR.

6. Conclusion

The urgency of transitioning to a sustainable economy in response to climate change has prompted central banks to take a more active role in addressing the green transition.

Empirical research assessing the effectiveness of green monetary policies faces significant identification challenges, due to the endogeneity of these actions to broader macroeconomic conditions and market expectations. To mitigate this issue, we treat the decision of central banks to join the NGFS – a global alliance of central banks dedicated to promoting the green transition – as a quasi-natural experiment. We interpreting the unexpected announcement of new memberships as green monetary policy surprises–unexpected shifts that deviate from market participants' prior expectations. Since joining the NGFS requires no modification to a central bank's mandate, we can use participation as an indicator of the institutions green preferences, thereby isolating the causal effects of green monetary policies on financial markets.

Our analysis indicates that NGFS membership correlates with the fulfillment of primary objectives, such as price stability and a positive output gap, suggesting that central banks view green policies as subordinate to their primary mandates. We then investigate the financial market reaction to such unexpected announcements of NGFS membership. Through two high-frequency event studies, we show that green stocks exhibit significant contemporaneous abnormal returns in the days following such announcements. In terms of magnitude: the market response to the Federal Reserve's accession to the NGFS is approximately twice the magnitude of the abnormal returns observed during the announcement of the Paris Agreement. Moreover, using granular firm-level data, we find reveals that these effects are especially pronounced for low-carbon firms.

Finally, we examine the transmission mechanisms of these green monetary policy surprises into capital debt markets. We find that green bond issuance in a country experiences a sustained increase following a central bank surprise announcement, with effects lasting for several years. The persistent effect underscores the ability of central banks to permanently stimulate capital flows towards environmentally sustainable projects.

Overall, our results highlight the pivotal role that central bankers can play in facilitating a sustained transition to a more sustainable economy through their commitments to green monetary policy.

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Appendix

Table A1: Founding members of the NGFS

	Institution	Type	Country
1.	Banco de Mexico	Central Bank	Mexico
2.	Bank of England	Central Bank	England
3.	Banque de France and Autorité Contrôle Prudentiel et de Résolution (ACPR)	Central Bank and supervisory authority	France
4.	De Nederlandsche Bank	Central Bank	Netherlands
5.	Deutsche Bundesbank	Central Bank	Germany
6.	Finansinspektionen	Supervisory authority	Sweden
7.	Monetary Authority of Singapore	Central Bank	Singapore
8.	People's Bank of China	Central Bank	China

Note: This table reports the eight founding members of the network "Network for Greening the Financial Sector" (NGFS) launched in December 2017 during the One Planet Summit event in Paris.

Table A2: Network development over time

Year	2017	2018	2019	2020	2021	2022	2023
Panel A: Overall development							
Announcements of network enlargements (central banks join the NGFS)	1	3	4	4	4	1	1
Number of central banks joining the NGFS	7	12	19	18	10	6	4
GDP per capita (in tUSD)							
- NGFS members	35.0	40.1	33.5	28.9	24.6	22.6	
- non-NGFS members	13.6	10.9	8.4	6.9	6.8	6.5	
GDP of countries with central bank joining the NGFS (in trUSD)	24.1	5.8	15.9	22.4	4.1	1.1	0.4
Total GDP of countries with central bank being a NGFS member (in trUSD)	24.1	29.9	45.8	68.2	72.3	73.4	73.9
Panel B: Geographical distribution							
Africa - total	0	1	3	5	5	9	11
- joining	-	1	2	2	-	4	2
Americas - total	1	1	4	8	13	14	15
- joining	1	-	3	4	5	1	1
Asia - total	2	3	8	14	16	17	18
- joining	2	1	5	6	2	1	1
Europe - total	4	12	21	27	30	30	30
- joining	4	8	9	6	3	-	-
Oceania - total	0	2	2	2	2	2	2
- joining	-	2	-	-	-	-	-
World - total	7	19	38	56	66	72	76
- joining	7	12	19	18	10	6	4

Note: Panel A shows the evolution of the network at year-end over time, as reflected in the official press releases on the NGFS website until June 2023, along several line-by-line characteristics: The number of announced expansions of the network, the number of central banks joining the NGFS per year, the absolute number of countries whose central banks are members of the network, and the GDP contribution per announcement and in absolute terms (in trillions of U.S. dollars). Data source for GDP data: World Development Indicators (WDI). For 2022 and 2023 the values for Barbados, Cayman Islands, Mauritania, Lebanon, Libya, Pakistan and Uganda for GDP are as of 2021, due to data availability. Panel B shows the geographic distribution of network development according to the United Nations geoscheme.

Table A3: MP Frameworks – Data Sources

Variable	Definition	Source
Panel A: Cross-sectional determinant regressions		
Membership in 2021	Binary variable measuring whether a central bank has joined the NGFS by the end of 2021.	Deutsche Bundesbank
Renewable production	Share of electricity generated by renewable power plants in total electricity generated by all types of plants. Proxy for national renewable production.	WDI: EG.ELC.RNEW.ZS
Energy use	Energy use (kg of oil equivalent per capita) refers to use of primary energy before transformation to other end-use fuels. Proxy for energy use.	WDI: EG.USE.PCAP. KG.OE
CO2 emissions (tons per capita)	Carbon dioxide emissions (metric tons per capita) are those stemming from the burning of fossil fuels and the manufacture of cement.	WDI: EN.ATM.CO2E.PC
Urban population in low elevation coastal zone	Country-level estimates of urban, rural and total population and land area country-wide and in the Low Elevation Coastal Zone, if applicable.	CIESNIN, Columbia University
Agriculture, forestry, and fishing (% of GDP)	Agriculture, forestry, and fishing corresponds to ISIC divisions 1-3 and includes forestry, hunting, fishing, cultivation of crops and livestock production. Proxy for agricultural exposure.	WDI: NV.AGR.TOTL.ZS
GDP per capita constant 2010 US$	GDP per capita is gross domestic product divided by midyear population. GDP per capita is measured in thousands of US-Dollars.	WDI: NY.GDP.PCAP.KD
Central bank independence index	Central Bank Independence Index as constructed and provided by Romelli (2022). Proxy for the institutional level and the of autonomy of countries' central banks.	Romelli (2022)
Border	Information about joint borders of neighbouring countries (binary indicator taking the value 1 if countries share borders). Based on country-level data as provided by CEPII.	CEPII
Distance capital	Distances between capitals of countries. Calculated using measures of bilateral distances between countries using city-level data as provided by CEPII.	CEPII
Panel B: Panel determinant regressions		
Joining NGFS	Binary variable that takes the value 1 if central bank i joined the NGFS in year t and 0 otherwise.	Deutsche Bundesbank
Inflation gap	Annual CPI; HP Filtered Gap; 1980-2023.	WDI: FP.CPI.TOTL.ZG
GDP gap	GDP in 2010 US$; HP Filtered Gap; 1980-2023.	WDI: NY.GDP.MKTP.KD
Unemployment rate	Unemployment as % of total labor force. Unemployment refers to the share of the labor force that is without work but available for and seeking employment.	WDI: SL.UEM.TOTL.ZS

Table A3 (continued)

Panel C: Event study I - Global financial market reaction		
AR clean energy stocks [t]	Abnormal returns for clean energy stocks on each day of the specified event window. Calculated using an event study methodology.	Own calculation; Datastream
AR fossil fuel stocks [t]	Abnormal returns for fossil fuel stocks on each day of the specified event window. Calculated using an event study methodology.	Own calculation; Datastream
AR difference portfolio [t]	Difference between abnormal returns for clean energy and fossil fuel stocks on each day of the specified event window.	Own calculation; Datastream
CAR clean energy [t1;t2]	Cumulative sum of the calculated abnormal returns for clean energy stocks and the respective time interval specified.	Own calculation; Datastream
CAR fossil fuel [t1;t2]	Cumulative sum of the calculated abnormal returns for fossil fuel stocks and the respective time interval specified.	Own calculation; Datastream
CAR difference portfolio [t1;t2]	Cumulative sum of the difference between abnormal returns for clean energy and fossil fuel stocks and the respective time interval.	Own calculation; Datastream
Network enlargement [world]	Relative GDP contribution per joining date, measured in relation to the world-wide year end GDP in the respective joining year.	Own calculation; WDI: NY.GDP.MKTP.KD
Network size (ln)	Size of the network measured as the sum of each members' GDP after the respective announcement date.	Own calculation; WDI: NY.GDP.MKTP.KD
Abnormal network size	Demeaned size of the network measured as the sum of each members' GDP after the respective announcement date.	Own calculation; WDI: NY.GDP.MKTP.KD
Panel D: Event study II - US firm-level event study analysis		
Environmental score	Environmental pillar score as provided by Refinitiv	Datastream
Emissions score	Emissions score as provided by Refinitiv.	Datastream
Emission intensity	Calculated as the sum of Scope 1- and Scope 2 emissions (in kilotons) scaled by market capitalization (in million US-Dollars).	Own calculation; Datastream
Size	Logarithm of the book value of total assets (measured in thousands of US-Dollars).	Own calculation; Datastream
Sales growth	Year-on-year growth of net sales.	Own calculation; Datastream
Leverage	Total debt divided by the book value of total assets.	Own calculation; Datastream
Profitability	Net income scaled by the book value total assets.	Own calculation; Datastream
ETR	Measure of cash effective tax rate following Bauer et al. (2023). Calculated as (total) income tax paid scaled by pre-tax income.	Own calculation; Datastream
Return (Price), raw	Equity market returns from December 14 to December 15, 2020, based on adjusted closing prices.	Own calculation; Datastream
Panel E: Green bond issuance reaction		
Green Bonds	Issue amount of green and sustainability-linked bonds, designed specifically to support climate and environmental projects. Reported in billion US-Dollars per country and year.	IMF Dataset

Note: This table provides variable definitions and sources. Panel A reports variables used in the cross-sectional determinant regressions. Panel B reports variables used in the panel-data determinant regressions. Panel C and D report variables used in the stock market- and event study analyses (part I and II), respectively. Panel E reports the variables used for analysis of the medium-term transmission, focusing on green bonds issuances.

Table A4: Descriptive statistics

Variable	N	Mean	SD	Min	Max
Panel A: Cross-sectional- and panel determinant regressions					
Membership in 2021	152	0.43	0.50	0.00	1.00
Renewable Production	152	0.00	1.00	-1.02	2.06
Energy use	124	0.00	1.00	-0.81	5.47
CO2 emissions	151	0.00	1.00	-0.89	5.51
Urban population in coastal zone	147	0.00	1.00	-0.73	4.67
Agriculture, forestry, and fishing	148	0.00	1.00	-0.96	4.77
Central bank independence index	152	0.00	1.00	-2.51	1.42
GDP per capita	151	0.00	1.00	-0.75	4.70
NGFS Border	152	0.57	0.50	0.00	1.00
Panel B: Panel determinant regressions					
Joining NGFS	590	0.12	0.33	0.00	1.00
Inflation gap	590	-0.03	0.88	-2.94	3.87
Output gap	590	0.05	1.52	-5.03	3.71
Unemployment rate	590	7.61	5.08	0.12	34.01
GDP per capita	590	23.05	22.92	0.83	104.62
Panel C: : Event study I - Global financial market reaction					
CAR clean energy stocks [-1;1]	17	-0.642	2.062	-4.390	2.332
CAR clean energy stocks [-1;3]	17	-0.330	2.865	-6.400	4.721
CAR difference portfolio [-1;1]	17	-0.054	3.318	-7.427	6.404
CAR difference portfolio [-1;3]	17	0.204	3.738	-8.146	8.417
GreenMPSurprise	17	0.035	0.060	0.001	0.240
Network size (ln)	17	3.888	0.371	3.256	4.302
Abnormal network size	17	0.000	0.371	-0.632	0.414
Panel D: Event study II - US firm-level event study analysis					
Environmental score	3,097	0.28	0.27	0.00	0.98
Emissions score	3,097	0.28	0.31	0.00	1.00
Emission intensity	1,034	0.29	0.91	0.00	6.51
Size	3,097	14.52	1.83	10.89	19.14
Sales growth	3,097	0.08	0.63	-0.87	4.66
Leverage	3,097	0.25	0.24	0.00	1.05
Profitability	3,097	-0.05	0.20	-1.05	0.29
ETR	3,097	0.09	0.42	-2.60	1.61
Return (Price), raw	3,097	1.88	2.58	-6.79	10.63
Panel E: Green bond issuance					
Green Bonds	975	2.125	7.772	0.000	99.429
NGFS-Membership	975	0.237	0.425	0	1
Year-Dummy	975	–	–	2010	2022

Note: This table provides descriptive statistics for our variables defined in Table A3 and adopts the structure. Panel A reports variables used in the cross-sectional determinant regressions. Panel B reports variables used in the panel-data determinant regressions. Panel C and D report variables used in the stock market- and event study analyses (part I and II), respectively. Panel E reports the variables used for analysis of the medium-term transmission, focusing on green bonds issuances. The data in Part A is mostly demeaned and standardized (except for dummy variables).

Table A5: ETFs underlying the industry proxies

Industry	ETF	ISIN
Clean energy		
	VanEck Vectors Environmental Svcs ETF	US92189F3047
	First Trust ISE Global Wind Energy Index Fund	US33736G1067
	VanEck Low Carbon Energy ETF	US92189F5026
	iShares Global Clean Energy ETF	US4642882249
	Invesco Global Clean Energy ETF	US46138G8472
	Invesco Wilderhill Clean Energy ETF	US46137V1347
	First Trust NASDAQ Clean Edge Green Energy Index Fund	US33733E5006
	Invesco Solar ETF	US46138G7060
Energy intensive		
	First Trust Energy AlphaDEX ETF	US33734X1274
	iShares US Oil & Gas Explor&Prodtn	US4642888519
	iShares Global Energy	US4642873412
	iShares United States Energy	US4642877967
	VanEck Vectors Oil Services ETF	US92189H6071
	Invesco S&P 500 Equal Wt Energy ETF	US46137V3657
	United States Oil ETF	US91232N2071
	Vanguard Energy ETF	US92204A3068
	SPDR S&P Oil & Gas Equipment & Svcs ETF	US78468R5494
	Energy Select Sector SPDR ETF	US81369Y5069
	SPDR S&P Oil & Gas Explor & Prodtn ETF	US78468R5569

Note: This table provides details on the ETFs used to calculate the stock market performance of the industry proxies used in the event study. The ETF selection is based on Antoniuk & Leirvik (2024) and Wallace & McIver (2019) and incorporates exchange traded funds which invest in the stocks of the respective industries.

Online Appendix (not intended for publication)

This online appendix provides supplementary material for the accompanying paper, "Measuring the Effect of Green Monetary Policy Surprises". Section I details the construction of the five datasets utilized in the main paper. Section II presents robustness checks and additional analyses, expanding upon the results presented in the paper.

B1. Sample construction process

In this section we provide information on the construction of our five datasets following the structure of the paper.
The first two datasets, based on a confidential dataset as provided by the Deutsche Bundesbank (German Federal Bank), are country-level. They enable us to: (1) analyze cross-country determinants of central bank membership in the Network for Greening the Financial System (NGFS) and (2) investigate the roles of both primary (price stability) and secondary (economic slack) central bank objectives on NGFS membership decisions within a panel framework.
Datasets 3 to 4 focus on market reactions to NGFS network expansions, which we consider as a form of green monetary policy surprise, by focusing on two different dimensions. Dataset 3 leverages public announcements of NGFS enlargements to conduct a high-aggregate event study, examining the global financial market's overall response to central banks network entries. Dataset 4, at the (more granular) firm level, analyzes the stock market reaction following the Federal Reserve's December 2020 entry into the NGFS.
Finally, dataset 5 complements these short-term analyses by examining the medium term transmission of NGFS membership through central banks green bond issuances at the country-level.

Cross-sectional determinants of central bank's NGFS membership

To examine cross-sectional factors influencing NGFS participation, we utilize a confidential dataset from the Deutsche Bundesbank, which includes the exact joining dates for each member until April 2023.[19]
First, we complement the dataset with 1) macroeconomic data from the World Bank's World Development Indicators, (2) population data from the CIESIN (Center for Integrated Earth System Information, Columbia University), (3) the central bank independence index developed by Romelli (2022), and (4) geographical data on shared borders and inter-capital distances from the CEPII (Centre d'Etudes Prospectives et d'Informations Internationales). This expanded dataset encompasses up to 217 countries.

[19]This initial dataset covers 126 observations, including central banks and (non-central bank) financial supervisory institutions.

Second, focusing on country-level macroeconomic variables, we exclude 2 supranational central banks (e.g., the European Central Bank) and 40 non-central bank financial supervisory institutions (e.g., the Swedish Finansinspektionen).
Finally, we construct a binary indicator being 1 if the central bank i was a NGFS member as of 2021. All covariates stem from pre-2021, to address potential endogeneity concerns and are demeaned and standardized to facilitate the interpretation of the coefficients. In total, this first (cross-sectional) dataset covers up to 152 observations.

The role of primary and secondary objectives

To empirically examine the relationship between central banks' primary (price stability) and secondary (economic slack) objectives and their decisions to join the NGFS, we again utilize the confidential dataset as provided by the Deutsche Bundesbank. First, we create a binary variable that is equal to 1 if central bank i joined the NGFS in year t and 0 otherwise, to construct a panel dataset.[20] Second, we complement this panel dataset (1) information on central banks' primary (price stability) objectives, represented by the absolute deviation from trend inflation ($|\pi_t - \hat{\pi}|$) and (2) secondary (economic slack) objectives, represented by the output gap ($x_t - \hat{x}$).[21] Annual consumer price indices and GDP data (in constant 2010 US dollars) from the World Bank's World Development Indicators are used to calculate these key independent variables. Finally, we further include unemployment rates again sourced from the World Bank. In total, this second (panel) dataset covers up to 567 central bank-year observations.

Event Study I: Global financial market reaction

Interested in examining the (global) market reaction o NGFS network expansions (green monetary policy surprises), we construct a third dataset that allows us to examine the aggregate global financial market response. More precisely, we employ an event study approach with short event windows to assess the stock market impact of NGFS enlargements.
First, to determine the exact date on which the markets became aware of the addition of a new NGFS member, we manually collect information from press releases published on the NGFS website (NGFS, 2023) between January 2018 and June 2023. This procedure yields 17 distinct events across 76 central banks (following the foundation event). Second, we complement this dataset with data on daily market, 'brown' and 'green' stock price data from Refinitiv Datastream. We proxy the (global) stock market performance of specific climate-sensitive industries (i.e., "brown" and "green") by the performance of thematically aligned ETFs

[20] Again, we exclude 2 central banks at the supranational level (e.g., the European Central Bank) and 40 non-central bank financial supervisory institutions.

[21] Deviations in inflation and output from trend are estimated using an HP filter applied to annualized inflation rates and real output data (1980-2023) sourced from the World Bank's World Development Indicators.

(Antoniuk & Leirvik, 2024; Bauer et al., 2024; Ramiah et al. (2013); Wallace & McIver, 2019).[22]

Third, using event study methodology, we calculate (cumulative) abnormal returns for an equally-weighted portfolio of sector-specific ETFs for each of the 17 events. Given the global investment focus of most ETFs and the nature of our event data, we use daily returns of the MSCI World Index as a proxy for the market (portfolio) returns in the event study. Methodology-wise, we employ a market-model event study specification, where we use an estimation period of approximately 200 trading days, ranging from -230 to -30 trading days prior to the respective events (following Antoniuk & Leirvik, 2024). In addition, we calculate cumulative abnormal returns across different event windows ranging from -3 to +1 trading day around the events. We match these cumulative abnormal returns to the dataset containing the NGFS joining dates as described above.

Finally, we complement the dataset consisting of 17 with absolute GDP data (in constant 2010 US dollars) for all joining members, sourced from the World Bank's World Development Indicators. Interested in the correlation between the announcements and cumulative abnormal returns, we measure our key independent variable *GreenMPSurprise* in terms of GDP contribution of new NGFS members on each joining date relative to contemporaneous worldwide year-end GDP.

In total, our third dataset covers 17 distinct announcement dates related to 76 central banks joining the NGFS during the 5.5-year sample period (January 2018 to June 2023).

Event study II: US firm-level reaction

Interested in examining stock market reactions following the Federal Reserve's December 2020 entry into the NGFS, we construct our fourth dataset on the more granular firm-level, following the methodology of Bauer et al. (2024).

Given that the Federal Reserve announced to join the NGFS on December 15, 2020, and the announcement was made public at 9 a.m., we use (raw) equity market returns from December 14 to December 15, 2020 to capture the short-term market reaction. Interested in the role of "green" and "brown" firm characteristics in the cross-section we include three different measures of firms' greenness: (1) Environmental score, (2) emissions score and (3) emission intensity.[23]

In constructing the dataset, we proceed in five steps. First, we carefully start constructing our sample by retrieving all available U.S. securities included in the

[22] We are unable to find press statements for eight cases listed in the NGFS member list as provided by the Deutsche Bundesbank. We ignore events when central banks join the network for which we are unable to find an official press release, as it is arguably difficult to identify the timing of the flow of information in these cases. In total, we find 17 events cover 76 different central banks joining the network.

[23] While the first two metrics, as designated by Refinitiv, offer indirect measures of environmental performance, we incorporate firms' self-reported emissions data to provide a more direct and granular assessment of their greenness. We calculate emission intensity as the sum of Scope 1 and Scope 2 emissions, standardized by market capitalization.

Refinitiv U.S. ESG-Universe as of December 9, 2024 (Bauer et al., 2024). Our initial dataset consists of 3,649 individual securities. Second, we then exclude securities with missing emissions scores for 2020, reducing the sample to 3,130 securities. Third, in line with established practices, we further refine our sample by excluding non-equity and non-primary security types (e.g., Ince & Porter, 2006). Fourth, as we focus on U.S. firms (more precisely, equity returns of firms being traded on U.S. stock exchanges on our event day), we also exclude all firms not listed on either the NYSE, NASDAQ, or AMEX, following the approach of Bauer et al. (2024).[24] Fifth, we exclude firms with earnings announcements or closing prices below $1 on the event days (December 14 to December 15, 2020), and require non-missing firm-level control covariates as per 2020.[25] These refinements result in an intermediate sample of 2,693 firms. To encounter a survivorship bias (e.g., Hanauer, 2014), we supplement this sample with delisted or dead companies.[26] By applying the same filtering criteria as above we account for additional 404 firms. In total, our fourth dataset covers a maximum of 3,097 firm observations.

Green bond issuance reaction

For our fifth dataset, we complement the short-term analyses from above by examining the medium-term transmission of NGFS membership through central banks green bond issuances at the country-level. As such, we focus on the implications of NGFS expansions, i.e., green monetary policy surprises, specifically examining whether our surprises can persistently stimulate capital flows to green projects, rather than just having immediate or short-term impacts (e.g., Diluiso et al., 2021).

To analyze this medium-term relationship, we merge our first dataset (see above) of country-level green monetary policy surprises (i.e., the NGFS joining dates) with the IMF's Climate Change Green Bonds database (Mertzanis, 2024). This database compiles fixed-income instruments designed to finance or refinance sustainability projects, commonly referred to as 17 "green bonds".

In total, this fifth dataset encompasses green bond issuances across 75 countries from 2010 to 2022, and up to 975 country-year observations.

[24] This constituent list corresponds to Refinitiv list identifier *LA4CTYUS*.

[25] These control covariates include: firm size (measured as the natural logarithm of market capitalization), sales growth (year-on-year change in net sales), book leverage (total debt scaled by total assets), and profitability (net income scaled by total assets), the effective tax rate (ETR, calculated as the ratio of total income taxes paid to pretax income), and industry controls based on the Fama-French classification scheme, which categorizes firms into 17 industries based on SIC codes. To account for potential outliers, we winsorize all variables (except for E-/emission scores) at the 1% percentiles.

[26] Given that the U.S. ESG-Universe exclusively encompasses active companies, we supplement our intermediate sample with delisted and dead firms that satisfy the same selection criteria as the U.S. sample mentioned above. These firms are identified via the global ESG/Sustainable Finance inactive list (*LA4GLINA*).

B2. Robustness of results and additional analyses

This section details robustness checks and supplementary analyses, focusing primarily on the U.S. firm-level event study examining stock market reactions to the Federal Reserve's December 2020 NGFS membership.

Event Study I: Global financial market reaction

This section presents additional robustness checks for the global financial market reaction. A potential concern is that the MSCI World Index, used in our first event study, may overrepresent the United States, with approximately 74% of its constituents being US firms.[27]

To further address this concern, we replicate the global event study results from Table 3, using the MSCI World All Country Index as the market benchmark returns when calculating our cumulative abnormal returns. This index features a lower US firm share of approximately 67%.[28] The results are depicted in Table B1.

[27] See index methodology from MSCI, available at https://www.msci.com/index-methodology.
[28] See index methodology from MSCI, available at https://www.msci.com/index-methodology.

Table B1: Event study I results – global financial market reaction with alternative market (benchmark) returns

	Dependent variable CAR:				
	clean energy - fossil fuel				clean energy
	(1)	(2)	(3)	(4)	(5)
GreenMPSurprise	34.29***	37.34*	35.48***	27.06***	25.53***
	(4.26)	(2.03)	(3.47)	(4.57)	(4.03)
Abnormal Network size			-2.01	-1.13	-1.73
			(-0.92)	(-0.73)	(-1.08)
Constant	-1.00	-0.56	-1.04	-1.30	-1.06
	(-1.06)	(-0.40)	(-1.08)	(-1.60)	(-1.16)
Observations	17	17	17	17	17
R-squared	0.30	0.30	0.33	0.32	0.24
Method	OLS	Median	OLS	OLS	OLS
Event window	[-1;+3]	[-1;+3]	[-1;+3]	[-1;+1]	[-1;+3]

Note: This table reports the results of OLS- and median regressions of the cumulative (average) abnormal returns (CAR) of clean energy stocks and a difference portfolio on the respective network enlargements by national banks joining the Network for Greening the Financial System. The difference portfolio is computed as the difference in cumulative returns between clean energy and fossil fuel stocks, mimicking a portfolio that is long in clean energy- and short in fossil fuel stocks. *GreenMPSurprise* is defined as the network enlargement, and calculated as the relative GDP contribution per joining date, in relation to the world-wide year end GDP in the respective joining year. Abnormal network size is calculated as the demeaned size of the network measured as the sum of each members' GDP after the respective announcement date (Specifications 3 to 5). Robust t-statistics are in parentheses. ***, **, and *denote statistical significance at the 1%, 5%, and 10% levels. A detailed description of the variables used is provided in Table A4.

Event study II: US firm-level reaction

In this section, we provide additional robustness tests and analyses regarding the firm-level stock market reaction following the NGFS joining of the FED on December 15, 2020. We proceed in several steps. First, following Bauer et al. (2024) we utilize the Frisch-Waugh-Lovell Theorem to examine the cross-sectional baseline regressions (see Table 4) in more detail. Second, as common in empirical finance studies, we check whether our estimates are robust to the exclusion of financial firms. Third, we re-estimate our baseline regression from Table 4 using lagged control variables. Finally, we conduct additional analyses regarding the emission intensity.

To examine our baseline regression results of the US firm-level analysis in more detail, we further investigate the cross-sectional correlations between firms' green characteristics and their returns by utilizing portfolio (decile) regressions. We follow Bauer et al. (2024) and orthogonalize returns and green characteristics by our control covariates. Invoking the Frisch-Waugh-Lovell theorem, by regressing the orthogonalized returns on the respective orthogonalized green characteristics, we exactly recover our regression coefficients for the E-/Emissions score and emission intensity from Table 4. We then sort our greenness characteristics in decile portfolio and plot them against their respective mean portfolio returns. By conducting this exercise, we end up with three plots which allow us to inspect the correlations in more detail. The corresponding results are depicted within Figure B1.

Overall, we corroborate our initial regression results for all of our greenness characteristics. More precisely, we show that the overall statistical significances in our event return regressions are primarily driven by firms which are sorted into the lowest and highest deciles of E-/Emission scores, and emission intensities, respectively. Green firms, as characterized by high E-/Emission scores and low emission intensities outperform their counterparts on the event day.

Our findings reveal that, in magnitude, the returns of green firms exceed those of brown firms by approximately 1.25 percentage points when proxied using E scores and emissions scores, and by approximately 0.5 percentage points when proxied using emission intensity Finally, the (mostly) non-overlapping green and brown confidence intervals confirm the statistical significance of our results for all three greenness measures (Bauer et al., 2024).

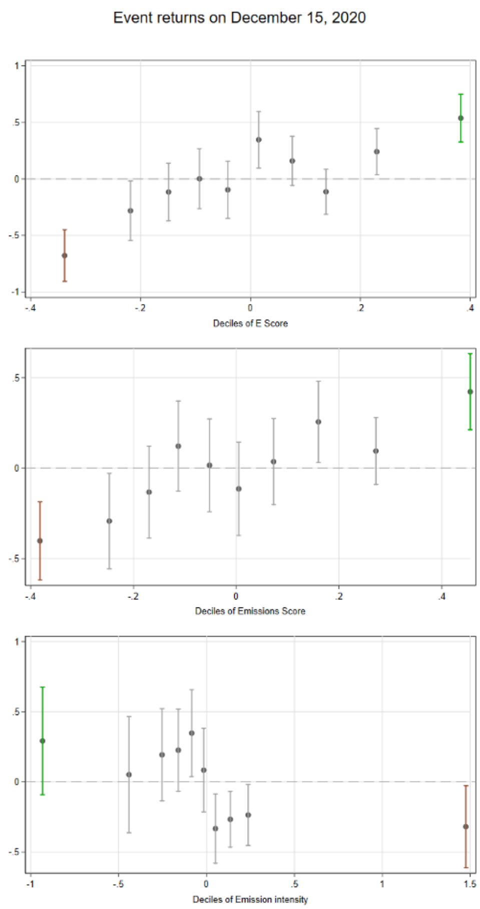

Figure B1 : Event returns across decile portfolios

Notes: This figure reports additional information on our baseline regressions as illustrated in Table 4. It presents event returns for decile portfolios sorted on three greenness metrics: Environmental scores, emission scores, and emission intensities. Portfolios are formed for the FEDs entry to the NGFS (on December 15, 2020). Event returns are calculated for each decile, controlling for firm-level covariates by orthogonalizing them with respect to firm size, sales growth, leverage, profitability, and effective tax rate (additionally, we account for industry-fixed effects when running regressions with emission intensity as our key independent variable of interest). All regressions include robust t-statistics that allow for clustering at the industry-level. For the emission intensity portfolios, all calculations incorporate industry fixed effects based on the Fama-French classification (17 industries). In all illustrations, the vertical bars represent 90% confidence intervals. Greenest (brownest) deciles are visually highlighted in green (brown).

Following standard practice in empirical finance research, we assess the robustness of our estimates by excluding financial firms. Specifically, we reestimate our baseline regression model from Table 4, omitting financial firms as defined by the Fama-French 17 classification scheme. The results, presented in Table B2, confirm the robustness of our findings, with coefficients for E scores and emissions scores exhibiting slightly higher statistical significance, while those for emission intensity show slightly lower significance. These results reinforce our initial conclusions.

Table B2: Event study II results – US firm-level reaction - US firm-level reaction excluding financials

	Dependent variable CAR:		
	Raw Return (Dec 14-15, 2020)		
	(1)	(2)	(3)
E (of ESG)	1.518***		
	[4.46]		
Emission score		1.054***	
		[3.64]	
Emission intensity			-0.272**
			[-2.87]
Constant	5.413***	5.162***	
	[11.41]	[9.38]	
Observations	2,401	2,401	863
Adjusted R^2	0.041	0.036	0.118
Industry fixed effects	No	No	Yes

Note: This table reports the results of regressions of the (individual) raw returns of US firms on three environmental measures and a set of firm controls. While specifications (1) and (2) employ the environmental and emissions score as proxies for measuring firms' greenness, specification (3) uses firms' emission intensity. All models include controls for firm size, sales growth, leverage, profitability, and effective tax rate. Additionally, specification (3) incorporates industry fixed effects based on the Fama-French classification (17 industries). Robust T-statistics are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels. A detailed description of variables used is provided in Table A4.

In our baseline regressions, we use firm-level environmental and accounting data from the end of 2020, as our event of interest took place in mid-December 2020, making year-end data the most relevant for capturing the firm's characteristics near the event date. To address potential concerns with this approach, we follow a standard methodology by lagging all control covariates by one period (i.e., by one year). Table B3 presents the results of this exercise. Our results remain robust to this analysis, with slightly reduced statistical significance across all greenness measures. However, all measures remain statistically significant at the 5% level.

Table B3: Event study II results – US firm-level reaction – lagged control covariates

	Dependent variable CAR:		
	Raw Return (Dec 14-15, 2020)		
	(1)	(2)	(3)
E (of ESG)	1.218**		
	[2.74]		
Emission score		0.786**	
		[2.48]	
Emission intensity			-0.223**
			[-2.37]
Size_{t-1}	-0.192**	-0.157**	-0.226**
	[-2.92]	[-2.52]	[-2.92]
$\text{Sales growth}_{t-1}$	-0.340***	-0.355***	-0.756
	[-4.43]	[-4.70]	[-1.54]
Leverage_{t-1}	0.345	0.319	0.125
	[0.78]	[0.72]	[0.34]
$\text{Profitability}_{t-1}$	1.617***	1.644***	-1.609
	[5.01]	[5.06]	[-1.50]
$\text{Effective tax rate}_{t-1}$	0.014	0.024	-0.114**
	[0.14]	[0.24]	[-2.46]
Constant	4.244***	3.860***	
	[5.36]	[5.07]	
Observations	2,916	2,916	1,013
Adjusted R^2	0.022	0.017	0.152
Industry fixed effects	No	No	Yes

Note: This table reports the results of regressions of the (individual) raw returns of US firms on three environmental measures and a set of firm controls. While specifications (1) and (2) employ the environmental and emissions score as proxies for measuring firms' greenness, specification (3) uses firms' emission intensity. All models include controls for firm size, sales growth, leverage, profitability, and effective tax rate. All control covariates are lagged by one period. Additionally, specification (3) incorporates industry fixed effects based on the Fama-French classification (17 industries). Robust T-statistics are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels. A detailed description of variables used is provided in Table A4.

Finally, following recent literature (e.g., Perdichizzi et al., 2023), we conduct a more detailed analysis of the correlation between emission intensity and firms' event returns. Defining emission intensity as the sum of Scope 1 and Scope 2 emissions standardized by market capitalization allows us to further decompose this measure into separate Scope 1 and Scope 2 intensities.

Table B4 presents the results: Model (1) replicates our baseline results for total emission intensity, while Columns (2) and (3) report the estimates for Scope 1 and Scope 2 emission intensities, respectively. Our findings indicate that the observed correlation between emission intensity and firms' event returns is primarily driven by Scope 1 emissions, as the coefficient for Scope 1 intensity is statistically significant, whereas that for Scope 2 intensity is insignificant. These results enhance our previous findings by demonstrating that emission activities directly "controlled" by firms - and thus more directly attributable to them by investors and the stock market - drive the observed negative correlation between emission intensity and equity returns on our event day.

Table B4: Event study II results – US firm-level reaction - CO_2 Scope analysis

	Dependent variable CAR:		
	Raw Return (Dec 14-15, 2020)		
	(Scope 1)	(Scope 2)	(Scope 3)
E (of ESG)	-0.280***	-0.318***	-0.708
	[-2.94]	[-2.96]	[-1.10]
Size	-0.268***	-0.267***	-0.248***
	[-4.97]	[-5.04]	[-4.50]
Sales growth	-0.591	-0.596	-0.597
	[-1.32]	[-1.34]	[-1.34]
Leverage	0.208	0.213	0.126
	[0.78]	[0.81]	[0.45]
Profitability	-0.234	-0.209	-0.189
	[-0.31]	[-0.27]	[-0.25]
Effective tax rate	-0.201**	-0.202**	-0.190**
	[-2.73]	[-2.83]	[-2.47]
Observations	1,034	1,034	1,034
Adjusted R^2	0.124	0.126	0.114
Industry fixed effects	Yes	Yes	Yes

Note: This table reports the results of regressions of the (individual) raw returns of US firms on three different measures of CO2 emission intensities and a set of firm controls. Specification (1), (2) and (3) employ firms' emission intensities as based on their total, Scope 1, and Scope 2 emissions, respectively. All models include controls for firm size, sales growth, leverage, profitability, and effective tax rate. All specifications incorporate industry fixed effects based on the Fama-French classification (17 industries). Robust T-statistics are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels. A detailed description of variables used is provided in Table A4.